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U.S. Department of Transportation
Federal Highway Administration

Selected Methods and Profiles for Conversion of Bridge Component-Level and Element-Level Condition Data

August 2024

FHWA-HIF-24-018

Federal Highway Administration

Office of Bridges and Structures
1200 New Jersey Avenue, SE
Washington, DC 20590

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As of June 30, 2023

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TECHNICAL REPORT DOCUMENTATION PAGE

1. Report No. FHWA-HIF-24-018	2. Government Accession No. None	3. Recipient's Catalog No. None
4. Title and Subtitle Selected Methods and Profiles for Conversion of Bridge Component-Level and Element-Level Condition Data, Final Report		5. Report Date August 2024 6. Performing Organization Code: None
7. Author(s) Saeed Nejad, Richard A. Walther, Jonathan C. McGormley		8. Performing Organization Report No. None
9. Performing Organization Name and Address Wiss, Janney, Elstner Associates, Inc. (WJE) 330 Pfingsten Road Northbrook, IL 60062		10. Work Unit No. None 11. Contract or Grant No. 693JJ319D000022 / 693JJ321F000144
12. Sponsoring Agency Name and Address Office of Bridges and Structures Federal Highway Administration 1200 New Jersey Avenue, SE Washington, DC 20590		13. Type of Report and Period Final Report, May 2021 – December 2023 14. Sponsoring Agency Code HIBS-30
15. Supplementary Notes The sponsoring agency technical lead was Derek Constable, Bridge Management Engineer		

16. Abstract

The safety, mobility, and accessibility of the United States' highway transportation network depends on the effective operation and maintenance of over 620,000 bridges nationwide, as well as strategic investment in new and replacement bridges. Critical to these efforts is the collection of condition and performance data for each asset. Historically, the health of our Nation's bridge inventory has been defined by two very different condition data sets. The first condition data set assesses only the bridge components defined as the deck, superstructure, substructure and culvert while the second, assesses the individual elements which define a bridge or culvert.

Federal Highway Administration (FHWA) and researchers developed various "translators" to convert structural element-level condition states into component ratings and vice versa. The 2013 FHWA "*Converter Technical Manual*" was one of the primary tools to establish the relationship between component ratings and element condition states collected in accordance with the AASHTO Manual for Bridge Element Inspection (MBEI). However, the developed profiles were derived from a limited data set available at the time. With the current nationwide efforts to collect element-level data, FHWA has amassed element-level data for all bridges on the National Highway System (NHS), making it possible to refine or create new "translator" models.

The primary objective of this report is to create multiple conversion profiles to convert element-level condition states to component-level condition ratings, while considering material composition as a major subfactor. These profiles included a universal conversion profile (element to component) that was representative of all element and component types and four component conversion profiles that were representative of each component (deck, superstructure, substructure, and culvert) irrespective of material type. Conversion profiles that considered the material composition of each component were also developed. Lastly, a universal conversion profile that converts the component-level condition rating into the element-level condition states was developed. This conversion profile was representative of all element and component types, irrespective of material type. These conversion profiles may support the forecasting of future component conditions when element-level deterioration models are used and support quality review of inspection data to identify potential gross discrepancies.

This report provides a step-by-step summary of the efforts undertaken to develop the various conversion profiles and includes sufficient details so that an independent party can repeat the process to update the profiles as additional data becomes available.

17. Key Words bridge management, bridge condition data, conversion profiles, component, and element conversions		18. Distribution Statement No restrictions. This document is available to the public through the National Technical Information Service, Springfield, VA 22161. https://www.ntis.gov	
19. Security Classif. (of this report) Unclassified	20. Security Classif. (of this page) Unclassified	21. No. of Pages 116	22. Price

Form DOT F 1700.7 (8-72) Reproduction of completed page authorized

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ACRONYMS AND ABBREVIATIONS

AASHTO .... American Association of State Highway and Transportation Officials

ADE .... Agency Defined Element

BME .... Bridge Management Element

BMS .... Bridge Management System

BrM .... AASHTOWare™ Bridge Management Software

CoRE .... Commonly Recognized Structural Elements

CR .... Component-level Condition Rating

CS .... Element-level Condition State

DOT .... Department of Transportation

DT .... Decision Tree

FHWA .... Federal Highway Administration

MBEI .... Manual for Bridge Element Inspection

ML .... Machine Learning

NBE .... National Bridge Element

NBI .... National Bridge Inventory

NHS .... National Highway System

INTRODUCTION

The safety, mobility, and accessibility of the United States highway transportation network depends on the effective operation and maintenance of over 620,000 bridges nationwide. Central to this is the inspection of bridges to assess condition, and strategic investment in maintenance, preservation, rehabilitation, and replacement.

Since 1972, inventory, condition, and performance data associated with all bridges on public highways in the United States has been collected and reported to Federal Highway Administration (FHWA). Bridge-specific information such as age and service, functional descriptions, geometric data, structure type and materials, loads and load ratings, inspection date and frequency, navigation data, condition ratings, and other data are collected through regularly scheduled bridge inspections. Data is then reported to an FHWA database known as the National Bridge Inventory (NBI).

General condition ratings are assigned to major bridge components including deck, superstructure, and substructure, as well as culverts. The condition ratings assigned during inspections utilize a 0 to 9 scale based on the severity, extent, and effect of the deterioration on strength or serviceability, with 0 being the lowest or worst condition and 9 the best. These ratings provide a consistent standard for the collection of bridge and bridge-length culvert data but lack granularity to support refined maintenance, preservation, rehabilitation, and replacement decision-making that include economic considerations.

Element-level data collection for bridges was introduced nationally and standardized in the 1990s by AASHTO's "*Guide for Commonly Recognized (CoRE) Structural Element*s" and more recently the "*Manual for Bridge Element Inspection (MBEI)*". It was introduced to support refined condition and needs assessment and asset management modeling, analysis, and decision making. Element-level data is designed to improve objectivity and provide quantitative information about the condition of each bridge element that comprises a bridge component along with detail on the severity and extent of deterioration or damage within each element.

Starting in 2014, States that were not collecting element data began collecting it for bridges on the National Highway System (NHS) for reporting to the NBI. To support the reporting of element-level data, FHWA issued the "Specification for the National Bridge Inventory - Bridge Elements", which references the AASHTO MBEI. Table 1 lists the bridge elements that have inventory and condition data reported to the NBI.

Element-level data collection does not relieve agencies from collecting and reporting component-level condition data to the NBI. Also, each data type has different utilities and applications within agency business processes for inspection program management, maintenance, asset management, and transportation performance management target setting.

To assist States in comparing the data sets, FHWA and researchers developed various "translators" to convert CoRE Manual element condition states into component ratings. With the introduction of the MBEI, FHWA later sponsored development of a new "convertor" which is documented in the April 2013 "*Component-Element Converter Technical Manual*". A universal profile was developed for converting element condition states to component condition ratings that is independent of component type, design, and material. A separate universal profile was also developed for converting component condition ratings to element condition states. These two profiles were developed from a limited data set available at the time. The "convertors" like the one developed by FHWA continue to support States. A particular use is in support of element-level asset management modeling and analyses. When forecasts and simulations of future conditions, work programs, and performance outcomes are based on element-level deterioration, work actions, costs, and benefits, the future condition outcomes often need to be converted to component ratings for ease of comprehension by stakeholders. Another use of convertors is the support of inspection data quality review. Converted element condition states are often compared to inspector component ratings to identify any gross differences representative of potential data errors or inspection inconsistencies.

Now that FHWA has amassed element-level data for all NHS bridges, it is possible to refine or create new conversion models. The primary objective of the project was to create multiple conversion profiles to convert element-level condition states to component-level condition ratings, while considering material composition as a major subfactor. These profiles included a universal conversion profile (element to component) that was representative of all element and component types and four component conversion profiles that were representative of each component (deck, superstructure, substructure, and culvert) irrespective of material type. Conversion profiles that considered the material composition of each component were also developed. Lastly, a universal conversion profile that converts the component-level condition rating into element-level condition states was developed. This conversion profile was representative of all element and component types, irrespective of material type.

This report provides a step-by-step summary of the efforts undertaken to develop the various conversion profiles and includes sufficient details so that an independent party can repeat the process to update the profiles as additional data becomes available.

Table 1. Bridge elements reported to the NBI according to Specification for the National Bridge Inventory Bridge Elements

Component	Element	Units	Element Number					
			Steel	Prestressed Concrete	Reinforced Concrete	Timber	Masonry	Other
Deck/Slab	Deck	SF		13	12	31		60
	Open Grid Deck	SF	28					
	Concrete Filled Grid Deck	SF	29					
	Corrugated or Orthotropic Deck	SF	30					
	Slab	SF			38	54		65
	Top Flange	SF		15	16			
Superstructure	Closed Web/Box Girder	LF	102	104	105			106
	Girder/Beam	LF	107	109	110	111		112
	Stringer	LF	113	115	116	117		118
	Truss	LF	120			135		136
	Arch	LF	141	143	144	146	145	142
	Main Cable	LF	147					
	Secondary Cable	EA	148					149
	Floor Beam	LF	152	154	155	156		157
	Pin, Pin and Hanger Assembly	EA	161					
	Gusset Plate	EA	162					
Substructure	Column	EA	202	204	205	206		203
	Column Tower (Trestle)	LF	207			208		
	Pier Wall	LF			210	212	213	211
	Abutment	LF	219		215	216	217	218
	Pile Cap/Footing	LF			220			
	Pile	EA	225	226	227	228		229
	Pier Cap	LF	231	233	234	235		236
Culvert	Culvert	LF	240	245	241	242	244	243
Bridge Rail	Bridge Rail	LF	330		331	332	334	333

Component	Element	Units	Element Number
Joint	Strip Seal	LF	300
	Pourable	LF	301
	Compression	LF	302
	Assembly with Seal (Modular)	LF	303
	Open	LF	304
	Assembly without Seal	LF	305
	Other	LF	306
Bearing	Elastomeric	EA	310
	Movable (roller, sliding, etc.)	EA	311
	Enclosed/Concealed	EA	312
	Fixed	EA	313
	Pot	EA	314
	Disk	EA	315
	Other	EA	316
Wearing Surfaces and Protective Coatings	Wearing Surfaces	SF	510
	Steel Protective Coatings	SF	515
	Concrete Protective Coatings	SF	521

LITERATURE REVIEW

The AASHTO CoRE guide describes a set of three to five condition states (CS1-3, CS1-4, or CS1-5) that are used to describe the condition of various bridge elements. Element-level data collection has progressively matured and is today an integral part of bridge asset management systems. The AASHTO MBEI replaced the AASHTO *CoRE* guide and offers significant changes to the condition state language and reconfigures the condition states to be consistent (CS1-4) across all element types. The MBEI classifies bridge elements as either National Bridge Elements (NBEs), Bridge Management Elements (BMEs), or Agency Defined

Elements (ADEs). The condition states describe the severity of distress or deficiencies using a four-point system as follows: CS 1 – Good, CS 2 – Fair, CS 3 – Poor, and CS 4 – Severe. Beginning in 2015, States and bridge owners are required to report their element-level data to the FHWA for bridges located on the NHS.

In the NBI data set, prior to 2015 only the condition of the three main bridge components (deck, substructure, and superstructure) and the condition of culverts are represented. Condition details for other bridge elements such as bearings, joints, etc. are not explicitly represented. Element-level inspection protocols however do consider these elements in addition to the overall deck, substructure, and superstructure. The collection and use of element-level condition data is fundamental to the ability to clearly understand asset conditions, predict future conditions, and program cost-effective actions that extend element and bridge service lives. The introduction of element-level bridge inspection techniques in the early 1990s represented a significant advancement in bridge inspection and management practices and has been adopted by transportation departments throughout the U.S. Elements are defined according to seven classifications that include Deck/Slab, Superstructure, Substructure, Bridge Rail, Joint, Bearing, Wearing Surface, and Protective Coatings. All elements are evaluated using a four-level condition-state scale.

As States expanded their use of element-level data collection systems, researchers set out to develop a translator algorithm that converted the new, more detailed element condition data into component condition ratings. A number of attempts were made to convert the element-level condition states to component condition rating and vice versa. An early project was conducted by Hearn et al. (1997) at the University of Colorado at Boulder, with the collaboration of the Colorado Department of Transportation (CDOT). The product, named NBI Translator, was able to combine CoRE elements into matching NBI fields. This methodology was later developed as a software tool known as the NBI Translator (or BMSNBI) and was adopted by Pontis (now AASHTOWare™ Bridge Management) as a built-in module. General skepticism about the estimation accuracy of the NBI Translator was later raised based on the study of several departments of transportation's (DOTs) bridge management systems (Hale et al 2007; Bektas et al. 2012). In a separate study, another conversion approach was proposed by Al-Wazeer et al. (2007) to improve the results of the NBI Translator. In this study, artificial neural network (ANN) models were developed based on the CoRE and NBI data collected from Wisconsin and Maryland. The results revealed that the ANN model yielded better estimations as compared to the NBI Translator model. However, this conclusion was only valid for the states that the ANN models were trained and tested on, and therefore, could not be generalized for wider use. In another study, Sobanjo et al. (2008) developed a conversion tool, called NewTranslator, that functioned similar to the Bridge Health Index calculation, which is a single-number assessment of a bridge's condition based on the bridge's economic worth determined from an element-level inspection. Comparison of Sobanjo et al.'s results with the BMSNBI indicated an improved accuracy level in the higher range of NBI ratings, but the model underperformed with the assignment of NBI ratings in lower condition ratings. Later in 2012, Bektas et al. (2012) proposed a new conversion methodology using the classification and regression trees concept. The method was developed using bridge condition data (NBI and CoRE elements) provided by three state departments of transportation. A similar technique was later proposed by Fiorillo and Nassif (2019) using deep convolutional neural networks for mapping the relationship between NBI component- and element-level data.

FHWA recently developed conversion profiles that correlate element condition states to component condition ratings and vice versa using MBEI data. These are termed their first generation MBEI conversion profiles. These profiles were developed using a limited data set and were independent of component type, design, and material. This work yielded a universal profile for converting element condition states to component condition ratings and a separate universal profile for converting component condition ratings to element condition states. A review of these methodologies and prior research provides several key observations relevant to this project:

- Models developed on the basis of complex statistical methods or artificial intelligence/machine learning approaches such as ANN or NN, while capable of better accuracies than analytical models, suffer from major drawbacks. These techniques are mostly inspired by natural rules and present solutions based on experience and development of various discriminators, which are not readily transparent. As a result, these models act as black boxes and cannot explicitly provide a transparent function correlating the output to the given inputs. The computations must be conducted in *a-priori* format requiring significant trial-and-error operations, which limit their availability using commonly available software such as a Microsoft Excel spreadsheet with embedded static tables/matrices.
- Most of the conversion models were developed using CoRE condition state definitions rather than the more current MBEI definitions. For the models developed using the MBEI condition state definitions, the models were derived using limited data sets and applied independent of component type, design, and material.
- As defined by the AASHTO MBEI, members are divided into two elements consisting of the base member and its protective system. As such, the protective system is evaluated separately from the base element. The expression and rate of change of deterioration in the protective coating systems (e.g., paint systems for steel members or asphalt with membrane wearing surfaces for decks) relative to the same experiences in the base member may be significantly different. There is no discussion in the conversion models regarding how these elements behave in an independent manner.
- The various models were generally found to have lower conversion accuracies at the low and high ends of the condition rating range (8-9 or 3-4), where there is a lack of historical data for model calibration. In addition, some of the models tend to constantly over-rate or under-rate compared to the actual condition ratings. This skew in the prediction capability of each model often exacerbates the errors at either the high or low end of the condition rating scale.
- The conversion of element-level condition states from component condition rating remains a challenge given the lack of granularity associated with component-level inspections as compared to that of element-level inspections. Therefore, the derivation of the element information from component data has a limitation on its accuracy.

PRELIMINARY INVESTIGATION OF NHS BRIDGES

The InfoBridge platform developed by FHWA was utilized to gain a general understanding of the format and structure of NBI component- and element-level data that are available for NHS bridges.

Figure 1 represents how the NHS bridges are geographically distributed nationwide while Figure 2 shows the distribution of the bridges based on their main material type (NBI Item 43A). Further, plots the distribution of NHS bridges based on deck material type (NBI Item 107). Similar plots for substructure and culverts are possible but have not been included herein.

Figure 4 through Figure 7 plot the distribution of current condition ratings (reported as of 2022) for the main components. A review of Figure 4 through Figure 7 generates the following observations:

1. Most NHS bridges share Reinforced Concrete, Steel, and Prestressed Concrete as their primary superstructure material (NBI Item 43A). The quantity of available data for other types of superstructure materials is minimal. Further, it was observed through a preliminary study of nationwide data that the prominent superstructure material types differ among states including the observation that some states build bridges using only one or two primary materials.
2. Most NHS bridges share concrete as their primary deck material.
3. Most NHS bridge components are rated at 5 through 8.

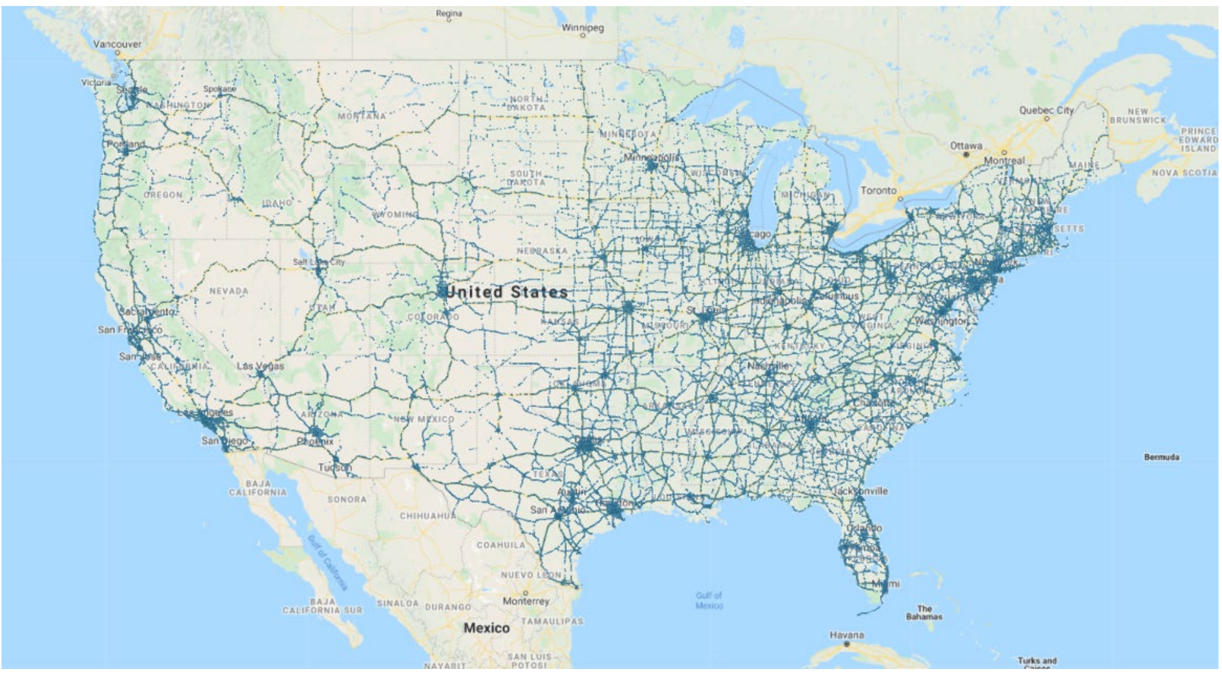


Figure 1. Geographical nationwide distribution of NHS bridges (nearly 146,400 bridges).

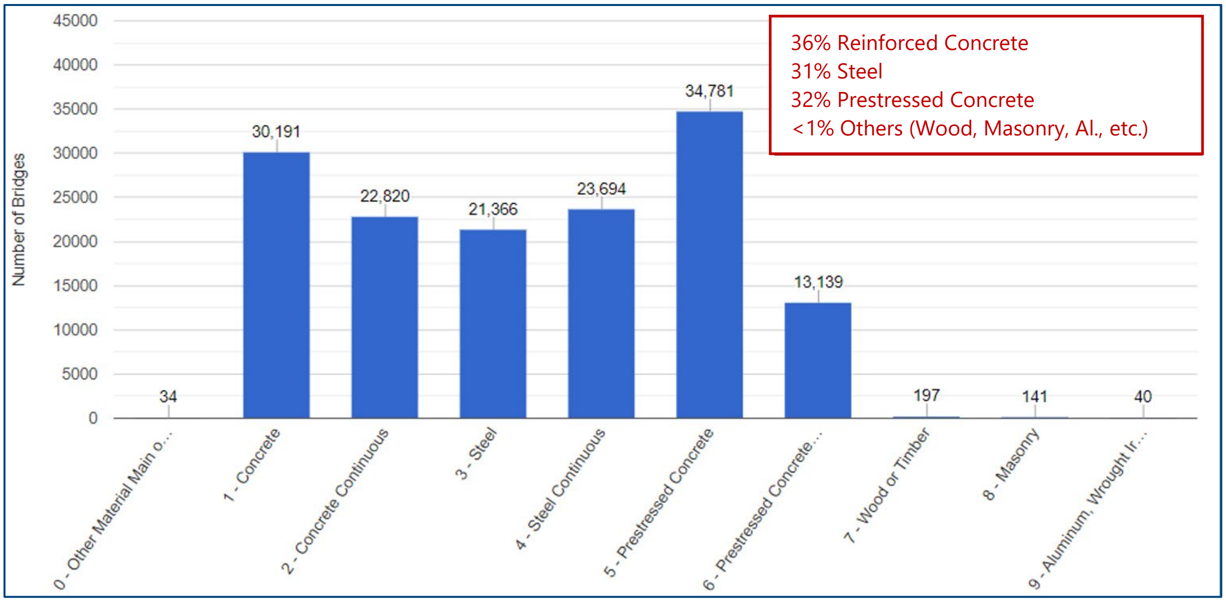


Figure 2. Distribution of NHS bridges based on main span (superstructure) material type (NBI Item 43A).

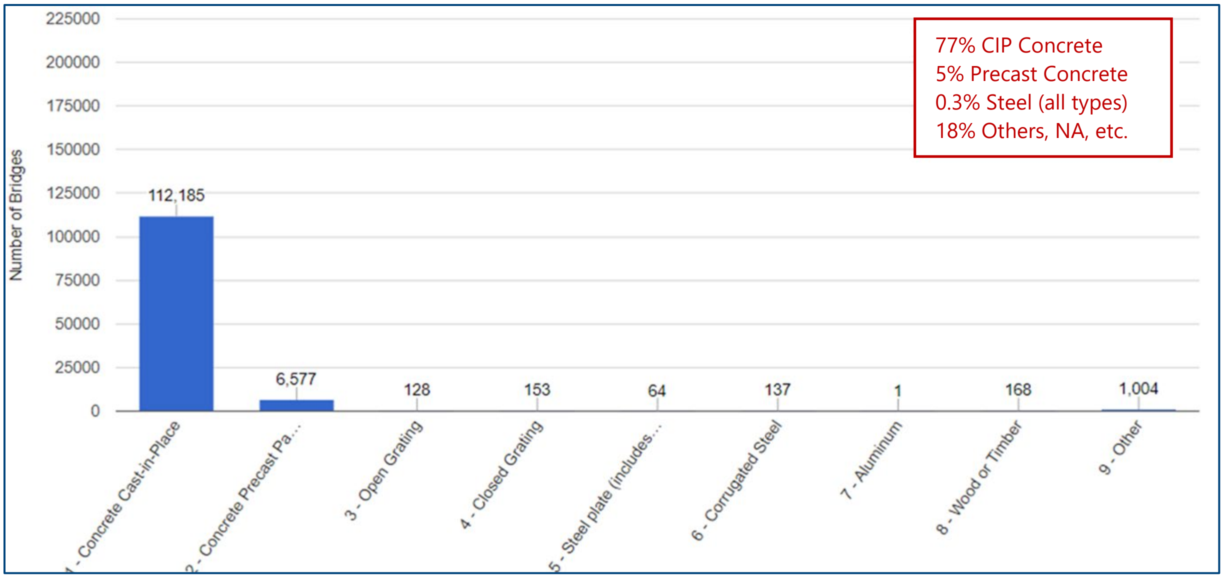


Figure 3. Distribution of NHS bridges based on deck type (NBI Item 107).

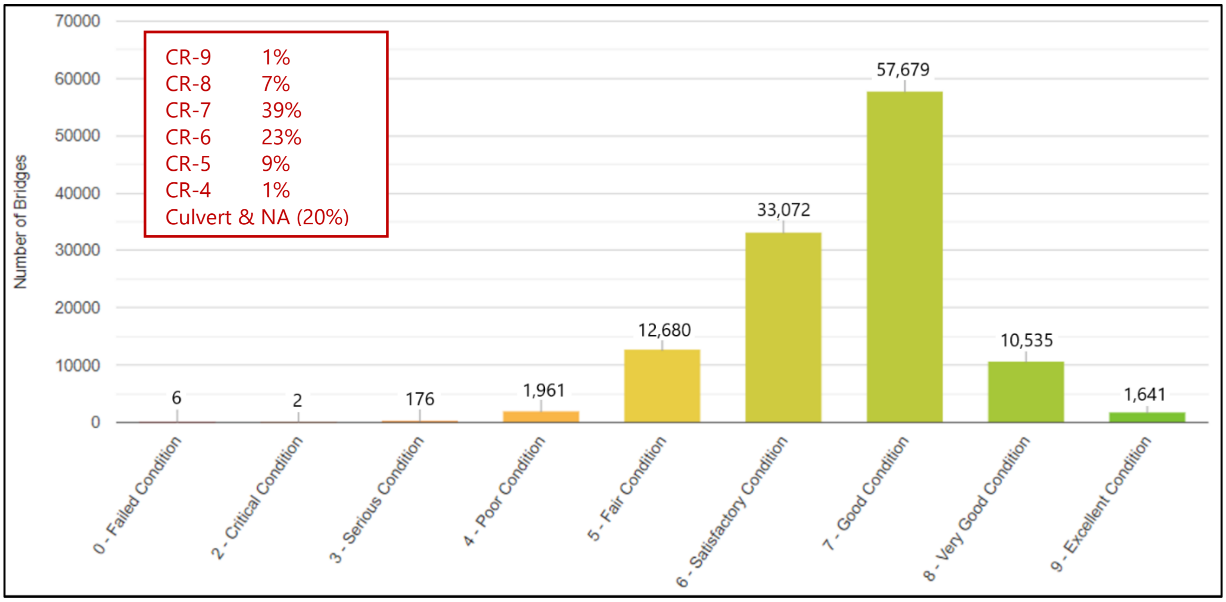


Figure 4. Distribution of NHS bridges based on deck condition rating (NBI Item 58).

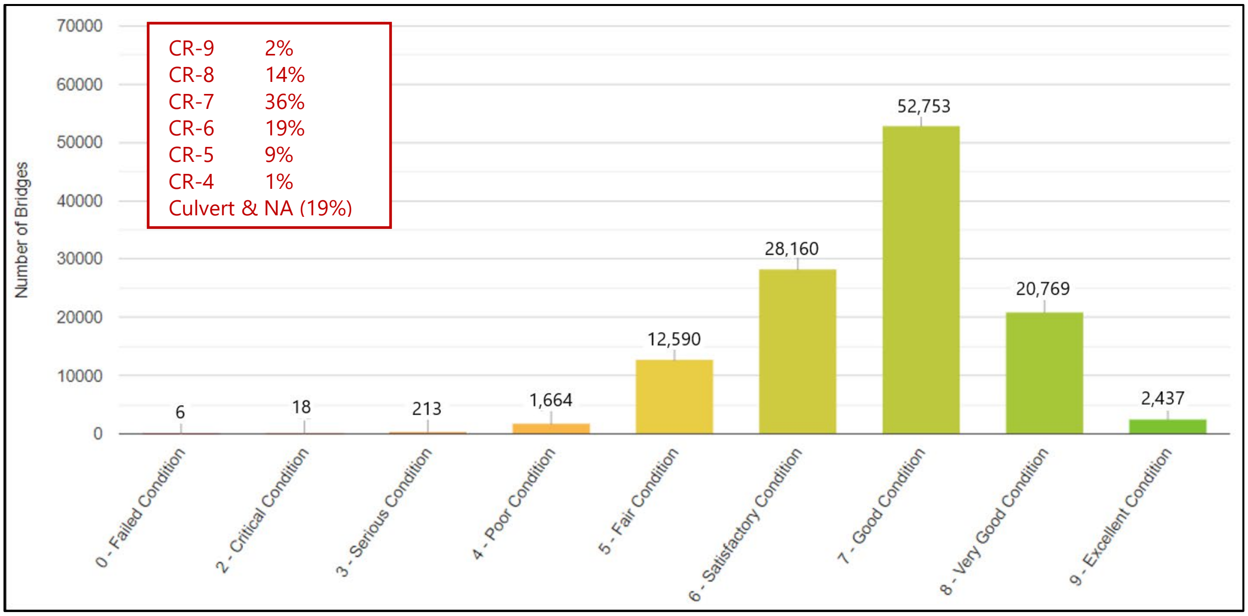


Figure 5. Distribution of NHS bridges based on superstructure condition rating (NBI Item 59).

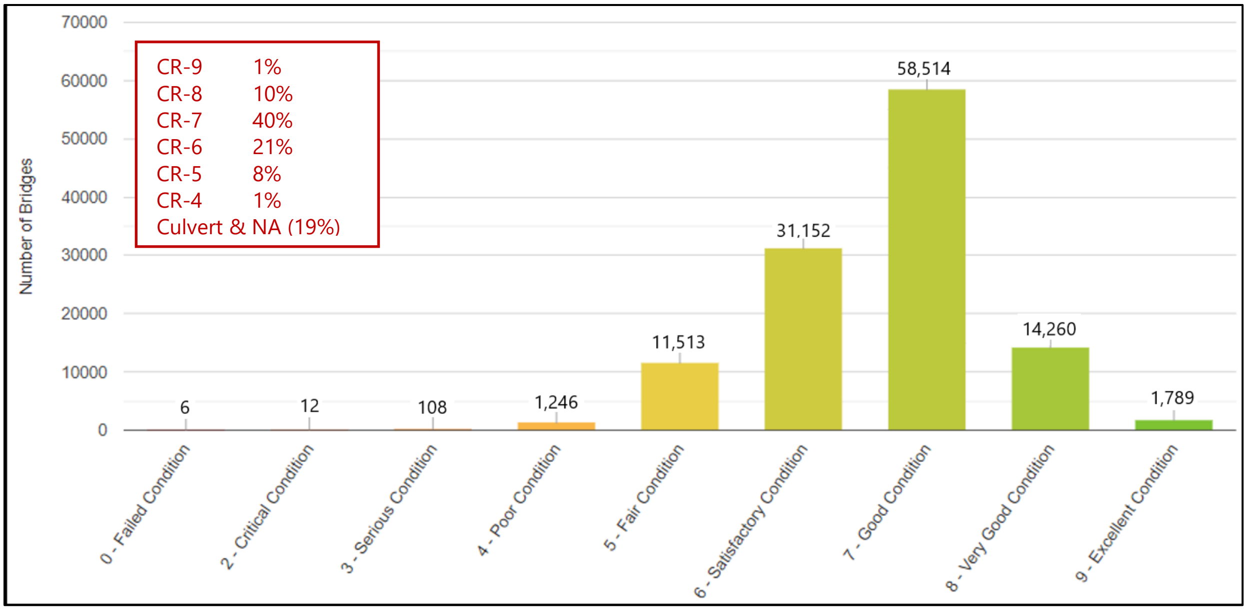


Figure 6. Distribution of NHS bridges based on substructure condition rating (NBI Item 60).

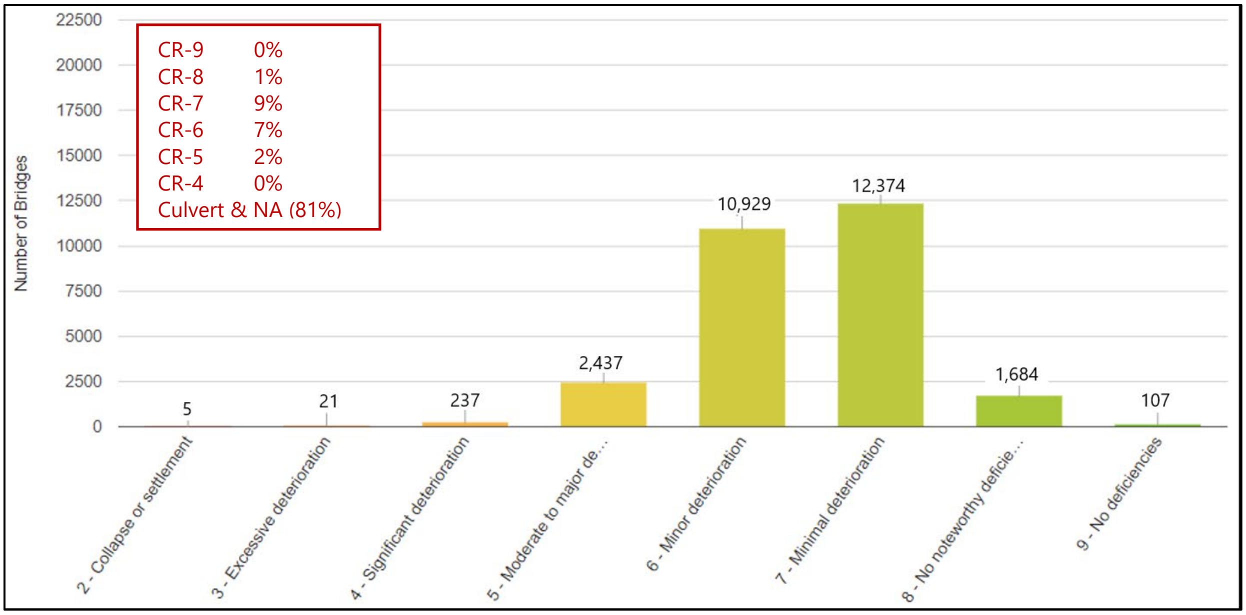


Figure 7. Distribution of NHS bridges based on culvert condition rating (NBI Item 62).

TECHNICAL APPROACH

Since the development of the FHWA first-generation MBEI data conversion profiles, all States now collect and report element data for all NHS bridges in their inventories. The increase in available data offers an opportunity to develop new, more refined, and more accurate conversion profiles to translate element-level condition states to component condition ratings and vice versa. The additional data also allows the extension of these profiles to include the consideration of material composition for both element and component. Figure 8 illustrates the process that was followed to develop the conversion profiles. Some steps were performed only once (e.g., data preparation and cleaning), which is denoted as "Data Processing" stage, while the final step was repeated to produce the different conversion profiles, which is depicted as the "Data Modeling" stage.

Data sets used in this study include element-level data sets, which are publicly available for the years 2015-2022 at the FHWA website (https://www.fhwa.dot.gov/bridge/nbi/element.cfm), and the other NBI data, which is available for the years 1992-2022 at the FHWA website (https://www.fhwa.dot.gov/bridge/nbi/ascii.cfm).

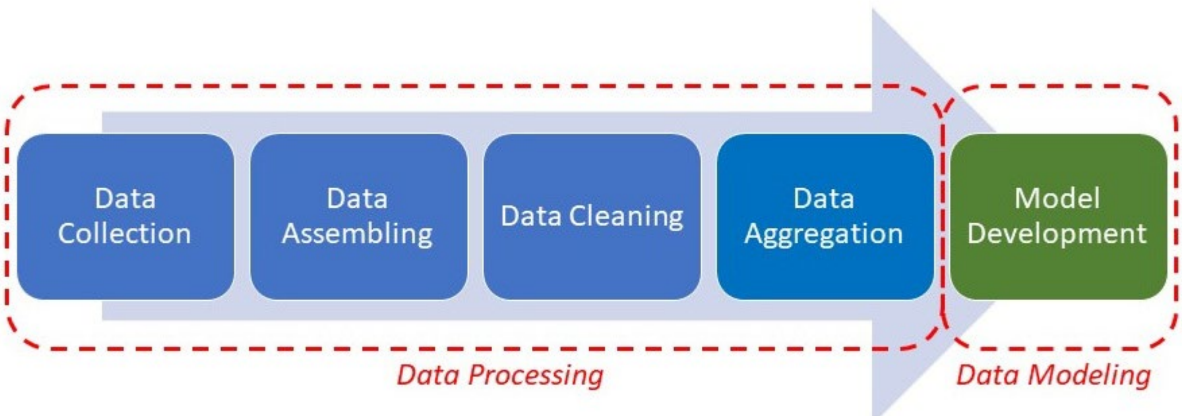


Figure 8. Deployed analytical framework.

The discrete efforts outlined in Figure 8 are briefly described below.

- **Data Collection**: The objective of this step was to identify and collect available data resources required for the development of conversion profiles.
- **Data Assembling**: The NBI component- and element-level data are separately reported and published by FHWA. In this step, the data were combined into a single fact table for further model development.
- **Data Cleaning**: In this step, the data set was thoroughly reviewed to identify null, miscoded, unmatched, or otherwise unreliable data elements. Multiple approaches were used to review and "clean" the data.
- **Data Aggregation**: Various aggregation techniques were employed to combine condition state quantities of multi-element components into unified condition states for later conversion profile development and validation.

- **Model Development (Element to Component)**: Multiple statistical models were studied and tested to deliver the final profiles for converting element condition states to condition ratings. When possible, the models were validated against a subset of the overall data set that was not used for model development. If this was not permissible given the size of the data set, then the models were validated against the same data used for model development.
- **Model Development (Component to Element)**: Similarly, a set of statistical analyses was conducted to develop a profile to convert component-level condition rating to element-level condition states. Reconstructing more granular information (element-level) from a coarse source (components) proved to be difficult.

Data Collection

The NBI component- and element-level data published by FHWA between 2015 and 2022 serve as the primary data sets for the conversion profile development. The NBI component- and element-level data from the following two sources were utilized for data modeling.

- https://www.fhwa.dot.gov/bridge/nbi/ascii.cfm
- https://www.fhwa.dot.gov/bridge/nbi/element.cfm

NBI component- and elemental-level data are collected, checked, and warehoused throughout the year by the bridge's respective owner (e.g., state transportation department, Federal agency, or tribal government), with newly collected or altered data added to their inventory database(s) within three months of the date collected or changed. The bridge owner then annually submits the NBI component- and element-level data to FHWA. Thus, by March 15th of each year the FHWA has received the NBI component- and element-level data from all bridge owners. These data are then checked and published to the two FHWA websites cited above. The annual NBI component- and element-level data published by FHWA are available for download by year. Each year's data file consists of that year's current data for all bridges regardless of when the bridge was last inspected. So, for example, a bridge that is on a 48-month inspection cycle and was last inspected in October 2017 will show the same data in the 2018, 2019, 2020, and 2021 report. A bridge that is on a 12-month reinspection cycle and is inspected in October each year will show new data assuming the condition has changed or the same data if the condition has remained unchanged in each annual report. As such, each year's data file can be considered as a snapshot of bridge conditions as of December 31st plus any data for bridges inspected and accepted by the bridge owner through the first three months of the reporting year.

The data published in 2015-2016, representing the first two submittals of element data to FHWA, were discarded due to uncertainty in the data quality, particularly with respect to whether the element-level data were "migrated" or "combined migrated and field collected" (i.e. some bridges have migrated data and others have field collected data). Migrated data are element data that have been converted from the AASHTO CoRE specification and format to the AASHTO MBEI specification and format, namely from CoRE to NBE/BME. If, however, there were 2017-2022 submittals that the owner reported contained "combined migrated and field collected data", those data years were removed as well. When downloading element-level data from the FHWA website, some States also included elements from non-NHS bridges. Only NHS bridges were considered for analysis per the scope of this project.

Data Assembling

Each annual NBI data set consists of one row of data (composed of many columns) for each bridge, while the element-level data set includes several rows of data (with a few columns) for each bridge. The two data sets were linked using a common data element(s) to become the fact table.

The NBI database includes over one hundred items, of which only a few are useful to the current project. To reduce the size of the data set required for modeling as well as to increase the model efficiency, the final fact tables only included applicable items. Table 2 lists the items that were extracted as part of the query.

Table 2. List of items to be extracted from NBI component- and element-level databases.

Bridge Keys	Element-level Fact Table	NBI Fact Table	Index
State Code (1)	Element Code/Parent Code	Component Name (D, SP, SU, Cul)	Error Code
Structure Number (8)	Total Quantity	Routine Inspection Date (90)	
Date of Data Submittal	CS1 Quantity	Component Rating * (58-60, 62)	
	CS2 Quantity	Type of Deck (107)	
	CS3 Quantity	NHS or non-NHS (104)	
	CS4 Quantity	Inspection Frequency (91)	
		Fracture Critical Inspection Date (93A)	
		Type of Main Material (43A)	
		Type of Main Design (43B)	
		Approach – Type of Material (44A)	
		Approach – Type of Design (44B)	
		General Rating (G, F, P)	
		Underwater Inspection Date (93B)	
		Other special inspection Date (93C)	

** The component rating (deck, superstructure, substructure, culvert) will be selected based on the category to which the element belongs (according to Table 1).*

Joining of element-level facts and NBI facts was accomplished using a key combination consisting of state code, structure number along with the date of data submission. Each row from the element-level table was joined to the corresponding NBI data for that state/structure number/submittal date key combination. The component rating (NBI Items 58-60 and 62) presented on each row corresponded to the element also present on that row. So, for example, NBI Item 58 Deck component ratings were paired on the same rows with deck-specific element-level data. If that element was inspected more than once within the 2017-2022 time horizon, multiple rows of that element (per inspection period) were available in the fact table. Usage of the term “data row” in this report corresponds to each individual row from the fact table. The fact table also included an index column for denoting possible data errors. This index facilitated the inclusion or exclusion of data should a particular data element be suspicious or unmatched. Table 3 provides a sample of one row from the fact table that was discussed in Table 2. Further details are discussed in the data cleaning section below.

Among the element-level data, some elements could be reported along with their protective systems (e.g. reinforced concrete deck (12) in concert with wearing surface (510) or steel beam (107) along with the steel protective coating (515)). These additional elements are called bridge management elements (BMEs). Since the NBI condition rating for main components (deck, superstructure, substructure, and culvert) are instructed to be collected regardless of the protective coating system, only the NBEs (Element Number<300) were considered within the modeling scheme.

Table 3. Example row from the fact table.

Sample	State Code	Structure Number	Date of Submittal	Element Code	CS1	CS2	CS3	CS4	Total Quantity	Comp. Ty.	Comp. Rating
#1	1	019595	2021	12	14,474	970	0	0	15,444	Deck	7

Insp. Date	Insp. Frequency	Ty. Main Material	Ty. Main Design	Ty. App. Material	Ty. App. Design	Ty. Deck	General Rating	Frac. Ctr. Insp. Date	Underwater Inps.	Other Spc. Insp. Date	Error Code
08.2019	24	5	2	5	2	1	G	-	-	-	1

Data Cleaning

Once the NBI component- and element-level data were integrated and unified in a common data format, multiple cleaning filters were employed to ensure the reliability of the data. It was assumed that data flags and errors identified by FHWA data validation checks had been corrected (NBI Data Checks 2020; Element Data Errors and Checks 2020). According to cleaning criteria listed below, data with pending flags or errors were removed for profile development. Errant data was denoted through the use of row identifiers (i.e., index column) that removed the data from statistical analyses but not physically from the data set. This allowed for data “cleaning” methods to be reviewed again and if necessary reversed.

Data conditions that warranted special attention included:

- The annual NBI component- and element-level data published by FHWA is available for download by year. Each year’s data file consists of that year’s current data for all bridges regardless of when the bridge was last inspected. So, for example, a bridge that is on a 24-month inspection cycle and was last inspected in October 2017 will show the same data in the 2018 and 2019 reports. To avoid repeatability in the fact table, only data rows associated with 2018 were kept and the repeated data row corresponding to 2019 was flagged to be excluded from data modeling. The error index for flagging such data rows in the fact table is defined as 1. To formulate this approach, the following steps were conducted in the data cleaning process:

- For 2018-2022 data submittal files, if the difference between the data file submittal year and bridge inspection year (NBI Item 90) was greater than 1, then the data row was flagged. For example, for data submittal 2019, only data rows with bridge inspection year (NBI Item 90) of 2018 and 2019 were left unflagged.
- For the 2017 data submittal file, if the difference between the data file submittal year and bridge inspection year (NBI Item 90) was greater than 2, then the data row was flagged. For this data submittal file, only data rows with bridge inspection year (NBI Item 90) of 2015 or 2016 were kept.
- Once the data file for each submittal year was processed individually, all the data submittal files (multiple years) for a given state were aggregated and checked for duplicates. Per the previous discussion, if the 2018 submittal included the 2017 inspection date (for a given bridge), that data row was kept; if the 2017 submittal file included the 2017 inspection date, that data row was also kept; therefore, there is a higher chance of duplication due to biannual frequency of inspection data. In this case, the record with the minimum difference between submittal and inspection years was kept in the fact table. To that extent, this step ensured that no data row for a given bridge associated with the same inspection date was duplicated in the final fact table. Due to the programming configuration, this step was conducted prior to the development of fact tables, therefore, no error index was assigned.

Bridges that have different main and approach span material types (as identified by NBI items 43A and 44A) were excluded from the modeling. In some cases, however, different material types that were closely aligned were considered to be uniform for profile development purposes. For example, concrete and concrete continuous were considered matching. Table 4 below describes how each data row in the fact table was processed to address closely matching material types between Items 43A and 44A. For each data row, if the 43A code in the left column did not associate with the 44A code in the right column, the data row was flagged with Index 2. For reference, the NBI material type coding is shown in Table 5.

Table 4. Main span vs. approach span material type.

NBI 43A (Main Spans)	44A (Approach Spans)
1, 2	0*, 1, 2
3, 4	0, 3, 4
5, 6	0, 5, 6
7	0, 7
8	0, 8
9	0, 9

** This included all the elements designated as “0”, “00”, or “000”.*

Table 5. NBI coding designation for items 43A and 44A.

Code	Description
1	Concrete
2	Concrete continuous
3	Steel
4	Steel continuous
5	Prestressed concrete*
6	Prestressed concrete continuous*
7	Wood and timber
8	Masonry
9	Aluminum, Wrought Iron or Cast Iron
0**	Other
99	Miscoded data

Includes post-tensioned concrete
***Not applicable for Item 44*

- Given that very few components in the data set were rated 2 or lower (<<100), component ratings of 2 or lower were excluded. This check was performed for each component independently. The error index for flagging such data rows in the fact table was defined as 3.
- Removed data rows with Total Element Quantity equal to 0 resulted in an error index in the fact table defined as 4.
- Depending on the type of conversion profiles, if any of the NBI ratings for main components (deck, superstructure, substructure, and culvert) were missing (null) or not applicable (N), the corresponding bridge-inspection period was removed. Alternatively, the elements for some bridges corresponded to a certain type of bridge (i.e., a culvert), however, the NBI component ratings corresponded to a bridge with three main components (deck, superstructure, substructure). The opposite scenario was also observed. This check was performed for each component independently. This data was reviewed and if found to be in error, it was flagged as a 5 in the fact table.
- It is well understood that main span material (NBI Item 43A) often corresponds to the superstructure component. Therefore, if a given bridge's superstructure elements did not match with the correct material type (43A), then that superstructure component (any associated data rows for that component in the fact table) was flagged with Index 6. Table 6 indicates how each data row in the fact table was processed to match NBI item 43A and the superstructure element codes.

Table 6. Main span vs. superstructure's elements material types.

NBI 43A (Main Spans)	Superstructure Element
1, 2	105,110,116,144,155
3, 4	102,107,113,120,141,147,148, 152,161,162
5, 6	104,109,115,143,154
7	111,117,135,146,156
8	145
9, 0	106,112,118,136,142,149,157

- Similar to the superstructure elements, if a given structure's culvert elements did not match the correct material type (43A), then that culvert (any associated data rows for that culvert component in the fact table) was flagged with Index 7. Table 7 lists how each data row in the fact table was processed to match NBI Item 43A and the culvert elements. According to Table 7, if the element number did not match the 43A code, the data row was flagged with Index 7.

Table 7. Main span vs. culvert's elements material types.

NBI 43A (Main Spans)	Culvert Element
1, 2	241
3, 4	240
5, 6	245
7	242
8	244
9, 0	243

- Similar to the superstructure, the NBI has a separate definition for deck material type (NBI Item 107). Therefore, if a given bridge's deck elements did not match the correct deck material type (NBI Item 107), the row data associated with that deck component was excluded from the modeling. Table 8 presents how each data row in the fact table was matched between NBI Item 107 and the deck elements. According to Table 8, if the element code did not match the NBI Item 107 code, the data row was flagged with Index 8. For reference, the NBI material coding for Item 107 is shown in Table 9.

Table 8. Deck structure type vs. deck element material types.

NBI 107	Deck Element
1, 2	13,15,12,38,16
3, 4, 5, 6	28,29,30
8	31,54
7, 9, N	60,65

Table 9. NBI coding designation for Item 107.

Code	Description
1	Concrete Cast-in-Place
2	Concrete Precast Panels
3	Open Grating
4	Closed Grating
5	Steel plate (includes orthotropic)
6	Corrugated Steel
7	Aluminum
8	Wood or Timber
9	Other
N	Not applicable
99	Miscoded data

- A bridge with a given component rating of 7 or above with any element (comprising the component) in Condition State 4 (CS4>0%) was flagged with an error index of 9. The data rows associated with that specific component were flagged and other components of that bridge were not flagged. For example, if a substructure component was rated as 7, and it was composed of three substructure elements and one of the elements was rated as 1% in CS4 but the other two elements were rated at CS4 equal to 0%, then all three rows were flagged. No other data rows associated with other main components (i.e. superstructure or deck) were flagged unless they experienced the same mismatch.
- A bridge with a given component rating of 6 or less with all elements (comprising the component) in Condition State 1 (CS1=100%) was flagged with an error index of 10. The data rows associated with that specific component were flagged and other components of that bridge were not flagged. For example, if a substructure component was rated as 6, and it was composed of three substructure elements and two of the elements were rated as 100% in CS1 but the last element was rated at CS1 equal to 99%, then none of the data rows were flagged. In turn, if all three elements were rated as CS1=100%, then all three data rows associated with these three elements were flagged. No other data rows associated with other main components (i.e. superstructure or deck) were flagged unless they experienced the same mismatch.

Appendix I provides a concise step-by-step flowchart to reproduce the fact table should additional data become available in the future.

Data Aggregation

Nearly 1.4 million data rows were retained after processing and cleaning the data. Each row represents a component rating and element condition states pair with some pairs representing the individual elements of multi-element components. The large quantity of data in the combined component- and element-level data sets, while beneficial to the stated outcomes, creates unique challenges in deciphering and finding meaningful relevancy between different data subsets. Before delving into the data aggregation techniques employed in this study, the following assessments provide rationale behind the exploration of specific aggregation techniques.

- In mapping the element-level condition states to component ratings, it is important to understand how these two inspection procedures are conceptually interlinked in practice and how the condition rating/condition states are assigned. For instance, for a given deck with a small area of spalling, but is otherwise in nearly "new" condition, a rating above 7 (described as having some minor problems present) will not typically be assigned. However, the same deck would receive 99%, 0%, 1%, and 0% for CS1, CS2, CS3, and CS4, respectively. Therefore, the application of a weighted average would not be justifiable for this case because the weighted score would overestimate the condition rating at 8 or better.
- To evaluate the effect of the element conditions of multi-element components on developed profiles and accuracy of the profiles, all the data rows no matter the component type (deck, superstructure, substructure, culvert) were considered for modeling. Some components included only one element while some others included multiple elements. Different aggregation methods (discussed later in this report) were developed to handle different types of components and evaluate the effect of aggregation techniques on profile accuracy.
- During the preliminary data analysis, it was observed that main components (deck, superstructure, and substructure) are often inclusive of one, two, or three element types. For deck components,

over 95% of bridges had a single element while the rest were composed of multi-elements (mostly two elements). For superstructure components, over 90% of the bridges were represented by a single element while the rest were multi-element. Finally, for substructure components, slightly over 15% of the bridges were represented by a single element while the rest were multi-element.

Aggregation Methods for Components Comprised of Multiple Elements

Superstructure and substructure components are typically composed of two or more elements, which are inspected and assessed individually. The manual for Bridge Inspector's Reference Manual, which is the primary reference for NHI Course No. 130055 Safety Inspection of In-Service Bridges, has set certain criteria to determine an overall condition rating for a multi-element component. This includes identification and quantification of defects on each element, and assignment of an overall rating based on a cumulative understanding of component condition and any safety concern. Inspectors taking NHI Course No. 130055 are considered correct in their condition assessment if they are within ±1CR of the NHI assessment. However, the decision-making process for the assignment of such rating still carries some level of variability due to the involvement of the inspector's judgment. Therefore, formulating an aggregation strategy for multiple elements to derive a single component condition rating proved very challenging. The issue stems from the fact that component ratings (0-9) are assigned based on the inspector's overall observation of a given component, which includes a part quantitative and a part qualitative human aggregation of observations from the various elements that comprise that component. Some sources of judgment and situational variation in assigning an overall condition rating for a multi-element component include:

- Some of the load-carrying elements (e.g. pier caps) can control the capacity of the structure, whereas other elements often do not (e.g. pier walls).
- The number of units per element could determine the criticality of a given defect to the assignment of a component rating. For example, if a pier cap is supported by six columns and one of the columns has spalling, this is a different situation when compared to a pier cap which is only supported by two columns, one of which has spalling.
- The number and arrangement of units or magnitude of element size (stringer total length for single or multi-span bridges) could impact the criticality of a defect.
- The severity of certain defects is subjective and will be quantified differently by each inspector. This often happens when there is a lack of specific quantification guidance from state DOTs. For example, some inspectors define early-age shrinkage cracking as minor, therefore, assigning a condition rating of 8-9 to a newly constructed bridge deck. While other inspectors define such cracks as significant enough to assign a rating of 7 to a newly constructed bridge deck.
- Depending on the technical background of an inspector, the criticality of different defects might be misunderstood. For instance,10 percent section loss in a flange at a bearing is not critical to the bridge's performance. However, 10 percent section loss at midspan might be critical to the load-carrying capacity. The defect is the same but just at a different location. An inspector who has taken the 2-week Safety Inspection of Bridges class but does not regularly apply the theories of flexure may give both of these bridges similarly lower condition ratings.

- Depending on the combination of elements constituting a component, the criticality of the element for determining the overall condition of the bridge can be different from one bridge to another. For example, the importance of a girder in a non-redundant girder system is different than it is in a redundant girder system.
- Some states and their inspectors may emphasize certain types of defects differently depending on geographical and environmental characteristics. For example, pitting on the top of the bottom flange of steel beam-ends may be common in states with harsh environments (due to the application of de-icing chemicals) while the same deterioration might be considered severe in states where de-icing chemicals are used less frequently.

Despite the above challenges, several aggregation methods were investigated to determine which one proved to be the most accurate. The aggregation methods were only applicable for the element-to-component conversion profiles. The aggregation methods studied are described below:

Case 0: No aggregation

For this case, no aggregation was applied to the elements of a component. As such, all element data rows were treated as a unique component of a given bridge. Table 10 represents a portion of four data rows from the fact table that included four elements of a substructure component from the same bridge, which received an overall component rating of 5. Table 11 represents the normalized condition states where each row was fed into the modeling step as a separate data point. As can be seen in Table 11, each element is treated independently. Therefore, that element receives the associated component rating (the one to which that the element belongs). In the case of Table 11, as an example, the modeling table is composed of four independent data rows.

Table 10. An example substructure component with multiple elements (condition states are in absolute quantity).

Element	Unit	CS1	CS2	CS3	CS4	Total	Component Rating
219- Abutment	LF	220	20	50	110	400	5
231- Pier Cap	LF	10	10	5	2	27	
202- Column	EA	4	4	0	0	8	
225- Pile	EA	3	2	1	0	6	

Table 11. An example substructure component with multiple elements (condition states are normalized to the total element quantity).

Element	Unit	CS1	CS2	CS3	CS4	Total	Component Rating
219- Abutment	LF	55%	5%	12%	28%	100%	5
231- Pier Cap	LF	37%	37%	19%	7%	100%	5
202- Column	EA	50%	50%	0%	0%	100%	5
225- Pile	EA	50%	33%	17%	0%	100%	5

Case I: FHWA Universal Conversion Profile (First Generation)

For this case, the same methodology used by the current FHWA universal conversion profile was applied. This methodology first split the data into categories based on their unit of measure. In all cases, the elements belonged to the same component group (i.e., deck, superstructure, substructure, and culvert). If the elements had the same unit of measure, then all elements within the group were combined using a weighted average. If the elements had different units of measure, then the combination of these elements was computed using a linear (unweighted) average.

Table 12 represents a portion of a four-element substructure component from a sample bridge, which was rated as 5. As seen in the table, the condition states are already normalized, however, the total quantity is kept at its absolute value. For the elements with common units, the weighted average of different condition states was taken based on their relative total quantity ratios (i.e., based on the ratio of the quantity of the element in question to the total quantity of all elements with the same units). These calculations are shown in full for CS1 in Table 13. Once this has been completed, the different units of measure are combined using a straight average, the calculation for which is shown in full for CS1 in Table 14. The resulting outcome is a single row (or final data point) for the given bridge which is used in the modeling step. This is unlike Case 0 where four data points were eventually fed into the modeling step.

Table 12. An example substructure component with multiple elements (condition states are normalized to the total element quantity).

Element	Unit	CS1	CS2	CS3	CS4	Total	Component Rating
219- Abutment	LF	55%	5%	12%	28%	400	5
231- Pier Cap	LF	37%	37%	19%	7%	27	
202- Column	EA	50%	50%	0%	0%	8	
225- Pile	EA	50%	33%	17%	0%	6	

Table 13. Calculation of representative elements for every unit type.

Element	Unit	CS1	CS2	CS3	CS4	Total	Component Rating
Representative (LF)	LF	(55%*400+37%*27)/(400+27) =54%	7%	12%	27%	100%	5
Representative (EA)	EA	(50%*8+50%*6)/(8+6) =50%	43%	7%	0%	100%	

Table 14. Finalized data point to be used for modeling.

Element	Unit	CS1	CS2	CS3	CS4	Total	Component Rating
Finalized	n/a	(54%+50%)/2=52%	25%	9.5%	13.5%	100%	5

Case II: Linear (Unweighted) Average

In this case, after the condition states were normalized, the unweighted average of all elements (regardless of the unit of measure) was used to aggregate the element data into a single row to be fed into the modeling step. Using the same example above, the normalized condition states in Table 11 are averaged and become the final data set for that bridge and element. This calculation is shown in full for CS1 in Table 15.

Table 15. Finalized data point to be used for modeling.

Element	Unit	CS1	CS2	CS3	CS4	Total	Component Rating
Finalized	n/a	(55%+37%+50%+50%)/4=48%	31%	12%	9%	100%	5

Case III: Linear (Unweighted) Average of Lowest-Scored Elements

After the condition states were normalized for all elements of a given component, the elements within each measurement unit type (SF, LF, EA) were ranked. Ranking was determined using a score that was calculated similar to the way a Health Index is commonly calculated, meaning that the normalized element condition states (for each element) are averaged based on 1, 2/3, 1/3, and 0 common weights, for CS1 through CS4, respectively. Once computed, the lowest scored element from each measurement unit type was considered the controlling element for that measurement unit type. Once this was established for every measurement unit type comprising the component, the linear (unweighted) average of the normalized condition state quantities for the lowest ranking element from each measurement unit were calculated and used for modeling. Table 16 shows this scoring procedure using the data shown in Table 11 as the example data set.

Table 17 then indicates the selected elements per measurement unit type that were used to calculate the final aggregated data row (Table 18) for model development.

Table 16. Calculation of scoring for every element.

Element	Unit	CS1	CS2	CS3	CS4	Score	Component Rating
219- Abutment	LF	55%	5%	12%	28%	**62**	5
231- Pier Cap	LF	37%	37%	19%	7%	68	
202- Column	EA	50%	50%	0%	0%	83	
225- Pile	EA	50%	33%	17%	0%	**78**	

Table 17. Calculation of representative elements for every measurement unit type.

Element	Unit	CS1	CS2	CS3	CS4	Score	Component Rating
219- Abutment	LF	55%	5%	12%	28%	**62**	5
225- Pile	EA	50%	33%	17%	0%	**78**	

Table 18. Finalized data point to be used for modeling.

Element	Unit	CS1	CS2	CS3	CS4	Total	Component Rating
Finalized	n/a	(55%+50%)/2=53%	19%	14%	14%	100%	5

Case IV: Linear (Unweighted) Average of Highest CS4 (Normalized) Elements

Because CS4 represents the worst conditions observed at the element level, the quantity of CS4 deterioration often is a controlling factor in an inspector's decision-making process when assigning component condition ratings. In Case IV, the elements from each measurement unit type (per component) that had the highest percentage rated CS4 were selected as the controlling element for that measurement unit type. If the values of CS4 for elements (per unit type) were equal, then the element with the highest

CS3 value was selected. If not, this process was continued with CS2 and CS1. Once the elements with the highest ratios of CS4 deterioration were determined, the unweighted average of the normalized quantities for the selected elements from all measurement unit groups was computed. Using the data shown in Table 11 as the example data set, the Case IV selection procedure is shown in Table 19 where elements 219 and 225 become the controlling element-level data for each measurement unit type. Table 20 then presents the unweighted average of the select elements to determine the final data set for modeling purposes.

Table 19. Calculation of representative elements for every unit type.

Element	Unit	CS1	CS2	CS3	CS4	Total	Component Rating
219- Abutment	LF	55%	5%	12%	28%	100%	5
225- Pile	EA	50%	33%	17%	0%	100%	

Table 20. Finalized data point to be used for modeling.

Element	Unit	CS1	CS2	CS3	CS4	Total	Component Rating
Finalized	-	(55%+50%)/2=53%	19%	14%	14%	100%	5

Case V: Linear (Unweighted) Average of Highest CS4 (absolute quantity) Elements

This case was very similar to Case IV. The only difference was that instead of choosing the highest CS4 normalized quantity value, the element with the highest absolute quantity of CS4 was selected within each measurement unit type. This approach gave more weight to elements having the greatest quantity of observed defects/deterioration. The rest of the procedure was the same as in Case IV. Assuming the data shown in Table 10 as the example data set, the elements with the greatest absolute quantities from each measurement unit group were selected for further aggregation as shown in Table 21. Table 22 then shows the calculated unweighted average (after normalization) of the select elements (per unit type) to determine the final data set for modeling purposes.

Table 21. Calculation of representative elements for every unit type.

Element	Unit	CS1	CS2	CS3	CS4	Total	Component Rating
219- Abutment	LF	220	20	50	110	400	5
225- Pile	EA	3	2	1	0	6	

Table 22. Finalized data point to be used for modeling.

Element	Unit	CS1	CS2	CS3	CS4	Total	Component Rating
Finalized	n/a	(55%+50%)/2=53%	19%	14%	14%	100%	5

Case VI: Highest CS4 (Normalized) Element

This case was similar to Case IV. However, in this case, the distinction between different measurement unit groups was ignored. Thus, the element with the absolute highest normalized CS4 percentage was selected as the controlling element of a given component. If the values of CS4 for two or more elements (per component) were equal, the element with the highest CS3 from this subgroup was selected and so forth for CS2 and CS1 until a controlling element was determined. Table 23 shows the Case VI procedure again using the data shown in Table 11 as the example data set (normalized condition states).

Table 23. Finalized data point to be used for modeling.

Element	Unit	CS1	CS2	CS3	CS4	Total	Component Rating
219- Abutment	LF	55%	5%	12%	28%	100%	5

Case VII: Lowest scored Element

This case was very similar to Case III but differed in that the element with the lowest score (regardless of the measurement unit type) was selected as the controlling element of a given component. According to Table 16, the "219 – Abutment" had the lowest score among all other elements and thus was selected as the controlling element, as shown in Table 24.

Table 24. Finalized data point to be used for modeling.

Element	Unit	CS1	CS2	CS3	CS4	Total	Component Rating
219- Abutment	LF	55%	5%	12%	28%	100%	5

Depending on the element types that constitute a component as well as their measurement unit type, absolute quantity values, and relative quantity (normalized) values, the various aggregation methods above yielded different controlling elements. However, the controlling element, and/or pseudo controlling element in cases where the final step was to average condition state values from all selected elements, supported the need to determine a representative data row that facilitates model development and achieves the desired modeling effort outcomes. Excluding Case 0, when a four-element component in the fact table comprises four data rows, with each row corresponding to one of the four elements, these four data rows within the fact table are consolidated into a single data row. This consolidated row represents the component and is characterized by aggregated CS values (CS1-CS4). For programming purposes, the fact table that has undergone the cleaning step was duplicated eight times, and each duplicate was processed independently using a distinct aggregation technique. Subsequently, each of the resulting fact tables proceeded to the modeling stage.

The final data points from each case for the example substructure have been collected and are presented in Table 25. In some instances, the cases yielded the same outcomes, however, this was not always the case. The chosen aggregation methods sought to address inherent human factors in how component ratings were assessed and applied in the field. More importantly, the application of different aggregation methods was intended to resolve the contribution of element types with different units of measure. Reviewing the aggregation methods discussed above, it was apparent that all methods would result in identical profiles for bridge components comprised of single elements. However, the aggregation methods yielded different profiles when bridge components were made up of multiple elements. Further discussion regarding this finding is provided later in the report.

Table 25. Summary of controlling data point from each aggregation case.

Case	Element	Unit	CS1	CS2	CS3	CS4	Total	Component Rating
0	219- Abutment	LF	55%	5%	12%	28%	100%	5
	231- Pier Cap	LF	37%	37%	19%	7%	100%	5

Case	Element	Unit	CS1	CS2	CS3	CS4	Total	Component Rating
	202- Column	EA	50%	50%	0%	0%	100%	5
	225- Pile	EA	50%	33%	17%	0%	100%	5
I	Finalized	n/a	52%	25%	9.5%	13.5%	100%	5
II	Finalized	n/a	48%	31%	12%	9%	100%	5
III	Finalized	n/a	53%	19%	14%	14%	100%	5
IV	Finalized	n/a	53%	19%	14%	14%	100%	5
V	Finalized	n/a	53%	19%	14%	14%	100%	5
VI	219- Abutment	LF	55%	5%	12%	28%	100%	5
VII	219- Abutment	LF	55%	5%	12%	28%	100%	5

Model Development (Element to Component)

To develop convergent and accurate conversion profiles, a large population of historical observations was extremely desirable. Six years of both NBI component- and element-level data (2017-2022), for nearly 146,000 NHS bridges, were processed for data analysis. Once the fact tables were passed through the cleaning and assembling steps, multiple aggregation methods were investigated to produce the final data set for conversion profile model development. To complete this effort, multiple models were developed for each aggregation case, and comparisons were made to investigate which approach(s) resulted in a higher level of accuracy. The following sections describe the process taken to develop and validate the conversion profile models.

Modeling Techniques

Several statistical modeling techniques were applied and compared against each other to investigate how element-level condition states can be used to predict the component-level condition ratings. It was important during this process to select modeling techniques that resulted in explicit equations that eventually could be programmed into Microsoft Excel. The intent was to deliver conversion profiles that were based on an equation, a table, or matrix formats, which could be easily integrated into common applications such as Microsoft Excel, rather than complex algorithms. Similarly, machine learning or evolutionary techniques that rely on “black box” approaches were avoided, however, a few of them were assessed to see if they resulted in better accuracy. In total, over seven different modeling approaches were investigated, including the translator model (which is primarily a conversion table) used by AASHTOWare™ Bridge Management (BrM) software, as well as the translators used by a few States. After a comprehensive evaluation of models and the outcomes, four modeling approaches outperformed the other techniques. The details of these four modeling techniques are discussed below:

FHWA Converter

FHWA’s first-generation MBEI data converter profile utilized a table-driven procedure that compared condition state quantity thresholds in the CS1 to CS4 categories to NBI condition ratings, as shown in Table 26. The quantities reported for each element were combined using the aggregation procedure described above for Case I. The resulting allocations to CS1 through CS4 were then compared to the values in Table 26 and the lowest resulting component rating was then selected. For example, using the example aggregation data presented in Table 14, the lowest NBI rating would be derived for the CS4 quantity of 13.5%, which yields a component rating 4. This compares to the inspector's reported component rating of 5 for this bridge.

For this study, the FHWA first-generation converter profile (the threshold table shown in Table 26) was used along with the various aggregation cases presented above to generate predicted ratings. The predicted values were then compared to the reported inspector ratings, which were taken as the "ground truth" value. Accuracy levels achieved by each aggregation case were reported and compared.

Table 26. FHWA First Generation Converter Table.

GCR	Condition state percentages			
	CS1%	**CS2%**	**CS3%**	**CS4%**
9	-	-	-	-
8	100	0	0	0
7		1-20	0	0
6			1-5	0
5			6-20	0
4				1-20
3				21-100
2	-	-	-	-
1	-	-	-	-

Logistic Regression (LR)

Logistic modeling (or logit model) techniques are applicable to categorical data where the output (predicted condition rating) is a binary (or multi-binary) value. The binary value used here refers to the predicted outcome being part of a categorical group or not part of that categorical group. In a multi-binary case, as an example, the predicted outcome or NBI rating is 9 or is not 9, is 8 or is not 8, and so on. As schematically shown in Figure 9, the logit model is a classification method and in its basic form uses a logistic function to model a binary dependent variable. The logit method is a statistical procedure to find the best fit for a set of independent variables (condition states here) versus the dependent variable (component rating) by minimizing the sum of the offsets or residuals of points from the actual response. Other details related to the development of the logit model are not discussed here for conciseness. The time for model training could rise depending on the size of training data. Although the final model can be programmed into a Microsoft Excel spreadsheet, the runtime for large data entries could exponentially increase.

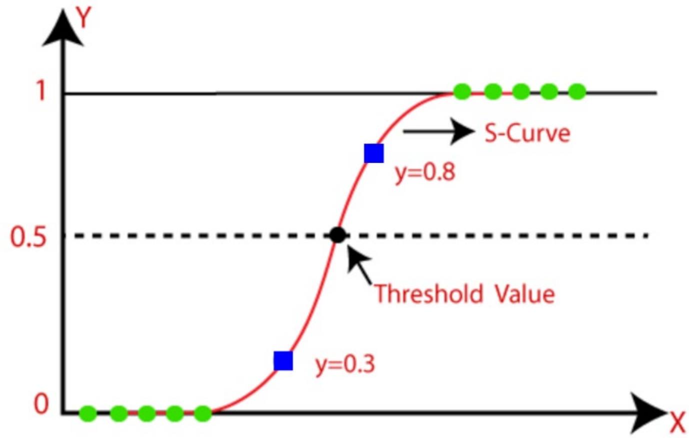


Figure 9. Conceptual definition of a Logit Model.

Classification Decision Tree

A Decision Tree (DT) is a supervised machine learning algorithm that is typically used for classification purposes. A DT builds classification models in the form of a tree structure. It breaks down a data set into smaller and smaller subsets while at the same time an associated DT is incrementally developed. When developing a model for a distinct dataset, a DT model employs internal objective functions to minimize impurity and node error during the development and splitting of optimal decision trees or nodes. For the case in present study, it means achieving the minimum difference between the predicted CR and the inspector-assigned CR (as reported in NBI). Techniques like Gini's Diversity Index, Deviance, Twoing rule are examples of different criteria to define impurity.

The ultimate outcome is a tree comprising decision nodes and branch nodes. Depending on the initial setup defined in the model such as the maximum number of decision splits or branch nodes, the decision tree could be concise or extensive. A concise tree will include fewer decision branches that will require less computation time but might suffer from lower accuracy. In contrast, an extensive tree might be very complex and time-consuming but could provide higher accuracy. Figure 10 shows an example of a DT that was developed based on processed data. An advantage of the DT method is its ability to be defined by discrete programmable statements that can be easily programmed into Microsoft Excel to create the universal profile. Due to its simplicity, a DT model does not require long run times for converting large sets of element data.

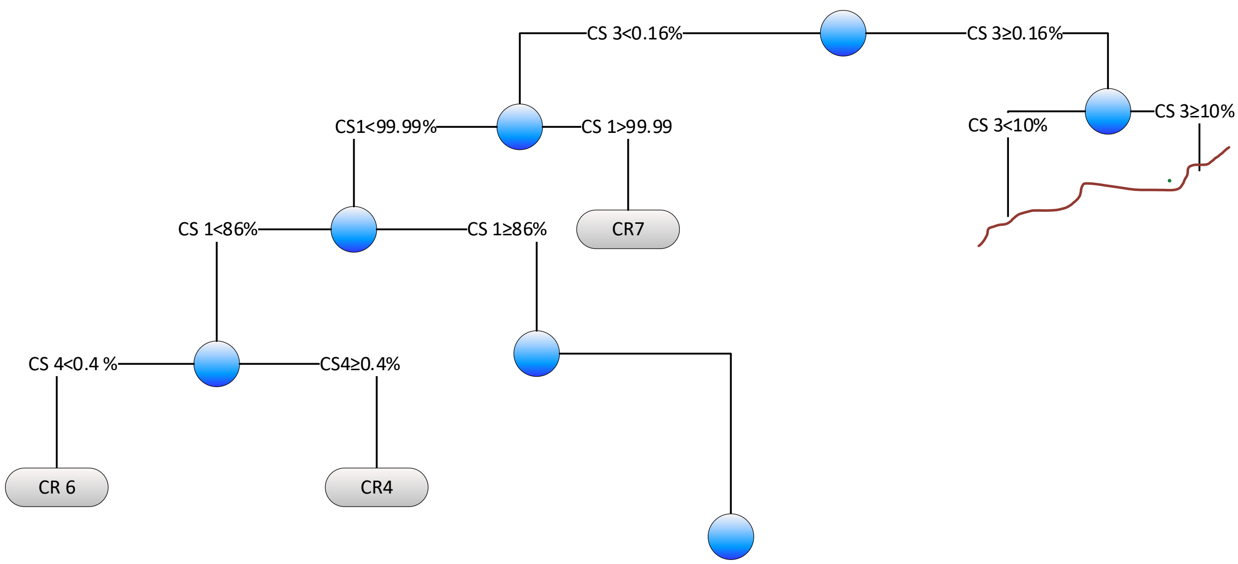


Figure 10. Schematic of a DT.

ML/AI Techniques

Several Machine Learning (ML) and Artificial Intelligent (AI) techniques were investigated to evaluate if such techniques will result in higher accuracies. Some of these techniques include but are not limited to, k-nearest neighbors (KNN), Support Vector Machine (SVM), and Discriminant, among others. As noted earlier, these techniques were not desired for this project by the FHWA because they are not convertible to simple/programmable formulation. Nonetheless, these techniques provide insight into the possible opportunities to achieve higher accuracy.

All the model types described above were used to develop multiple conversion profiles during the execution of this project and were reviewed by the FHWA. The level of performance varied from model to model and data set to data set. The models with consistent and reliable performance were eventually selected and their outcomes reported later in this report. However, the detailed results associated with all models are available upon request.

Model Accuracy Quantification

For each data aggregation technique, a distinct fact table was generated. Given that a different profile is generated from each dataset that is unique to an aggregation method, many models were generated and evaluated for accuracy. Consequently, several definitions of model accuracy were considered to aid in the final model selection and in reporting the ultimate accuracy results. These definitions were instrumental in guiding the final selection of the model, considering the multiple models created for each aggregation method. The accuracy quantification techniques used to evaluate and select the final conversion profile were as follows:

$$Total\ Accuracy\ \pm 0\ CR = \frac{\sum_{i=3}^{9}(\pm 0\ Correctly\ Predicted_{CRi})}{\sum_{i=3}^{9} Total_{CRi}} \times 100\%$$

$$Total\ Accuracy\ \pm 1\ CR = \frac{\sum_{i=3}^{9}(\pm 1\ Correctly\ Predicted_{CRi})}{\sum_{i=3}^{9} Total_{CRi}} \times 100\%$$

$$Total\ Accuracy\ \pm 2\ CR = \frac{\sum_{i=3}^{9}(\pm 2\ Correctly\ Predicted_{CRi})}{\sum_{i=3}^{9} Total_{CRi}} \times 100\%$$

$$Sum(CR4-5)_{\pm 0} = \frac{\sum_{i=4}^{5}(\pm 0\ Correctly\ Predicted_{CRi})}{\sum_{i=4}^{5} Total_{CRi}} \times 100\%$$

$$Sum(CR4-7)_{\pm 0} = \frac{\sum_{i=4}^{7}(\pm 0\ Correctly\ Predicted_{CRi})}{\sum_{i=4}^{7} Total_{CRi}} \times 100\%$$

$$Ranking\ Score = 1.0 \times Sum(CR4-5)_{\pm 0} + 0.4 \times Sum(CR4-7)_{\pm 0}$$

Where Total Accuracy ±0 through ±2 represents the percentage of predicted condition ratings that fall within ±0 to ±2 of the condition rating assigned by the inspector (i.e. as reported by NBI). For example, if a deck is rated at 7 and the model predicts it as 5, then this prediction will not be counted toward the ±0 and ±1 accuracy calculations but will be considered for ±2 accuracy calculations.

Three additional accuracy definitions were considered to evaluate the performance of conversion profile models only in the lower condition ratings where the outcomes of conversion profiles could be critical at defining the general condition of a bridge (Good [CR7-9], Fair [5-6], Poor [4 and below]), especially between ratings 4 and 5. This is important from a bridge management user perspective, if given a choice, the user would commonly choose higher accuracy for CR5 and CR4 than CR7 and CR6. The former represents the transition from a fair to poor condition, while the latter from a good to fair condition. Within condition and performance forecasting metrics for asset management, the number of bridges in poor condition or close to poor condition tend to draw the most attention and require the largest cost actions. There are fewer bridges in these lower CR states, and as such, the development of conversion profiles that are selected among other profiles (because they have highest total accuracy) are more likely to be influenced by the higher condition ratings because they represent the majority of the population. Hence, there was a need to consider revised accuracy definitions for lower condition ratings. Different data sampling techniques intended to address this issue were also evaluated as described later.

Model Validation and Reporting of the Accuracy

To gain a better understanding of the reliability and reproducibility of the final conversion profiles against an unknown data set as might occur when future NBI component- and element-level data is collected, the profiles were validated to a subset of the data set that was not used for model development. The existing NBI component- and element-level data sets were randomly parsed into a core (training) data set and a smaller blind (testing) data set. The conversion profiles were developed using the core data set and then checked against the blind data set to quantify profile performance.

During multiple stages of the project, accuracy values were calculated for both the training and testing data sets and noted that these values were typically close (in the range of ±1%). However, the difference becomes larger for small population sizes (<1000). To that end, a question remained unanswered as to which accuracy value should be reported. The research team conducted the following analysis to provide context into which approach would be most appropriate.

The data-driven models (LR, and variants of DTs utilized in this project) were trained on 80 percent of the entire data set and tested over the remaining 20 percent. This validation method is called “Hold-out”, a variant of the cross-validation technique. The hold-out method is good when a large data set is available.

The split between training and testing data sets was conducted randomly, therefore, the training and testing data sets used in the development of different models were not the same. During each split, the shuffling was made in a way that both training and testing data sets contained data points from each CR. This process, which is called stratification, was the process of rearranging the data to ensure that the training/testing set for each condition rating was representative of the whole.

The review of the results indicated that the accuracy values (all types) seem more consistent in the presence of large data sets. That is why the difference between training/testing accuracies was previously shown to be minimal. Conversely, the calculated accuracy values for smaller data sets vary significantly. Surprisingly, it was found that every execution of the program (multiple repeats for a given scenario) resulted in accuracy values with ±5% variability for small data sets. Thus, it was decided to use the 80/20 hold-out as the preferred validation on large data sets while using 100% of the data for both training/testing when dealing with small data sets. Utilizing the entire dataset, 100 percent of it, for both training and testing purposes can lead to potential problems, such as model overfitting. Nevertheless, the intention here was to make the most of the available data, especially for those profiles with very small populations. This approach was chosen to ensure that a sufficient amount of data was available to train the models effectively despite the challenges posed by limited sample sizes.

Finalized Modeling Approach

For the conversion of element-level condition states to component-level condition ratings, three sets of conversion profiles were developed. The first set was a universal conversion profile that was inclusive of all element and component types (single profile). The second set was inclusive of four individual profiles that were representative of each component – deck, superstructure, substructure, culvert and were inclusive of all materials and intended to be more accurate than the universal profile. The third set included multiple conversion profiles that were representative of each component refined by major material types for each component (multiple conversion profiles for each of the four components).

Figure 11 schematically depicts how the bridge data set was hierarchically clustered into multiple subsets depending on the bridge component and material type. In essence, the figure demonstrates how each hierarchy level corresponds to the type of conversion profile developed for each set. Furthermore, Figure 11 conceptually explains the population shrinkage when the data was divided into smaller clusters. The size of the box is an indicator of the size of the remaining sample. As the historical data was clustered into different categories, the sample size shrunk exponentially.

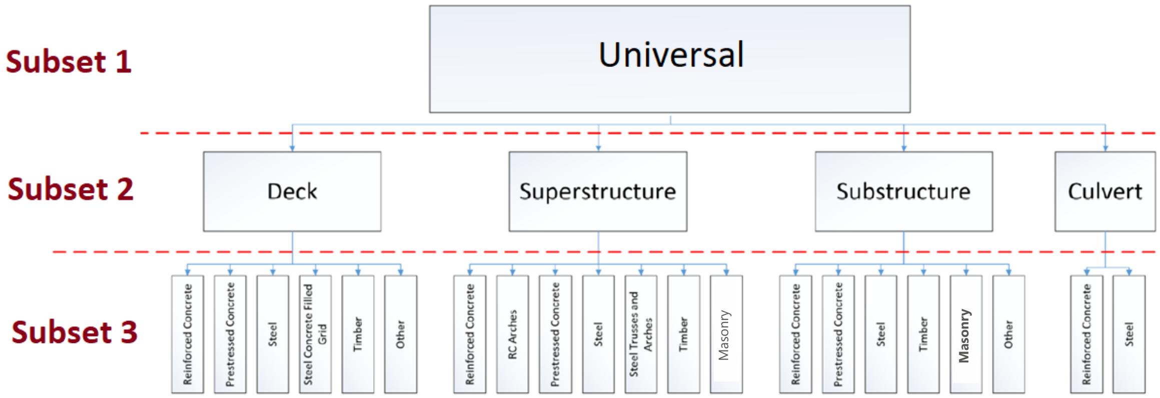


Figure 11. Requested conversion profiles under each respective subset.

During the execution of project, the effort required to study individual accuracies calculated for each condition rating or deploying different data sampling and modeling techniques, and aggregation methods resulted in a significant number of results tables. For conciseness, only the results and models associated with the best and finalized models (inclusive of data aggregation method, data sampling and modeling technique, accuracy definition, etc.) are provided in the following sections. Brief summaries of each selected model are provided below.

Single- vs. Multiple- vs. All-Element Models

As noted above, the primary reason behind the separation of multi- and single element components was only to determine which aggregation technique results in a highest accuracy for multi-element components. For evaluation, separate profiles were generated for data sets that included only single element components, only multi-element components, and all-element components (combination single and multi-element components). Comparing the profiles using the accuracy metrics it was found that on many occasions the all-element profiles were equal or better accuracy than the single- and multi-element profiles. Therefore, only the results and models associated with the all-element profiles are reported in the following sections.

Aggregation Methods

While all aggregation methods were tested under each modeling technique, only the best performing aggregation method is reported herein for each profile type. Case 0 was initially incorporated into the analysis but was subsequently excluded during the development of the final conversion profiles. This exclusion was due to the understanding that it would not yield a single CR for multi-element components.

Modeling Techniques

Seven aggregation techniques (designated as Case I-Case VII) along with all three modeling techniques (FHWA Converter, LR, DT) were studied during the modeling efforts. DT was observed to outperform the other techniques, and therefore, was selected as the primary modeling technique to develop conversion profile models. For comparison purposes, the other modeling techniques originally introduced (inclusive of AASHTOWare^{TM} BrM, etc.) were tested but are not provided in the report.

When generating the decision classification tree branches, the DT algorithm demonstrated a tendency towards maximizing the number of correct conversions in the response variable classes (i.e. condition ratings) that are higher population size than other classes. It was observed that the developed models yielded better accuracy for the condition ratings of higher population size and lesser accuracy for the condition ratings of lower population size. In general, the DT algorithm is effective for balanced data sets (i.e. similar population of data in each CR) and does not perform well using imbalanced data sets. By default, the DT determines class probabilities from class frequencies in the response variable. That being said, there are data sampling techniques that can be applied to resolve the data imbalance issues. Several different techniques were investigated and tested. The two best performing techniques (highest accuracy) were eventually selected for use in the final model development, including:

- Imbalanced (original or default) accuracy, where the classifier maximizes accuracy for the combined set of classes without regard for accuracy within each individual class (no matter the population size in each class). This technique is designated with "DT # Imbalanced" in the following results tables.
- Under-sampling majority class(s), where the class(s) with a large population is randomly under-sampled to prevent bias in the modeling. Using this technique, all condition rating classes having a population larger than the selected less populated class (i.e. CR3 or CR4 or CR5) could be under-sampled. After a thorough investigation and to improve accuracy of conversions to CR4, the final model was undersampled for class CR4. This technique is designated with "DT # Balanced" in the following results tables.

Given the promising results of DT for large data sets as well as its simplicity in terms of function generation for Microsoft Excel programming, further investigations were conducted to ascertain the multiple attributes of the DT classification technique. This included special attention to avoid the overfitting issue, which is a common difficulty for large data sets with lots of data variability, and the different approaches introduced above for handling imbalanced data.

General Attribute Selection - In the present study, MATLAB software has been utilized for programming and modeling purposes. However, other software such as Python or R (Studio) could be used instead. Several preliminary trial-and-error iterations (over fifty) were conducted to find an optimum initial setup that achieved both an acceptable level of complexity and accuracy. The optimum setup occurred when the number of decision splits (or branch nodes) was limited to 20. The model was executed by applying Pruning using the "error" prune criterion technique. A standard Classification and Regression Trees (CART) algorithm was used to select the split predictor that maximizes the split-criterion gain over all possible splits of all predictors. Among multiple split criterion techniques, 'deviance' resulted in slightly better results. The remainder of the DT parameters were left at their default values in MATLAB.

In addition, ML and AI techniques were employed against the fact table using multiple aggregation techniques. The example results suggested that the classification DT, which allows unlimited decision splits, can attain accurate predictive condition ratings 63% of the time, with a margin of error of ±0CR for total accuracy, when the Case 0 aggregation technique was applied to the entire dataset linked with the universal profile. Nevertheless, limiting the branches of the decision (decision split node) to 20 resulted in a decreased accuracy of 53%. In general, ML and AI yielded an approximately 10 percentage point higher accuracy compared to the classification DT (with limited decision splits). However, because ML and AI techniques could not be adapted to Microsoft Excel formats and were computationally time-consuming, they were not investigated further.

Data Availability to Derive Convergent Models

In the case of Subset 3, as depicted in Figure 11, any component comprised of multiple elements from different material types (as defined in Table 1) was excluded from the dataset. For example, a deck component with three elements (13- prestressed concrete deck, 12- reinforced concrete deck, 38- reinforced concrete slab) was eliminated from the Subset 3 dataset because the elements are comprised of more than one material type, namely prestressed concrete and reinforced concrete. However, a deck component with two elements (12- reinforced concrete deck, 38- reinforced concrete slab) was retained in the Subset 3 dataset for development of material-level profiles because the elements are comprised of one material type, namely reinforced concrete.

For the Subset 3 case presented in Figure 11, if the number of available data points for any material type dropped below a certain threshold, which was insufficient to develop convergent and reliable models, then modifications to the data sets were done. First, the material types were paired to form a similar family of materials e.g., pairing steel open grid deck and steel concrete filled grid deck. If appropriate material pairings could not be found, then the material type was dropped.

Figure 12 shows the finalized segmentation used for Subset 3, where some material types were either paired or removed. Based on experience gained from multiple modeling runs, it was found that any model established using less than 1000 data points did not deliver reliable and convergent models with an acceptable level of accuracy. However, models for such cases were still developed for completeness. Such models are highlighted in Figure 12 with a bold red box.

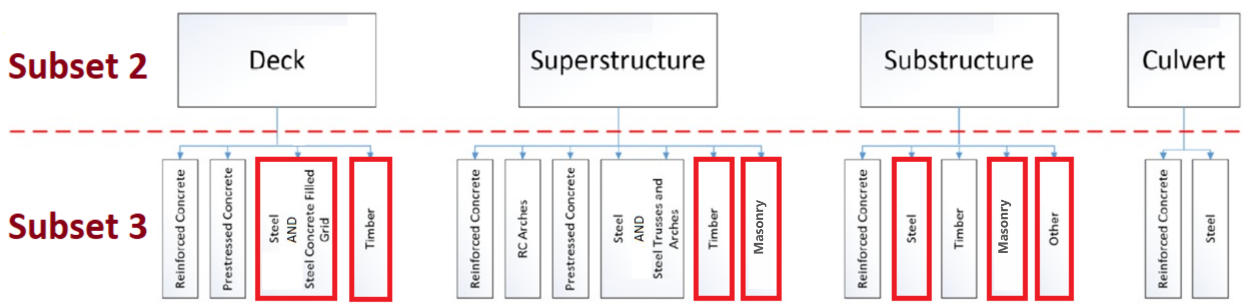


Figure 12 Seventeen conversion profiles developed under Subset 3 category.

Final Conversion Profiles

When seeking to achieve the highest overall accuracy during the development of a DT, the model gravitated toward maximizing the accuracy of correlations in the component condition ratings for which the component population largely resided, which were CR7 and CR6. The byproduct was far less accurate for the condition ratings that had a smaller population and therefore had less contribution to total accuracy, namely CR5 and CR4. After numerous discussions, the final models (that were developed for different aggregation methods as well as different modeling techniques) were chosen based on review of each model's total and individual CR accuracy values and sum(CR4-5), sum(CR4-7), and Ranking Score quantifications as defined previously. Appendix II provides a concise step-by-step flowchart to reproduce the final conversion profiles should additional data become available in the future. For additional details necessary for the reproduction and programming of conversion profiles, the details in the following as well as the previous sections should be followed.

Table 27 summarizes the finalized conversion profiles. Appendix III provides the full description of each conversion profile that is listed in Table 27. A universal profile was developed for Subset 1, as indicated in

Figure 11. For Subset 2, profiles were developed for each major component type. Finally, seventeen profiles were developed to address the various material compositions of each major component type as represented by Subset 3 in Figure 12. At the request of FHWA, two conversion profile types were developed for each of the above twenty-two profiles, one using DT#Imbalanced (IB), and one using DT#Balanced - undersampled CR4 (B) modeling techniques. For each finalized conversion profile in Table 27, the aggregation technique that yielded the highest accuracy for the testing dataset was selected. In the case of IB models, the model associated with the aggregation method that yielded the highest accuracy for $Total\ Accuracy\ \pm 0\ CR$ was selected. In cases where multiple models achieved the same accuracy, the $Total\ Accuracy\ \pm 1\ CR$ became the decisive selection criterion. If the models still did not differentiate based on $Total\ Accuracy\ \pm 1\ CR$, $Total\ Accuracy\ \pm 2\ CR$ was subsequently used to finalize the model selection. For the B models because they were developed to improve conversion accuracy of lower condition ratings as compared to the IB models, the Ranking Score was used to select the final models using the different aggregation methods. This approach is particularly important from the perspective of bridge management users, as they will commonly prioritize higher accuracy for CR5 and CR4 (transition from fair to poor) over accuracy for other condition ratings when making choices. In situations where multiple models achieved identical accuracy levels, a consistent hierarchy based on $Total\ Accuracy\ \pm 0\ CR$, $Total\ Accuracy\ \pm 1\ CR$, and $Total\ Accuracy\ \pm 2\ CR$ was employed to select the final model.

To further simplify the process and reduce the number of aggregation techniques, one representative aggregation technique was chosen for each component, which was then used to develop the final conversion profiles. This selected representative aggregation technique was applied not only to create component conversion profiles but also to construct conversion profiles for the materials falling under the same component category. The selection process involved comparing the accuracy results of all models developed for a given component using various aggregation techniques. The model associated with the aggregation technique that yielded the highest accuracy was chosen as the representative method for all subsequent material conversion profiles. For instance, if Case IV yielded the highest Ranking Score for the balanced superstructure profile, Case IV was employed to develop balanced conversion profiles for all material types under the superstructure component. The same process was applied to create imbalanced conversion profiles. In the later stages of the analysis, it was observed that the representative aggregation technique consistently performed equally or outperformed other aggregation methods, for both balanced and imbalanced datasets. Therefore, as depicted in Table 27, the representative aggregation method was applied to both balanced and imbalanced conversion profiles.

In Table 27, the type of validation and calculated accuracy are provided for each profile. If a large data set was used to develop the profile, the 80/20 hold-out method was used, therefore, two accuracies—one for training and one for testing—are listed. The designated 80/20 means 80% and 20% of the database was used for training and testing of a given profile, respectively. Therefore, the provided accuracy (e.g., 55%/54%) denote the calculated accuracy for training and testing data sets, respectively. For small data sets, the final developed profile was trained using 100% of the database and used the same data to test and report accuracy.

The six accuracy formulations described previously were used to evaluate the developed models and make final selections. Appendix IV provides three accuracy formulations for the selected profiles, Total Accuracy ±0 CR, ±1 CR, and ±2 CR margin of error. It also provides the accuracy within each condition rating.

Table 27. Summary of finalized conversion profiles.

ID	Subset	Component	Material	Modeling	Represented Aggregation	Validation*	Total Accuracy (±0CR)*
1	1	All	All	B	Case V	80/20	43%/43%
2				IB	Case V	80/20	53%/53%
3	2	Deck	All	B	Case V	80/20	43%/44%
4				IB	Case V	80/20	55%/54%
5	2	Superstructure	All	B	Case IV	80/20	46%/46%
6				IB	Case IV	80/20	51%/51%
7	2	Substructure	All	B	Case II	80/20	45%/46%
8				IB	Case II	80/20	56%/56%
9	2	Culvert	All	B	Case VII	80/20	48%/44%
10				IB	Case VII	80/20	58%/58%
11	3	Deck	Prestressed Concrete	B	Case V	100/100	67%/67%
12				IB	Case V	80/20	67%/66%
13	3	Deck	Reinforced Concrete	B	Case V	80/20	44%/45%
14				IB	Case V	80/20	54%/54%
15	3	Deck	Steel & Steel Concrete Filled Grid	B	Case V	100/100	74%/74%
16				IB	Case V	100/100	68%/68%
17	3	Deck	Timber	B	Case V	100/100	68%/68%
18				IB	Case V	100/100	78%/78%
19	3	Superstructure	Reinforced Concrete	B	Case IV	80/20	64%/66%
20				IB	Case IV	80/20	63%/62%
21	3	Superstructure	RC Arches	B	Case IV	100/100	55%/55%
22				IB	Case IV	80/20	56%/54%
23	3	Superstructure	Prestressed Concrete	B	Case IV	80/20	53%/52%
24				IB	Case IV	80/20	57%/58%
25	3	Superstructure	Steel & Steel Trusses and Arches	B	Case IV	80/20	46%/46%
26				IB	Case IV	80/20	50%/50%
27	3	Superstructure	Timber	B	Case IV	100/100	77%/77%
28				IB	Case IV	100/100	67%/67%
29	3	Superstructure	Masonry	B	Case IV	100/100	71%/71%
30				IB	Case IV	100/100	70%/70%
31	3	Substructure	Reinforced Concrete	B	Case II	80/20	45%/44%
32				IB	Case II	80/20	56%/56%
33	3	Substructure	Steel	B	Case II	100/100	71%/71%
34				IB	Case II	100/100	75%/75%
35	3	Substructure	Timber	B	Case II	100/100	71%/71%
36				IB	Case II	100/100	64%/64%

ID	Subset	Component	Material	Modeling	Represented Aggregation	Validation*	Total Accuracy (±0CR)*
37	3	Substructure	Masonry	B	Case II	100/100	69%/69%
38				IB	Case II	100/100	65%/65%
39	3	Substructure	Other	B	Case II	100/100	64%/64%
40				IB	Case II	100/100	56%/56%
41	3	Culvert	Reinforced Concrete	B	Case VII	80/20	46%/47%
42				IB	Case VII	80/20	58%/58%
43	3	Culvert	Steel	B	Case VII	100/100	55%/55%
44				IB	Case VII	80/20	57%/53%

** Training/Testing*

Model Development (Component to Element)

Similar to the conversion profiles developed to convert element-level condition states to component-level condition rating, a universal conversion profile was developed to convert component-level condition rating to element-level condition states. This profile encompassed all major components, including the deck, superstructure, substructure, and culvert, regardless of their material type. Six years of NBI component- and element-level data (2017-2022), for nearly 146,400 NHS bridges, were processed for data analysis. Once the fact tables were passed through the cleaning and assembling steps, a comprehensive statistical analysis was conducted on the data to extract the possible correlation between component- and element-level databases. The following sections explain the details of the different steps conducted to derive the final universal profile:

- The April 2013 FHWA Converter Technical Manual includes a procedure for synthesizing (i.e., estimating) element types and quantities from NBI component and geometry data. An update of the synthesis procedure was not within the scope of this project. The developed component to element condition conversion profile may be applied as a comparison to bridges with element data and known condition states (as represented in agency inspection data or the NBI for NHS bridges) or applied in software such as the National Bridge Inventory Analysis System that synthesize element types, quantities, and condition states using NBI design type, material type, and geometry data, and apply deterioration models to the synthesized elements to estimate future condition of bridges.
- To conduct statistical analysis, the entire data set comprising over 1.4 million datapoints from 2017-2022, was used. The fact table used for this analysis was similar to the "Case 0 – No Aggregation" case, where all elements exist regardless of the component or material type, i.e., multi-element components have each element represented as an individual data row for each CS, rather than a single aggregated data row for each CS.
- During the conversion of component condition rating to element CS, all identified elements for a given component received the same CS1-4 percent quantity in each condition state.

Figure 13 through Figure 19 show the distribution of the database for CR9 through CR3, respectively. Each figure comprises four subfigures representing the percentage of CS1 to CS4.

Each subfigure provides the histogram (frequency of repeat) for each CS (1-4) for a given CR. In developing each histogram, 100 bins with a uniform length of 1% were used. Edge(0) is the left edge of the first bin, i.e. [0%-1%), and edge(100) is the right edge of the last bin, [99%-100%]. The value X(i) is in the kth bin if edges(k) ≤ X(i) < edges(k+1). The last bin also includes the right bin edge, so that it contains X(i) if edges(end-1) ≤ X(i) ≤ edges(end).

Upon review of the histograms generated for CR3 through CR6, it is apparent that each graph contains some datapoints with 100% CS1. While it may be expected that data points with 100% for CS1 should not appear in the histogram (as such data was expected to have been removed during data cleaning), this observation was not necessarily unreasonable. During the data cleaning stage, it was specified that only components rated 6 or below with all elements rated 100% in CS1 were to be removed from the fact tables. For instance, a component (rated at CR5 with four elements) that consisted of three elements with 100% in CS1 and one element with 99% in CS1 successfully passed through the data cleaning filter and remained in the fact table. It is crucial to note that the fact table used for this analysis closely resembles the "Case 0 – No Aggregation" case, where all elements that have passed through the data cleaning stage exist, regardless of the component type, i.e., multi-element components have each element represented as an individual datapoint for each CS, rather than a single aggregated datapoint for each CS.

Table 28 summarizes the statistical analysis of Figure 13 to Figure 19 by reporting the average (μ) and standard deviation (σ) values for each CR/CS. For better visualization, Figure 20 presents the same results graphically. The table provides three values of converted CS for each CR: the average, one standard deviation (μ-σ to μ+σ), and two standard deviations (μ-2σ to μ+2σ). The results show a consistent trend between the rate of CS1 decrease and CR drop, as well as between the increase in CS2, CS3, and CS4 and CR drop. The μ values provided in Table 28 serve as the definitive universal conversion profile for converting component-level condition rating into element-level condition states, under the assumption that all elements within multi-element components will share the same CS1-4 percent quantity in each condition state.

The data presented here deviate from a normal distribution. In normal distributions, there is a 68% probability that the actual value will fall within one standard deviation from the mean, and a 95% probability that it will fall within two standard deviations. However, due to the skew observed in the data, these probabilities do not apply in this case.

Figure 21 presents the final average values (μ) for data processed in the current study, as well as the values published in the FHWA Technical Manual (first-generation component-element converter). The comparison between these curves indicates that:

- The computed average values using the 2017-2022 data outperform the values published by the FHWA first-generation converter, which did not rely on fully data-driven methods; and
- Due to the consistency of the average values obtained through the current study, it is recommended to use the average values as the final CR-CS conversion profiles, without the need for further modeling.

Table 28. NBI condition rating to element condition state.

Component Condition Rating		Element Condition States %*			
		CS1	CS2	CS3	CS4
CR9	μ	98.92	1.03	0.06	0
	(μ-σ,μ+σ)	(91.96 to 105.87)	(-5.71 to 7.76)	(-1.36 to 1.47)	(0 to 0)
	(μ-2σ,μ+2σ)	(85.01 to 112.83)	(-12.44 to 14.49)	(-2.77 to 2.88)	(0 to 0)
CR8	μ	97.28	2.55	0.17	0
	(μ-σ,μ+σ)	(86.97 to 107.58)	(-7.36 to 12.46)	(-2.05 to 2.4)	(0 to 0)
	(μ-2σ,μ+2σ)	(76.67 to 117.88)	(-17.27 to 22.38)	(-4.28 to 4.62)	(0 to 0)
CR7	μ	90.77	8.35	0.87	0
	(μ-σ,μ+σ)	(70.34 to 111.21)	(-11.02 to 27.73)	(-4.56 to 6.31)	(0 to 0)
	(μ-2σ,μ+2σ)	(49.91 to 131.64)	(-30.4 to 47.1)	(-10 to 11.75)	(0 to 0)
CR6	μ	73.2	22.31	4.44	0.05
	(μ-σ,μ+σ)	(40.16 to 106.24)	(-8.09 to 52.72)	(-8.15 to 17.02)	(-1.37 to 1.48)
	(μ-2σ,μ+2σ)	(7.12 to 139.27)	(-38.5 to 83.12)	(-20.73 to 29.6)	(-2.79 to 2.9)
CR5	μ	61.35	27.32	11.05	0.28
	(μ-σ,μ+σ)	(24.49 to 98.21)	(-4.51 to 59.15)	(-9.26 to 31.36)	(-2.82 to 3.39)
	(μ-2σ,μ+2σ)	(-12.37 to 135.06)	(-36.34 to 90.98)	(-29.57 to 51.67)	(-5.93 to 6.49)
CR4	μ	49.19	27.64	20.94	2.23
	(μ-σ,μ+σ)	(10.72 to 87.67)	(-3.04 to 58.31)	(-6.43 to 48.31)	(-7.08 to 11.54)
	(μ-2σ,μ+2σ)	(-27.76 to 126.14)	(-33.72 to 88.99)	(-33.8 to 75.69)	(-16.39 to 20.85)
CR3	μ	43.72	28.48	21.32	6.49
	(μ-σ,μ+σ)	(4.21 to 83.24)	(-3.35 to 60.3)	(-6.71 to 49.34)	(-11.8 to 24.78)
	(μ-2σ,μ+2σ)	(-35.31 to 122.75)	(-35.17 to 92.12)	(-34.73 to 77.36)	(-30.09 to 43.06)

* In practice, feasible ranges would be capped at 0% minimum and 100% maximum. Values less than 0 and greater than 100 are the result of applying a normal distribution to the skewed data set.

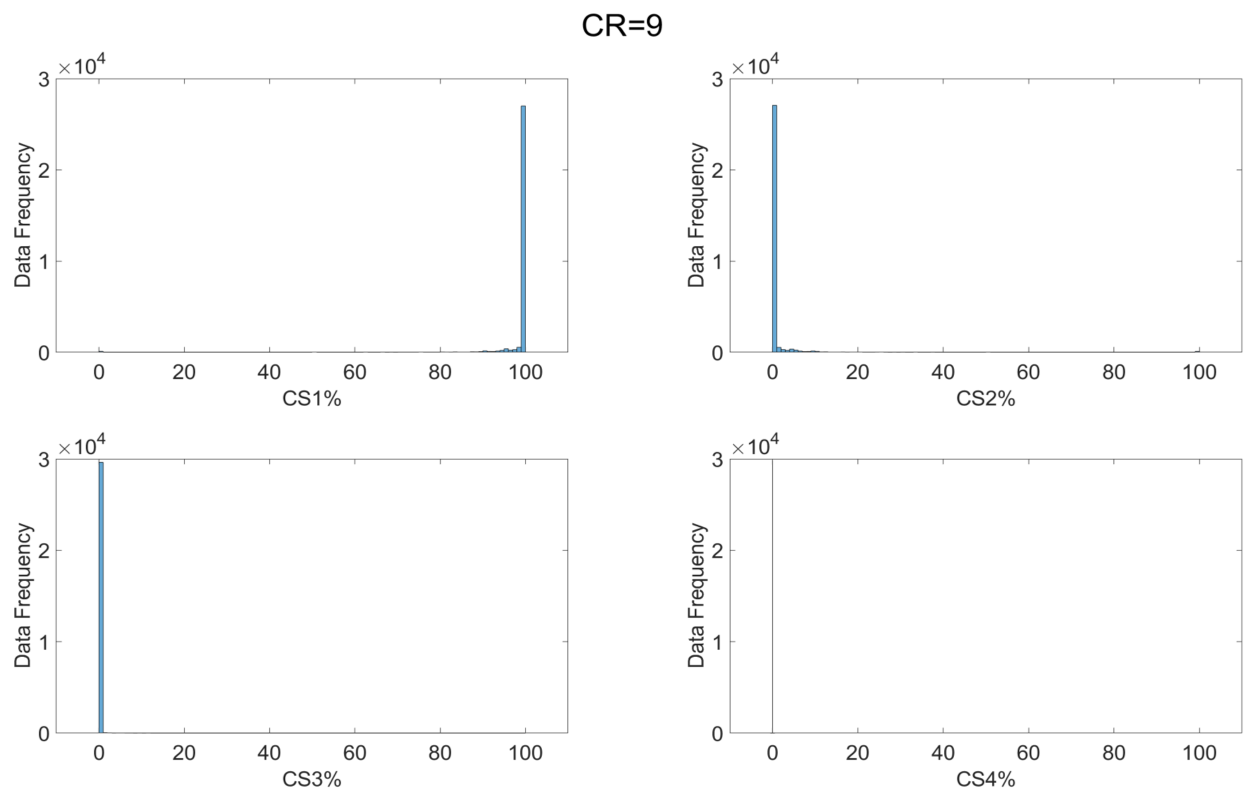


Figure 13. The histogram distribution illustrating the CR9-rated component data.

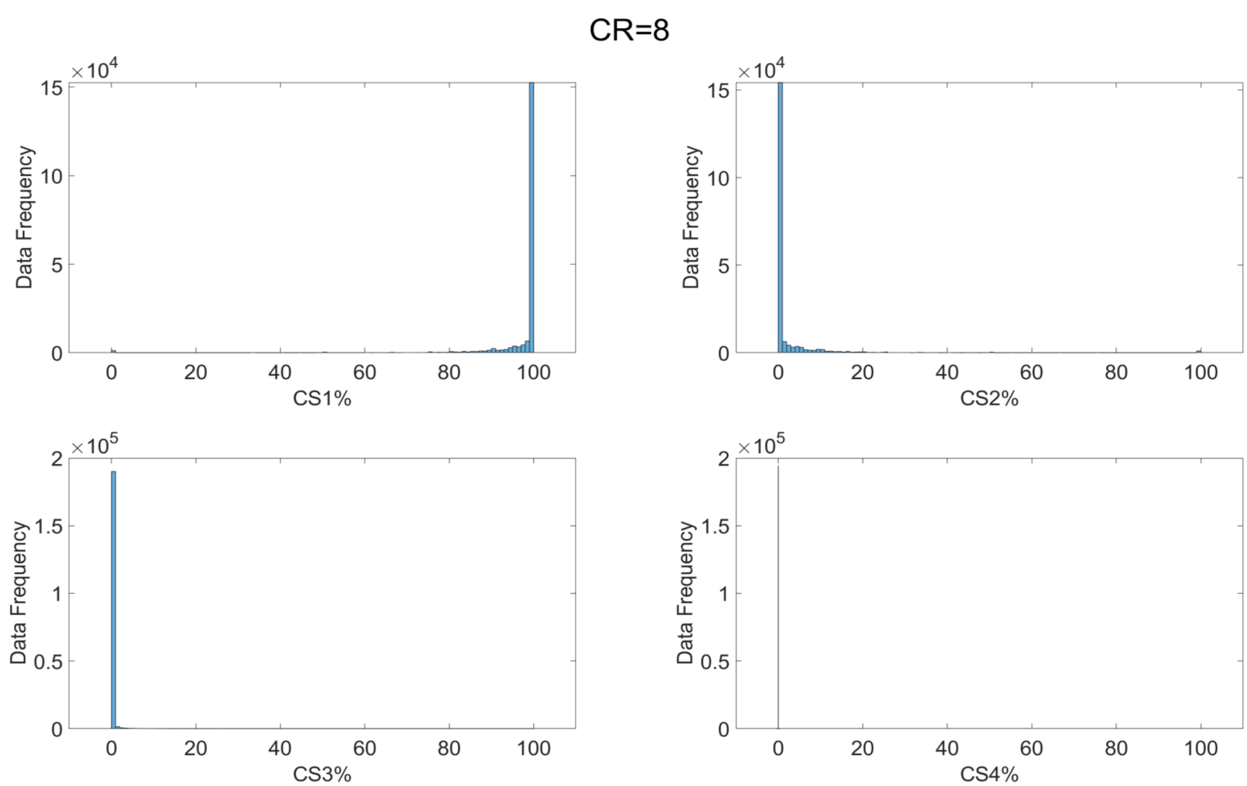


Figure 14. The histogram distribution illustrating the CR8-rated component data.

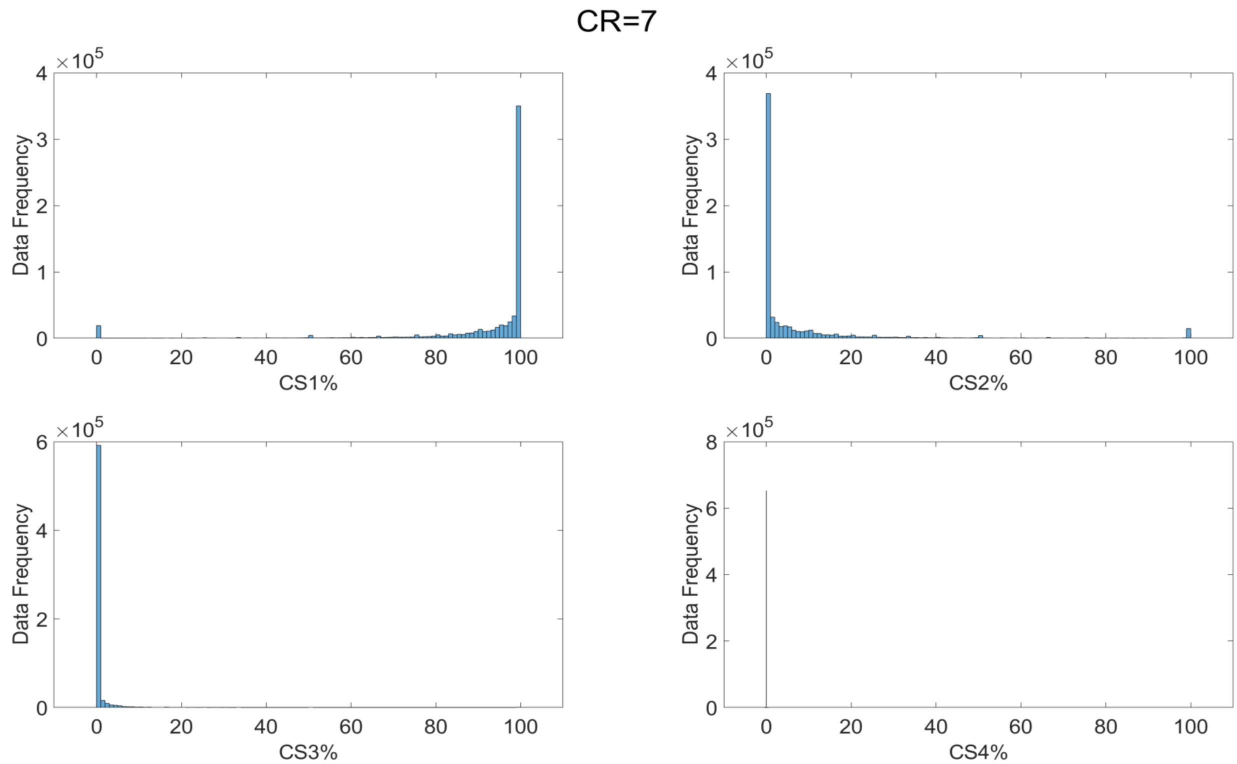


Figure 15. The histogram distribution illustrating the CR7-rated component data.

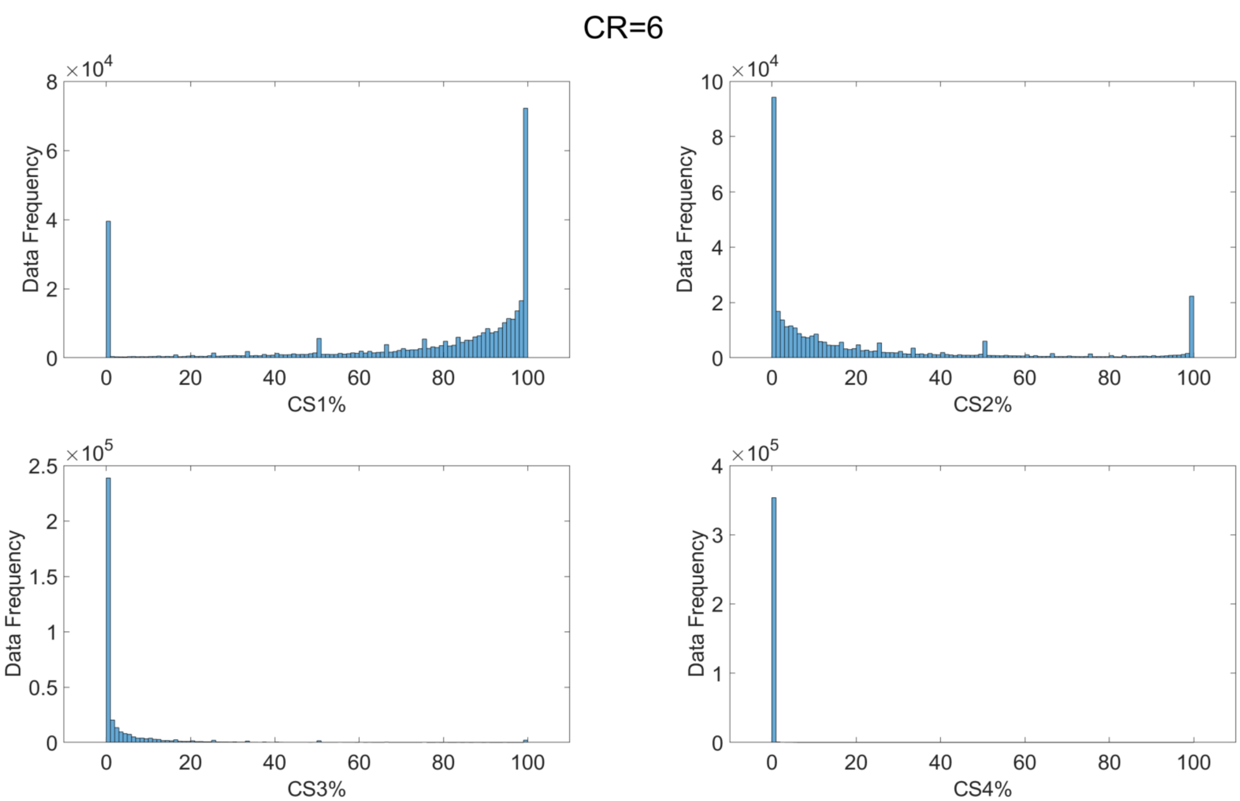


Figure 16. The histogram distribution illustrating the CR6-rated component data.

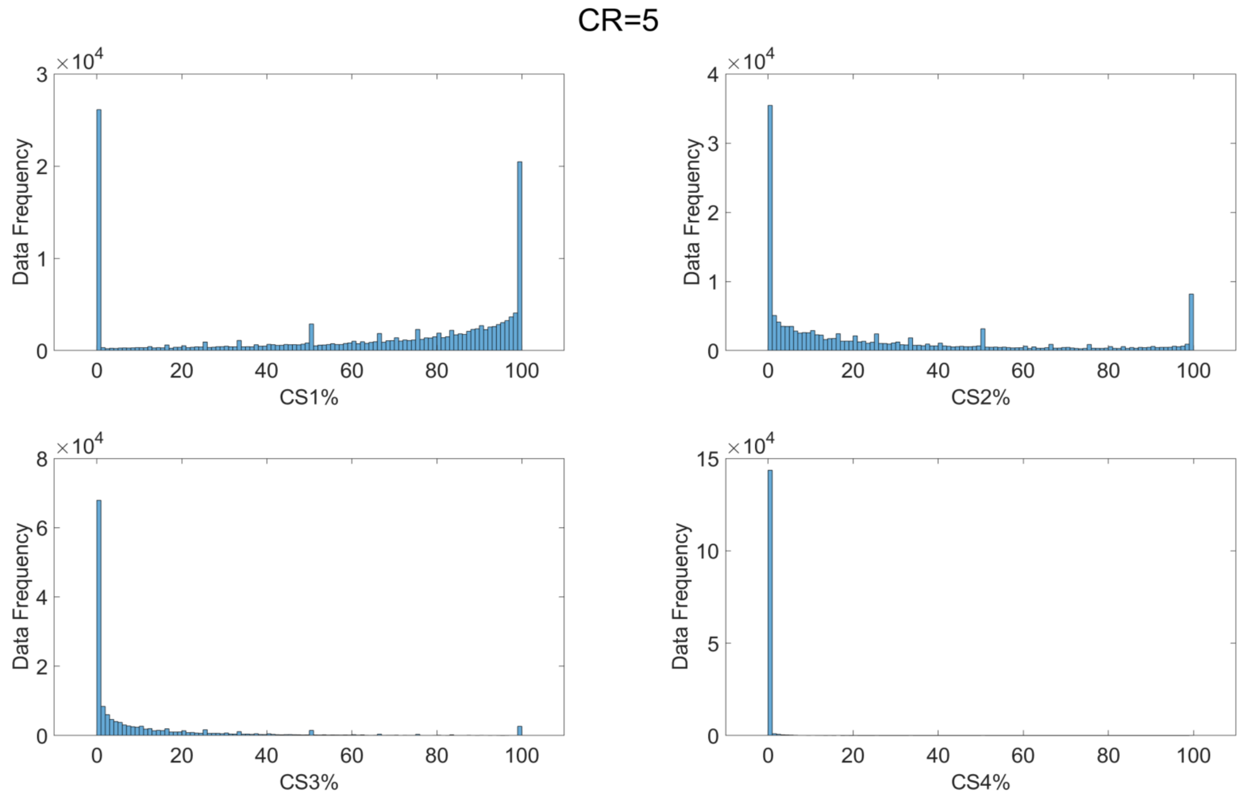


Figure 17. The histogram distribution illustrating the CR5-rated component data.

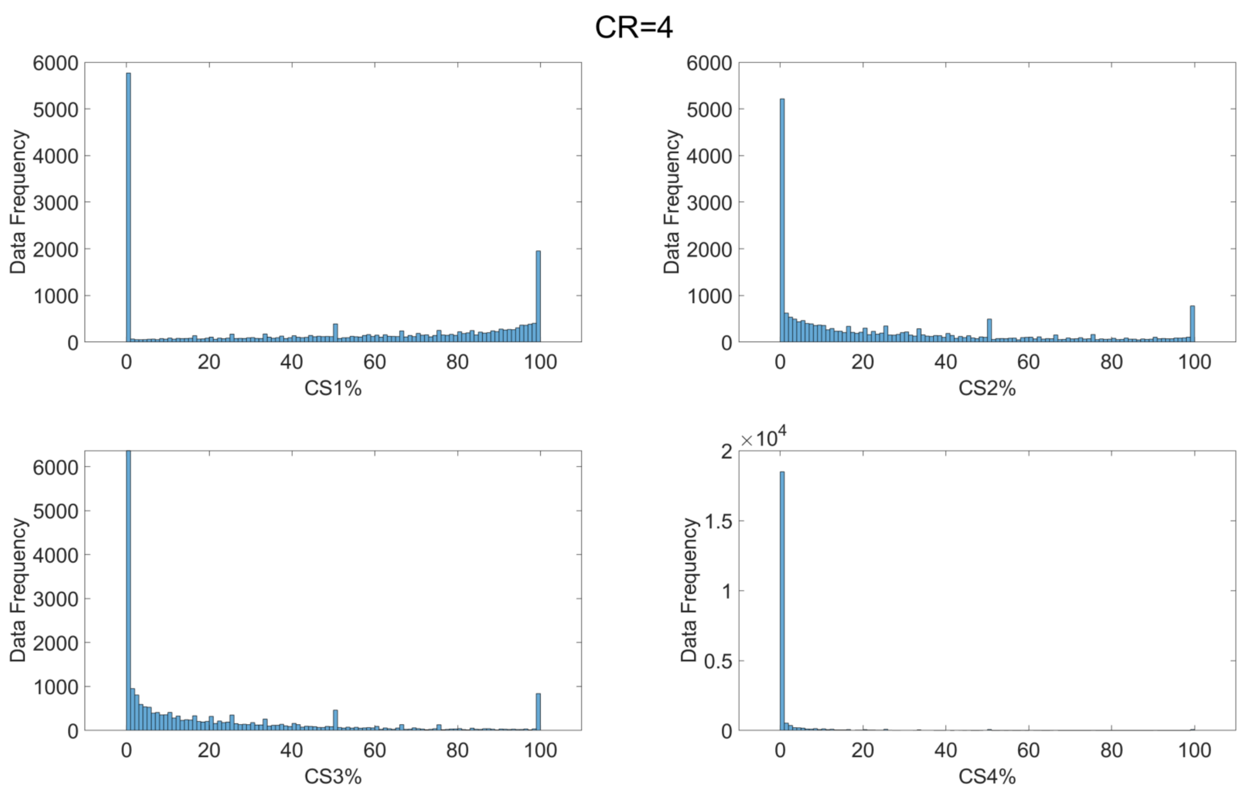


Figure 18. The histogram distribution illustrating the CR4-rated component data.

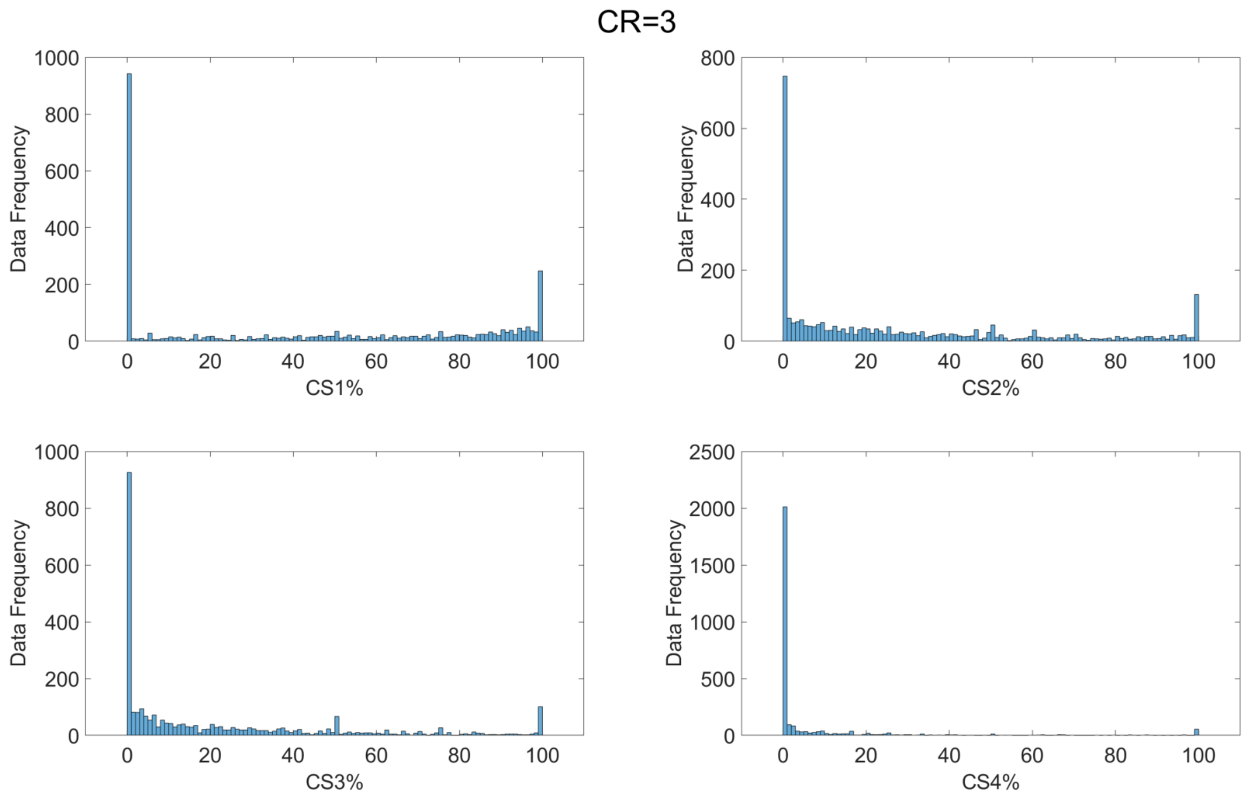


Figure 19. The histogram distribution illustrating the CR3-rated component data.

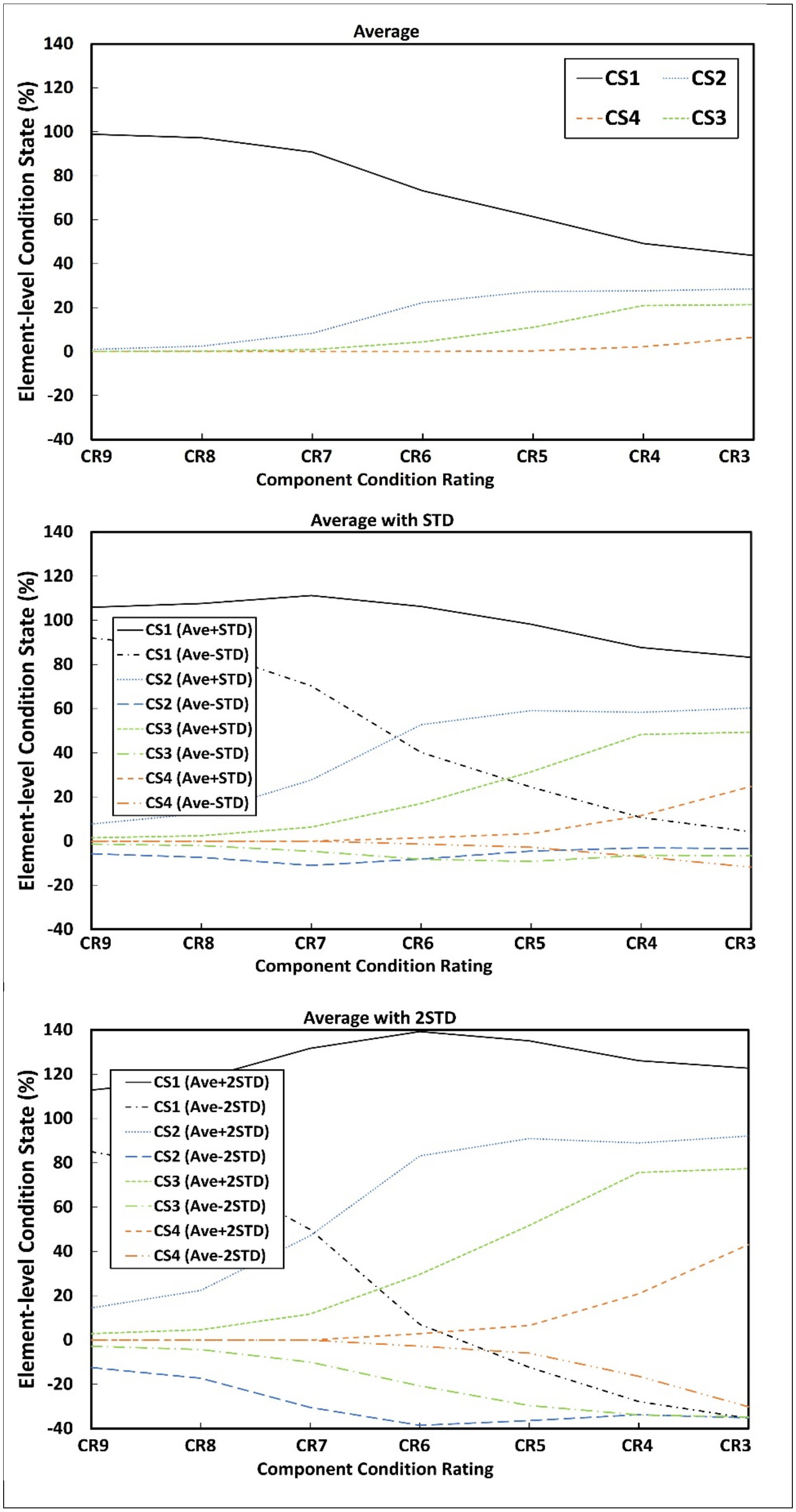


Figure 20. CR-CS conversion profiles developed based on average, one, and two standard deviations.

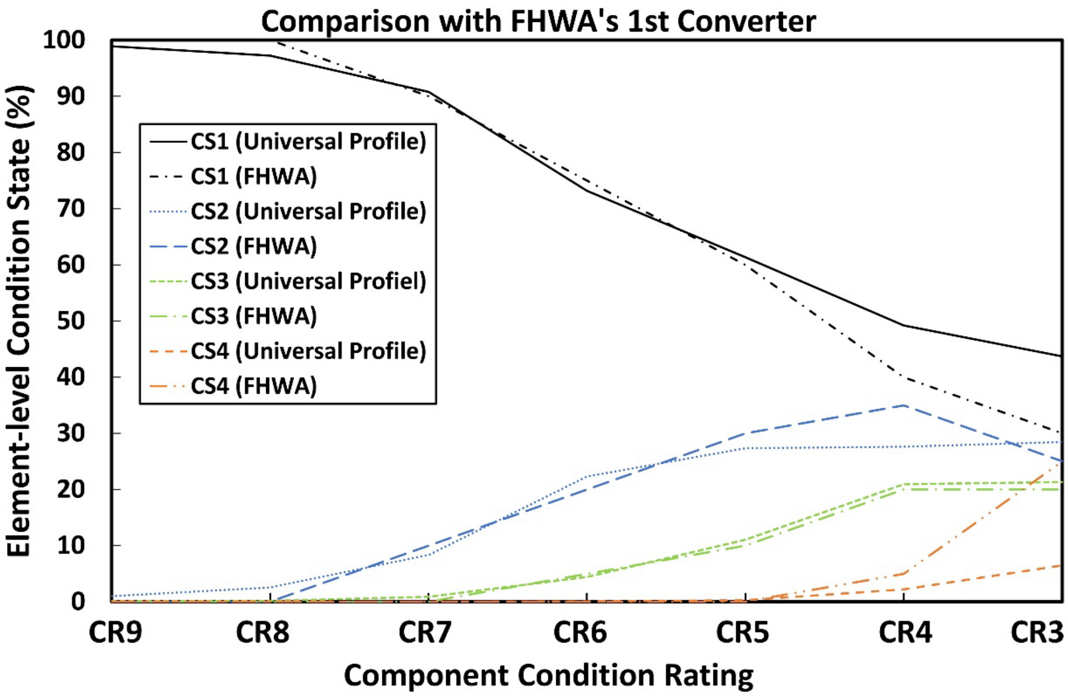


Figure 21. The CR-CS conversion profiles developed using the 2017-2022 data (referred as Universal Profile) as well as the values published by the FHWA Technical Manual (first-generation MBEI data component-element converter).

SUMMARY

This report presents the step-by-step procedures that have led to the development of multiple conversion profiles for converting element-level condition states to component-level condition ratings, and vice versa. The data sets utilized in this study were collected from a substantial pool of nearly 146,000 bridges on the NHS network. The collected NBI data comprised both component and element-level data sets, spanning from 2017 to 2022, and are publicly accessible on the FHWA website. Since the NBI component- and element-level data were separately reported and published by FHWA, the data were combined into an informative fact table for further model development. Rigorous data cleaning processes were subsequently implemented to identify and rectify any issues, including null, miscoded, unmatched, or otherwise unreliable data elements. Over 1.4 million data rows were retained after processing and cleaning of the data.

Following the creation of the fact tables, various data sampling techniques and multi-element component aggregation techniques were employed, which were then utilized in the development and validation of conversion profiles. Multiple statistical models were explored and tested. Ultimately the Decision Trees (DT) model was employed as the primary modeling technique for developing the conversion profile models due to its promising results and its simplicity in function generation for Microsoft Excel programming. The final models were rigorously validated using a subset of the overall data set, which was kept separate during the model development process to ensure unbiased evaluation.

Due to the primary objective of developing Microsoft Excel-compatible profiles, certain model attributes, such as branch numbers, were constrained. As a result, the developed models achieved total accuracy ranges of 40-80%, 80-100%, and 90-100% for ±0, ±1, and ±2CR, respectively. It was further noticed that, without these limitations, the total accuracy ranges could potentially increase to 50-90%, 90-100%, and almost 100% for ±0, ±1, and ±2CR, respectively.

In a similar manner, a set of statistical analyses was conducted to develop a universal profile capable of converting component-level condition ratings to element-level condition states. This profile encompassed all major components, including the deck, superstructure, substructure, and culvert, regardless of their material type. By utilizing the 2017-2022 data, the developed conversion profile outperformed the FHWA's first-generation converter profile.

Developing component-to-element conversion profiles presented unique challenges, as reconstructing granular information from a coarse source proved to be difficult. While the developed models are expected to improve in accuracy with the availability of more data, the inherent theoretical limitations will persist. The April 2013 FHWA Converter Technical Manual included a procedure for synthesizing (i.e., estimating) element types and quantities from NBI component and geometry data. However, updating this synthesis procedure was not within the current scope of this project. Nonetheless, the component-to-element condition conversion profile developed in this study can be applied for comparison to bridges with available element data and known condition states, as represented in agency inspection data or the NBI for NHS bridges. Furthermore, it can be applied in software applications such as the National Bridge Inventory Analysis System, which synthesizes element types, quantities, and condition states using NBI design type, material type, and geometry data, and applies element-level deterioration models to the synthesized elements to estimate future condition states of bridges and also converts to future component ratings.

The developed conversion profiles are based on national data and, as such, were not customized for individual states to reflect potential differences at the state level. Such variations could be attributed to the number of specific bridge types, including certain material types, as well as different interpretations of structural defects due to geographical and environmental characteristics, and other local or agency-level differences. To achieve better estimation accuracies, a more customized conversion profile trained on state-level data could be completed.

During the development of the conversion profiles, a limitation was encountered where the conversions were not achieved for all condition rating values. This was mainly due to the scarcity of available data to support component values of 0, 1, and 2, resulting in observed component/element combinations only covering values between 3 and 9. Lastly, it is crucial to recognize that data serves as the fundamental basis for data-driven models. As time progresses, more inspections will take place, leading to increased data including within the condition ratings with less data points and the component material types with smaller data sets as indicated in the Table 27 validation column. Consequently, the current models can be revisited to verify the assumptions and inputs used for model development and can be updated by retraining thereby ensuring their continued accuracy and relevance.

REFERENCES

AASHTO. Guide for Commonly Recognized (CoRE) Structural Elements, American Association of State Highway and Transportation Officials, Washington, DC. 1997.

AASHTO. Guide Manual for Bridge Element Inspection (MBEI). American Association of State Highway and Transportation Officials, Washington, DC. 2013.

Al-Wazeer, A., C. Nutakor, and B. Harris. Comparison of Neural Networks Method Versus National Bridge Inventory Translator in Predicting Bridge Condition Ratings. Presented at 86th Annual Meeting of the Transportation Research Board, Washington, D.C., 2007.

Babanajad S, Moon F, Parvardeh H, Maher A. FHWA Technical Report 2017: LTBP Deterioration Modeling Module", Office of Infrastructure Research and Development, FHWA, Washington DC, in press

Bektas, B. A., Carriquiry, A., and Smadi, O. Using Classification Trees for Predicting National Bridge Inventory Condition Ratings. Journal of Infrastructure Systems. Volume 19 Issue 4, 2012.

FHWA. Component-Element Converter Technical Manual. Federal Highway Administration, U.S. Department of Transportation, Washington, DC. 2013.

FHWA. Bridge Inspector's Reference Manual. Publication No. FHWA NHI 12-049. Federal Highway Administration, U.S. Department of Transportation, Washington, DC. 2012.

FHWA. Recording and Coding Guide for the Structure Inventory and Appraisal of the Nation's Bridges. Federal Highway Administration, U.S. Department of Transportation, Washington, DC. 1995.

FHWA. InfoBridge website https://infobridge.fhwa.dot.gov/Home. Federal Highway Administration, U.S. Department of Transportation, Washington, DC. 1995.

FHWA. NBI Data Checks. Website https://www.fhwa.dot.gov/bridge/nbi/checks/nbi_data_checks_2020_final.pdf, Federal Highway Administration, U.S. Department of Transportation, Washington, DC. 2020.

FHWA. Element Data Errors and Checks. Website https://www.fhwa.dot.gov/bridge/nbi/checks.pdf

, Federal Highway Administration, U.S. Department of Transportation, Washington, DC. 2020.

Fiorillo, G. and Nassif, H. Application of Machine Learning Techniques for the Analysis of National Bridge Inventory and Bridge Element Data. Transportation Research Record: Journal of the Transportation Research Board, Vol 2673, Issue 7, 2019.

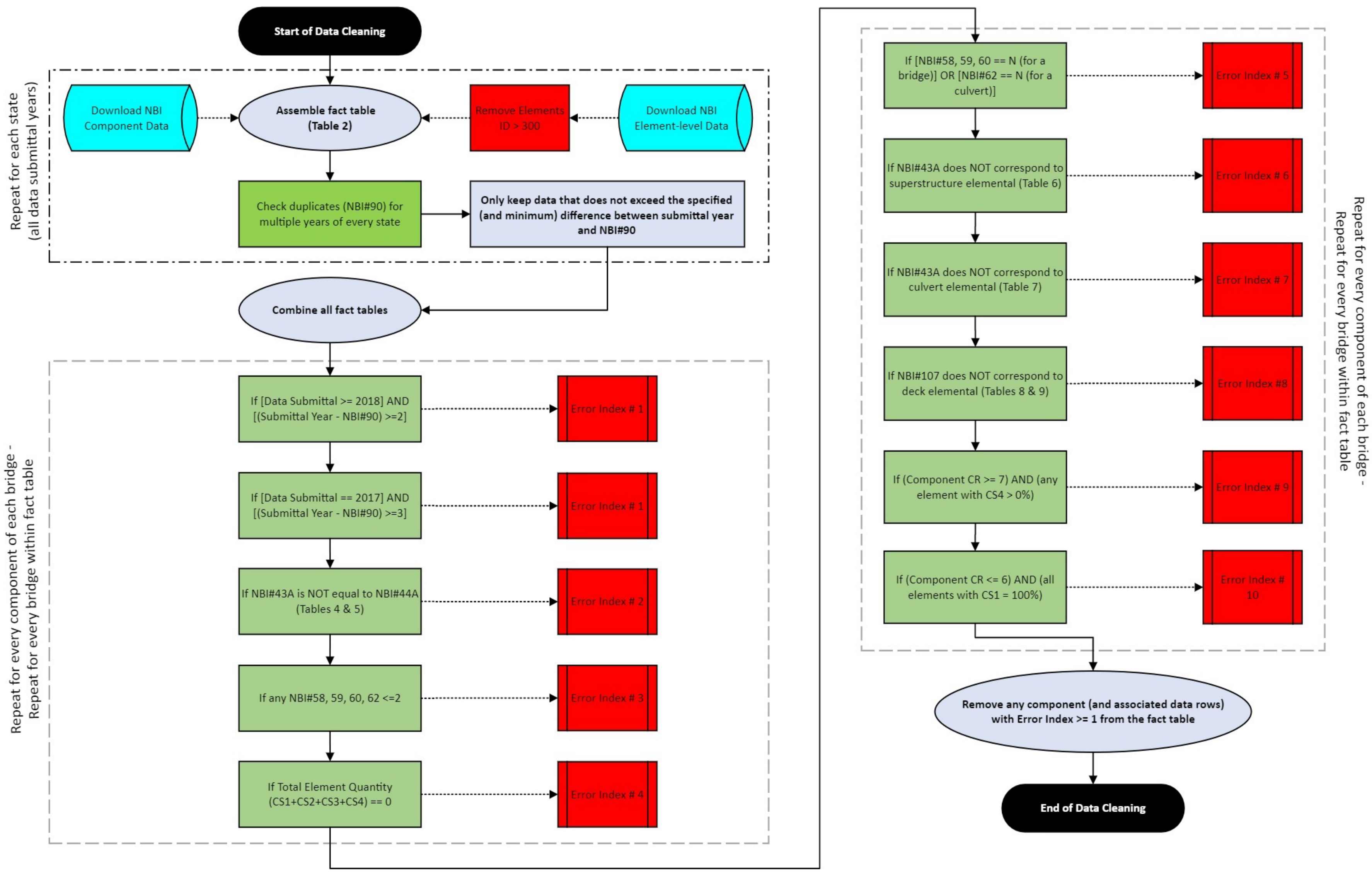
Hale, J. E., D. P. Hale, and S. Sharpe. Asset Management GASB 34 Compliance Phase III (Bridges). Final Report, ALDOT Report Number 930-553R. Aging Infrastructure Systems Center of Excellence and University Transportation Center for Alabama, February 1, 2007.

Hearn, G., J. Cavallin, and D. M. Frangopol. Generation of NBI Ratings from Condition Reports for Commonly Recognized Elements. University of Colorado at Boulder, Colorado Department of Transportation, Denver, and Federal Highway Administration, 1997.

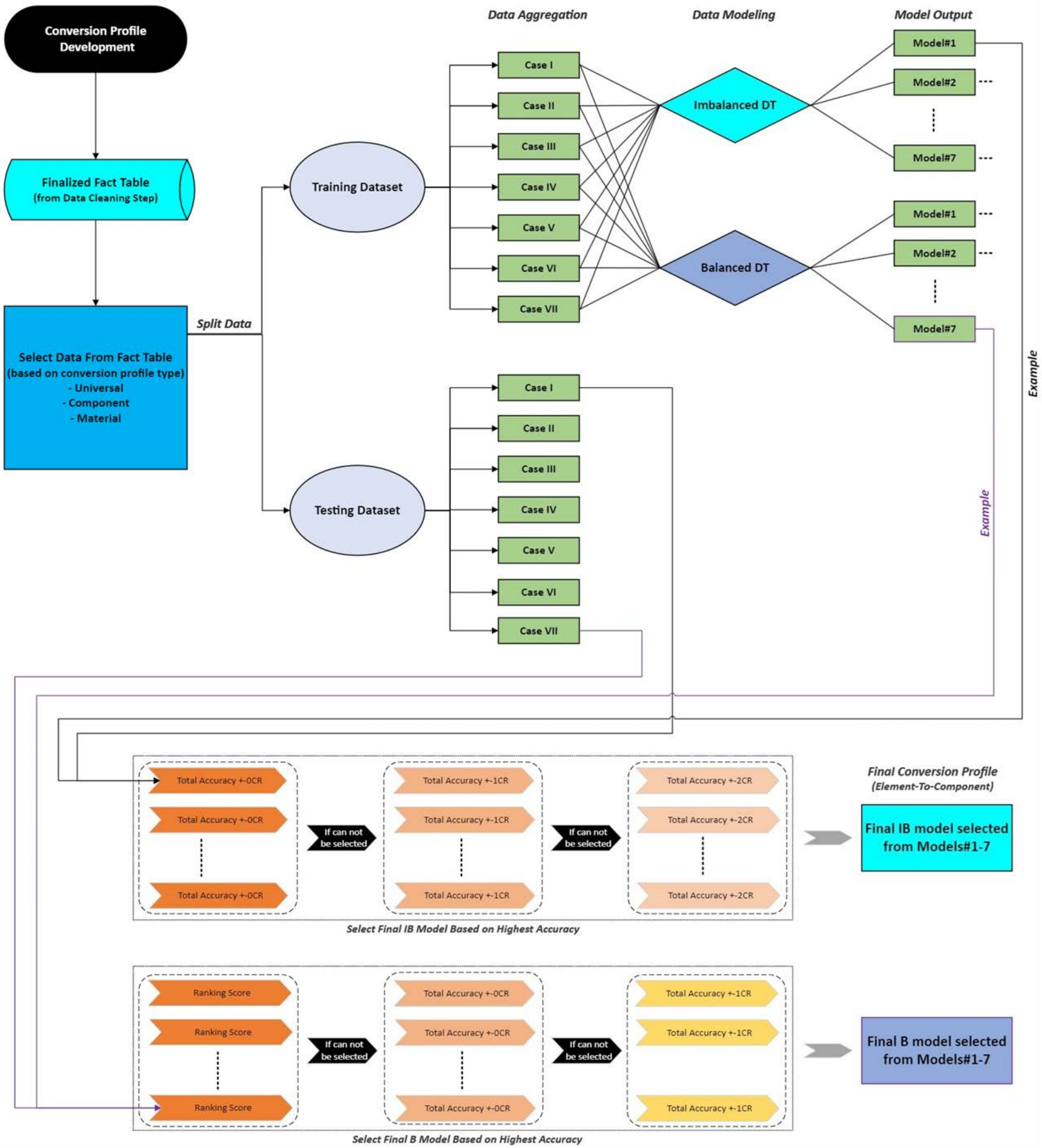
Pontis for Windows XP/2000®, Bridge Management System, Version 4.4.2, Build 442. American Association of State Highway and Transportation Officials, 2005.

Sobanjo, J.O., P.D. Thompson, and R. Kerr, Element-to-Component Translation of Bridge Condition Ratings. Transportation Research Board Annual Meeting 2008 Compendium of Papers DVD, 2008. Paper #08-3149.

APPENDIX I – DATA CLEANING REPRODUCTION FLOWCHART



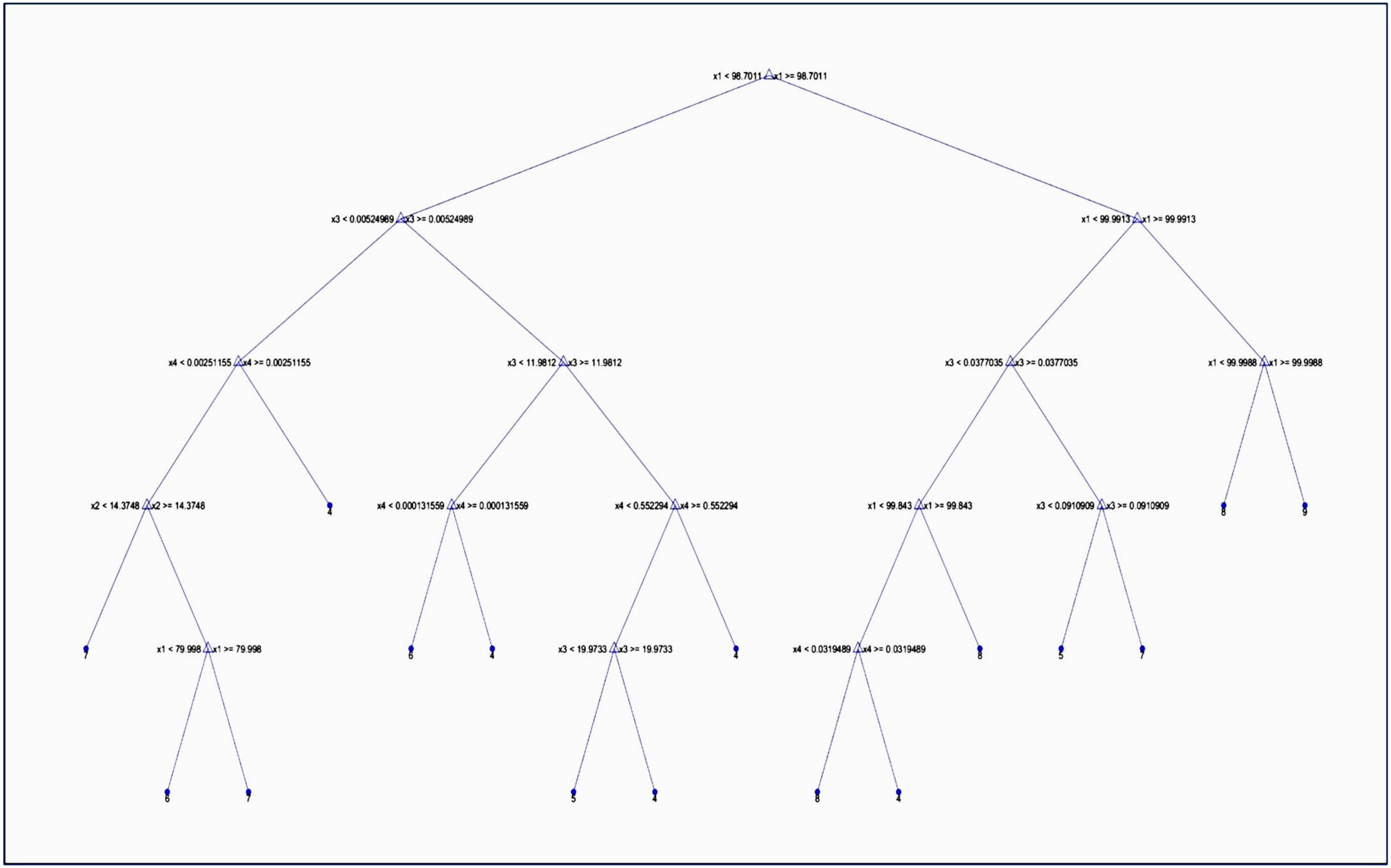
APPENDIX II – CONVERSION PROFILE (ELEMENT-TO-COMPONENT) REPRODUCTION FLOWCHART



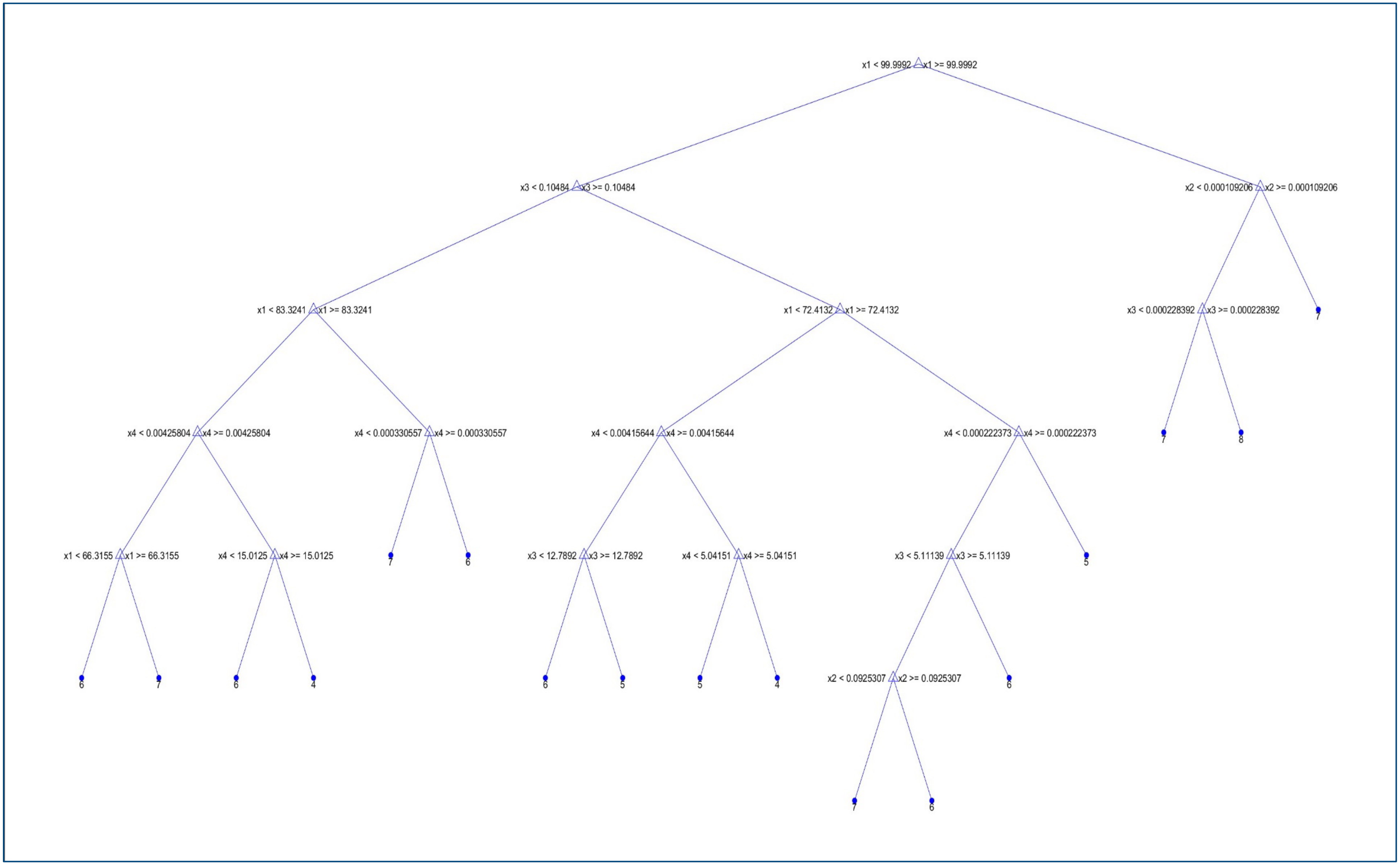
APPENDIX III – FINALIZED CONVERSION PROFILES

The finalized conversion profiles, represented in the form of visual decision trees, are provided to facilitate the conversion of element-level condition states to component-level condition ratings. In the following decision trees, x1, x2, x3, and x4 correspond to CS1 through CS4 percentages, respectively. It is important to emphasize that the threshold values at the tree nodes should not be rounded. The outcome at the end of each branch determines the NBI component condition rating.

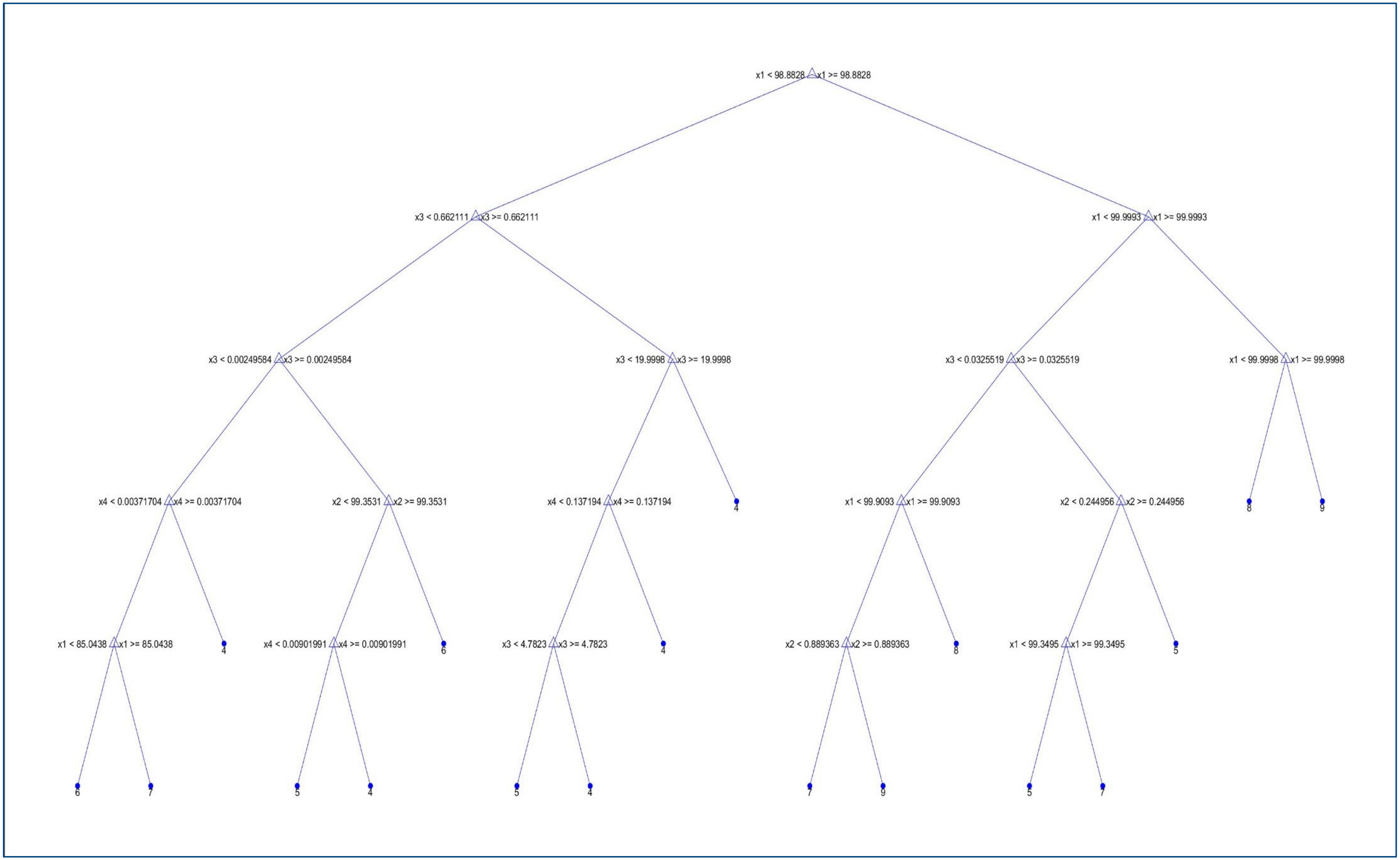
ID#1 (Universal - Balanced)



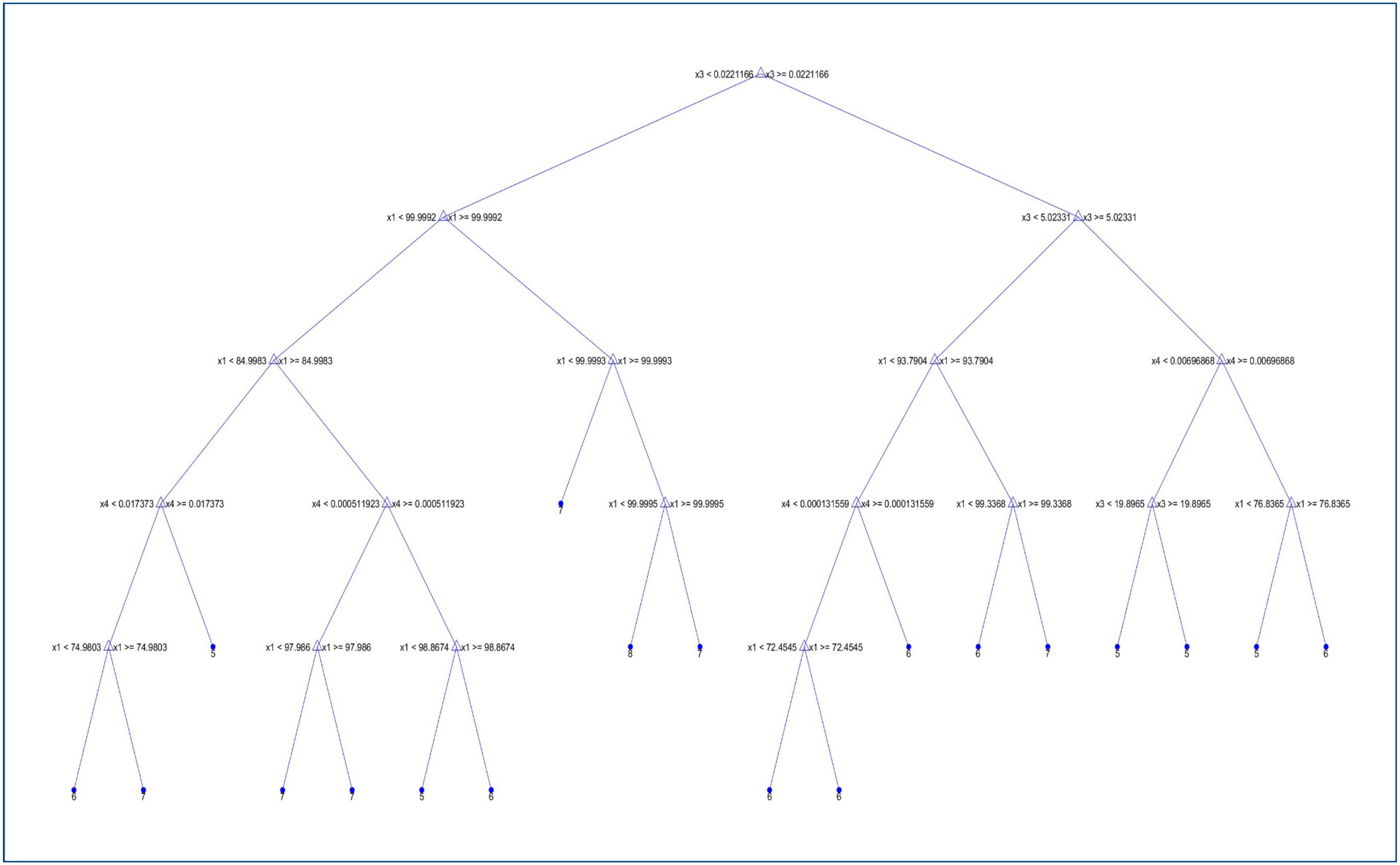
ID#2 (Universal - Imbalanced)



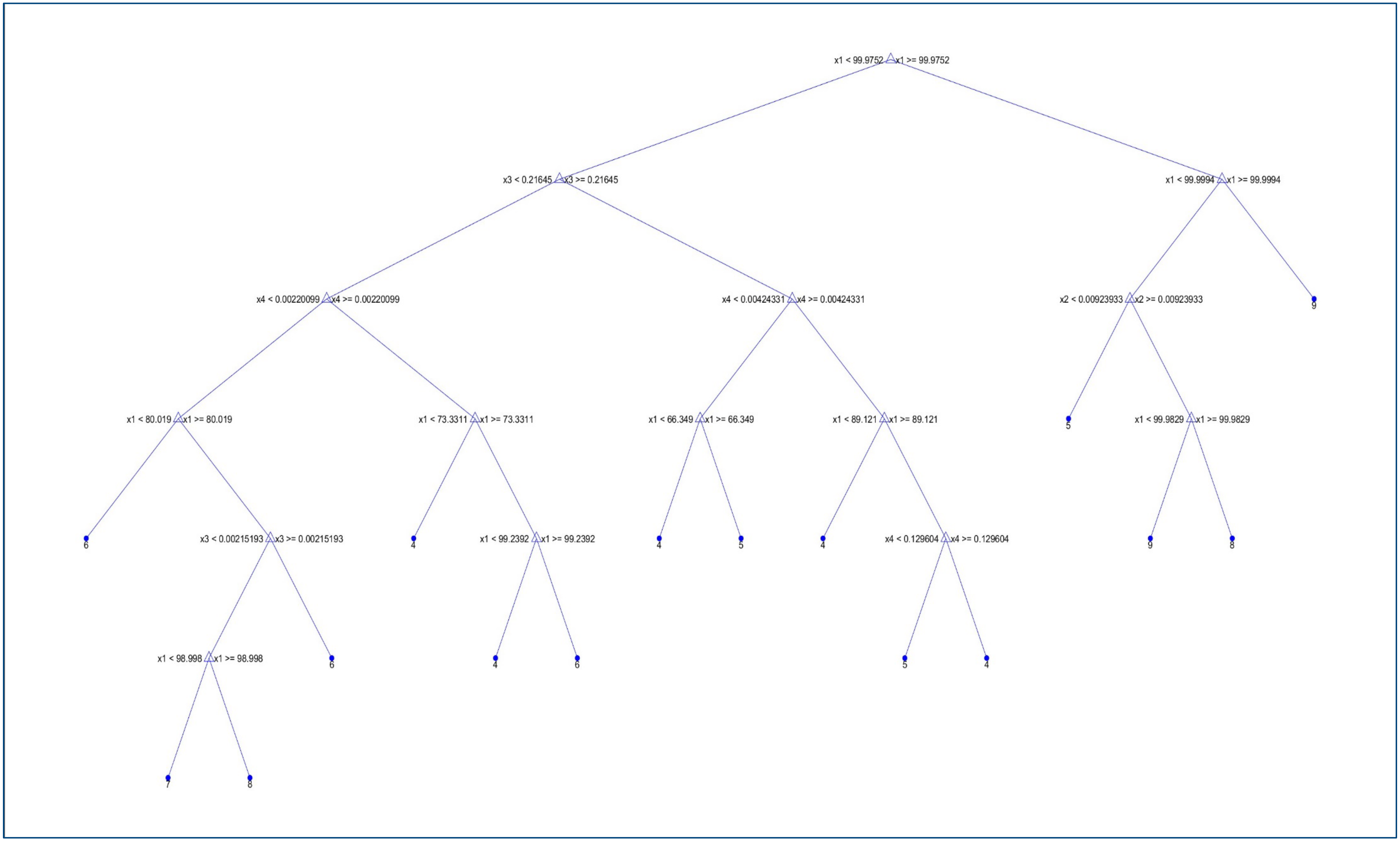
ID#3 (Component - Deck - Balanced)



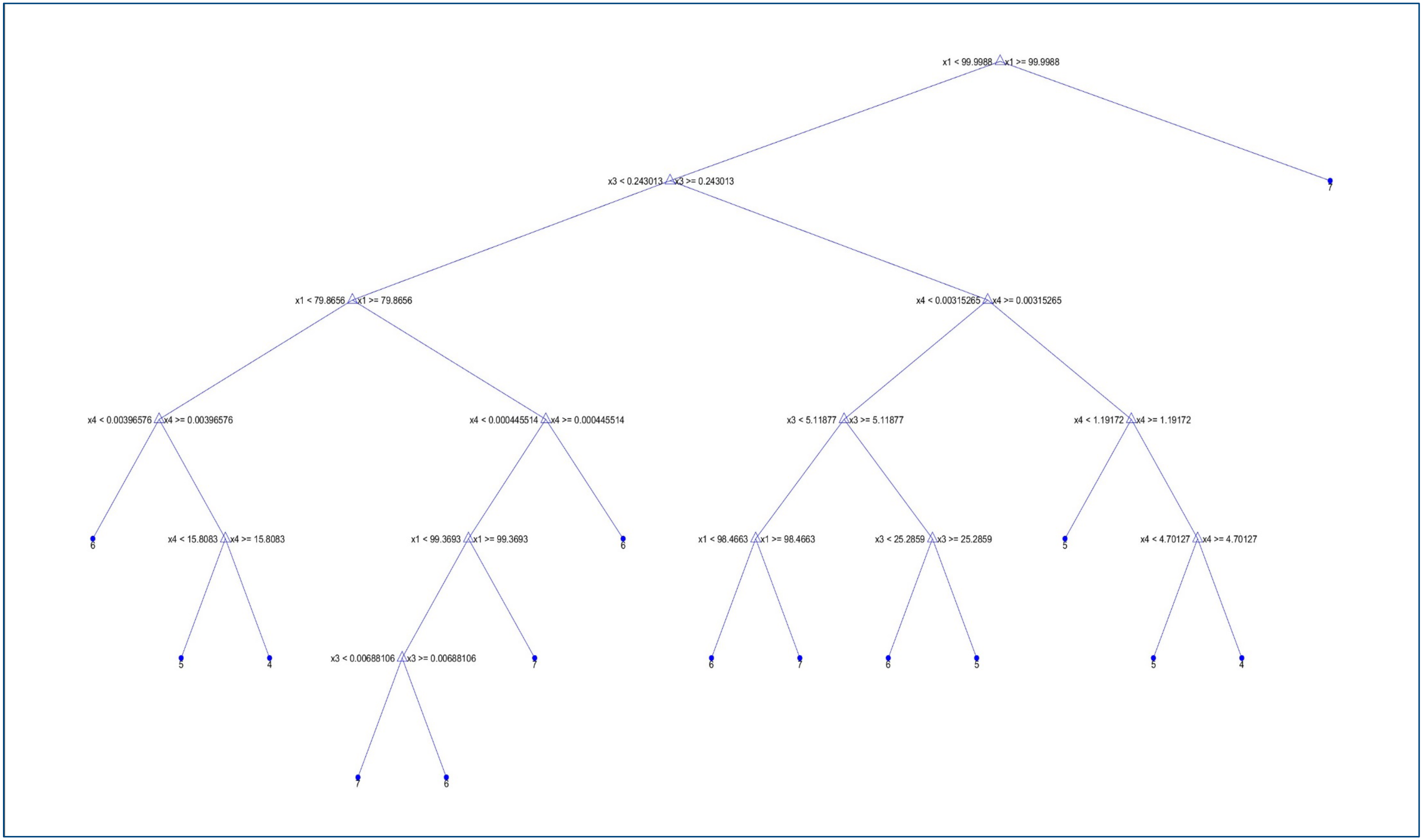
ID#4 (Component - Deck - Imbalanced)



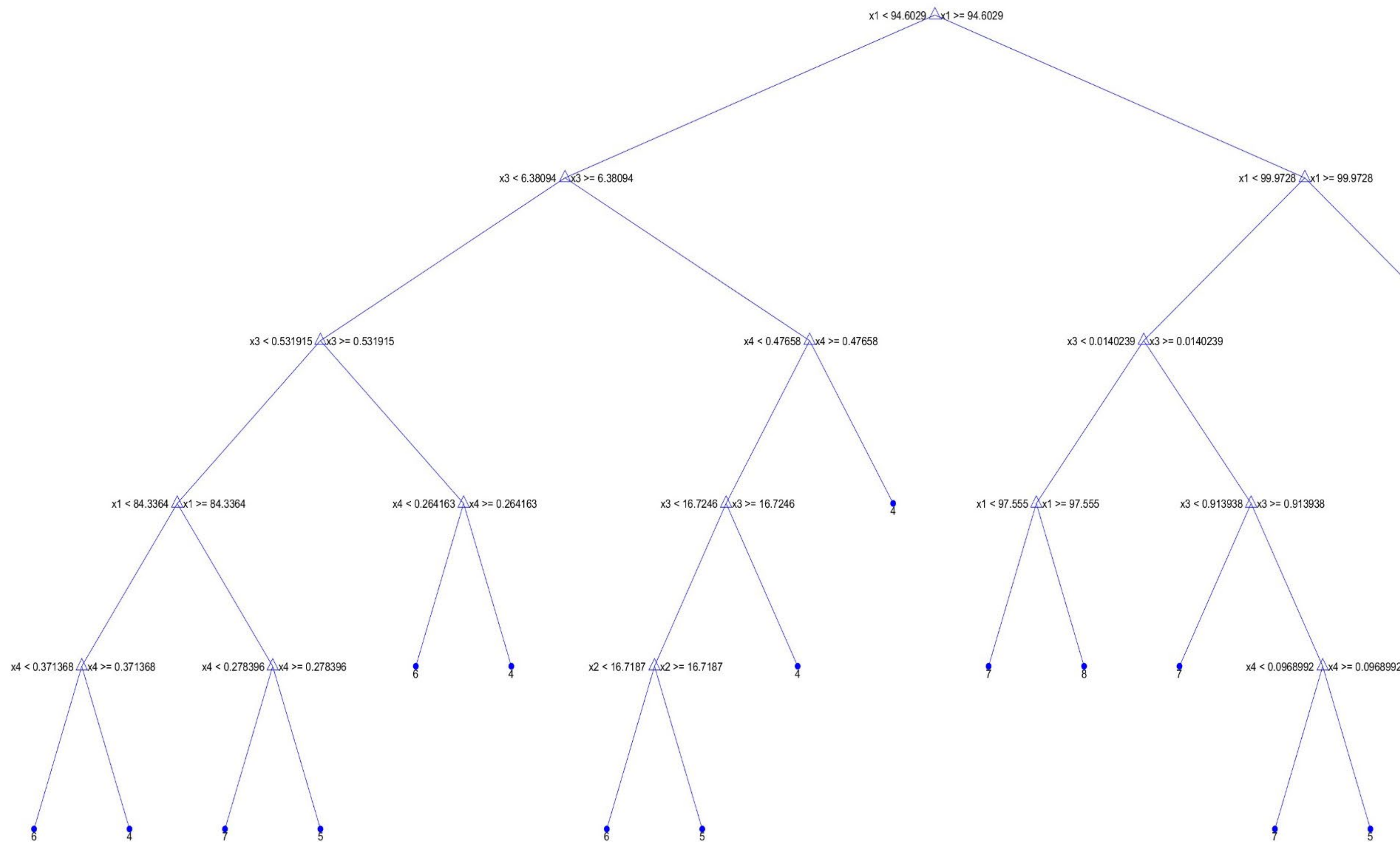
ID#5 (Component - Superstructure - Balanced)



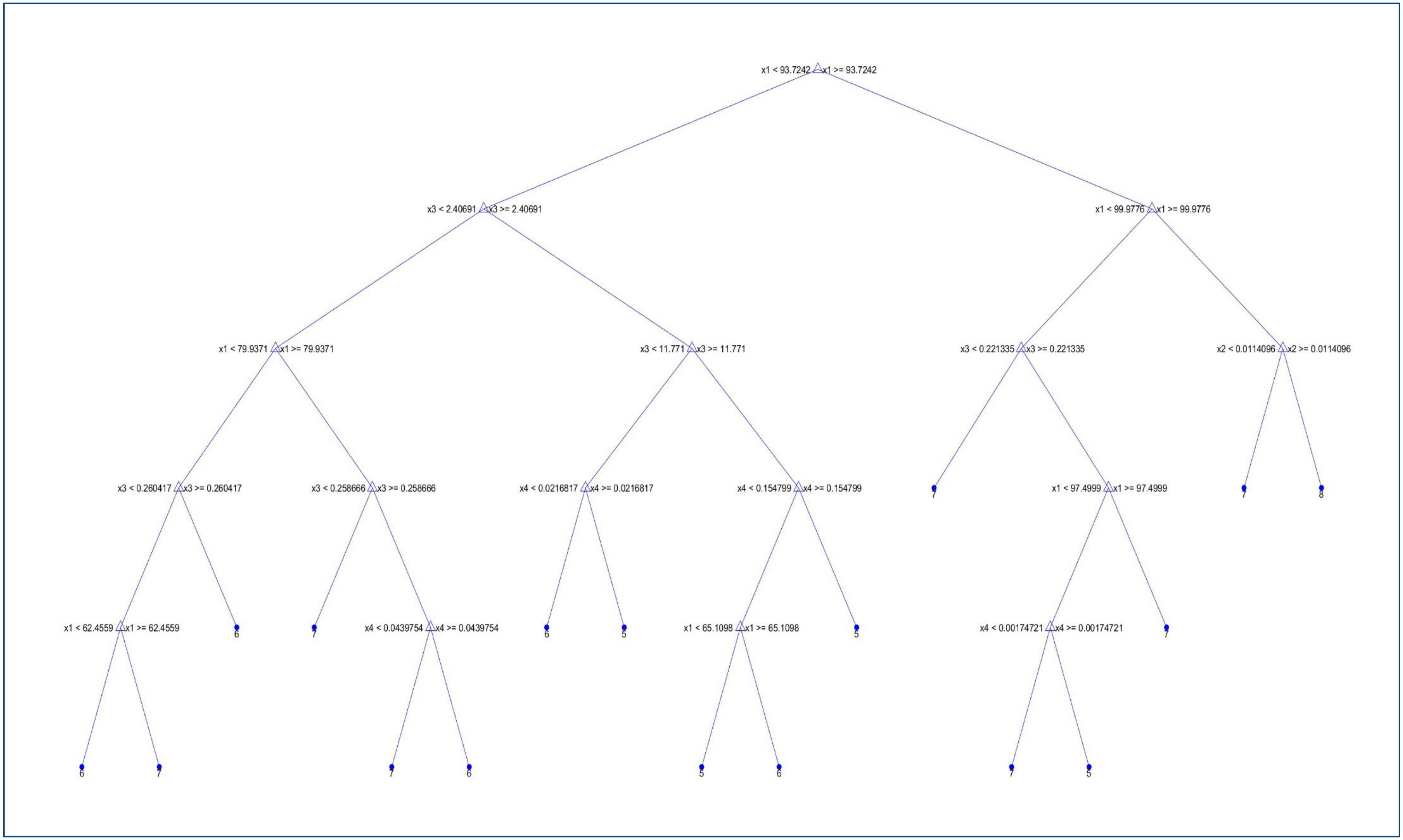
ID#6 (Component - Superstructure - Imbalanced)



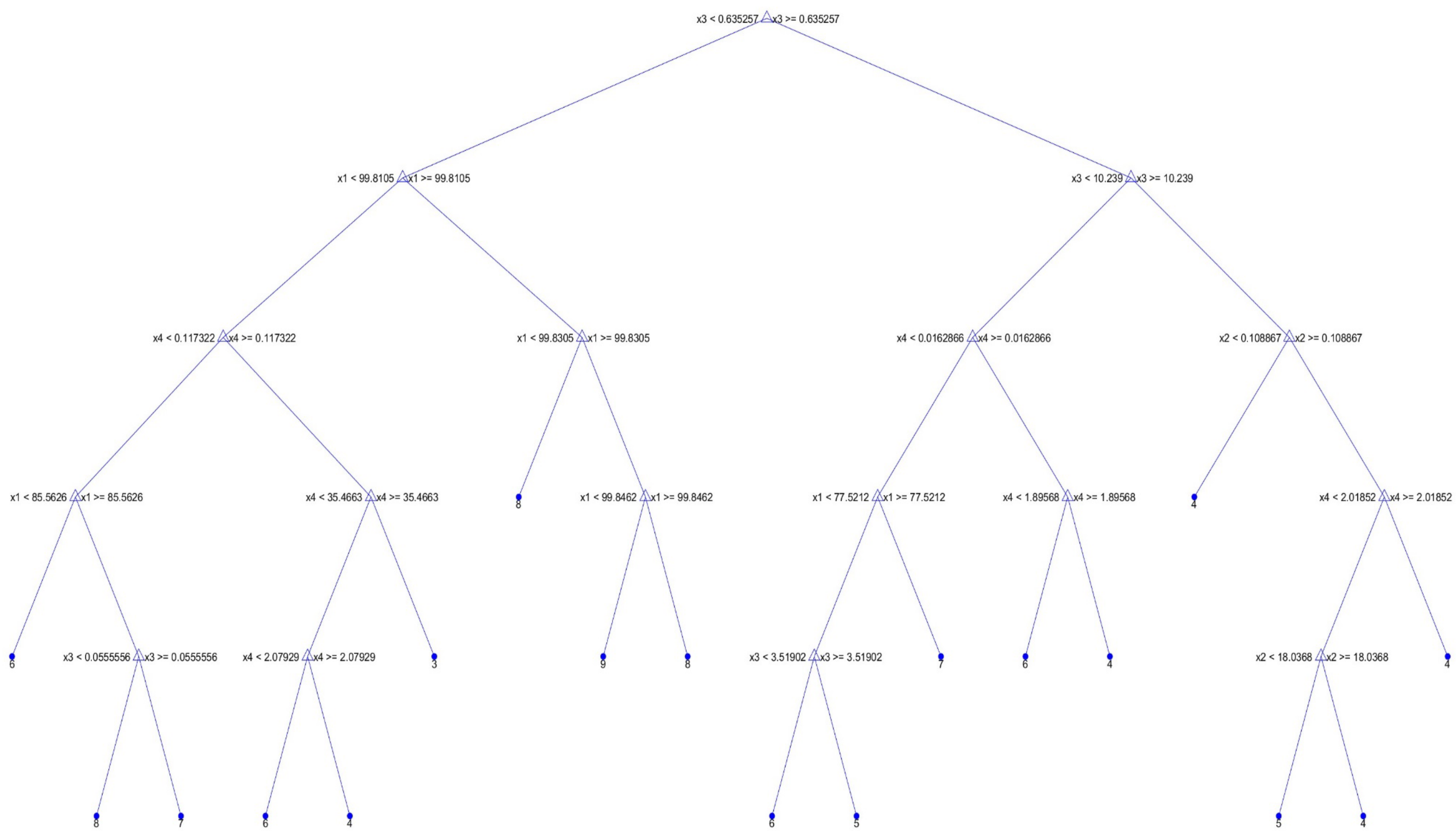
ID#7 (Component - Substructure - Balanced)



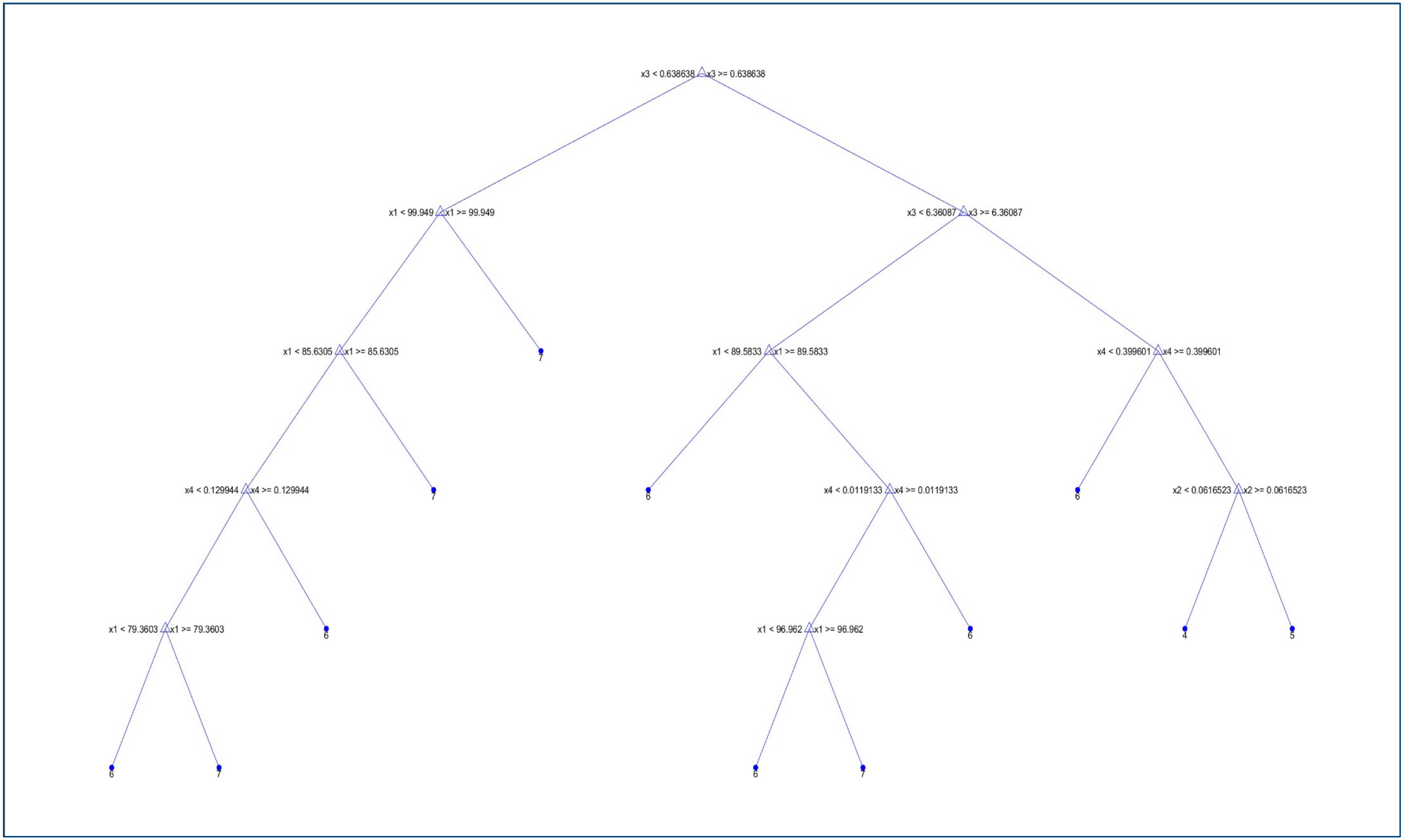
ID#8 (Component - Substructure - Imbalanced)



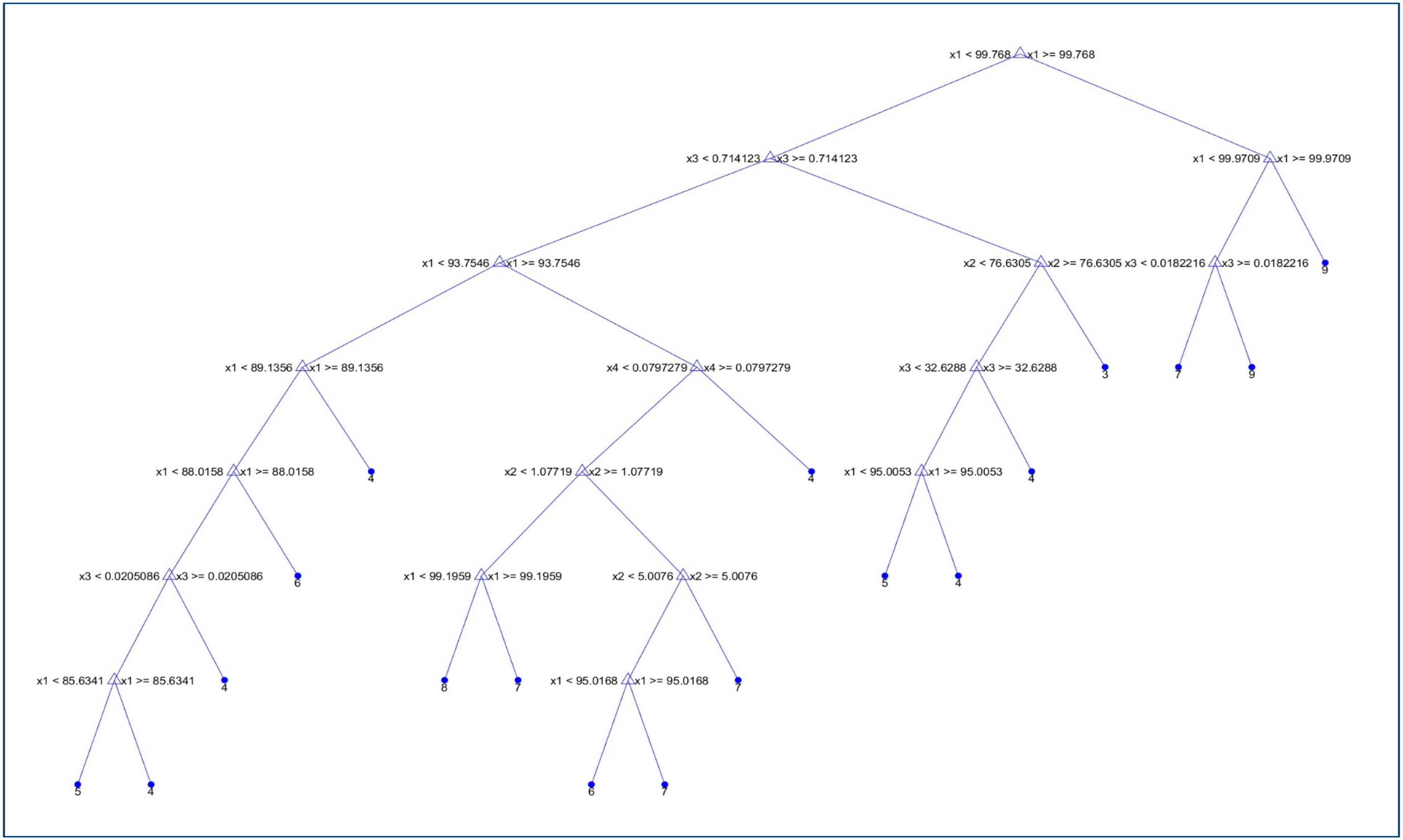
ID#9 (Component - Culvert - Balanced)



ID#10 (Component - Culvert - Imbalanced)



ID#11 (Deck – Prestressed Concrete - Balanced)



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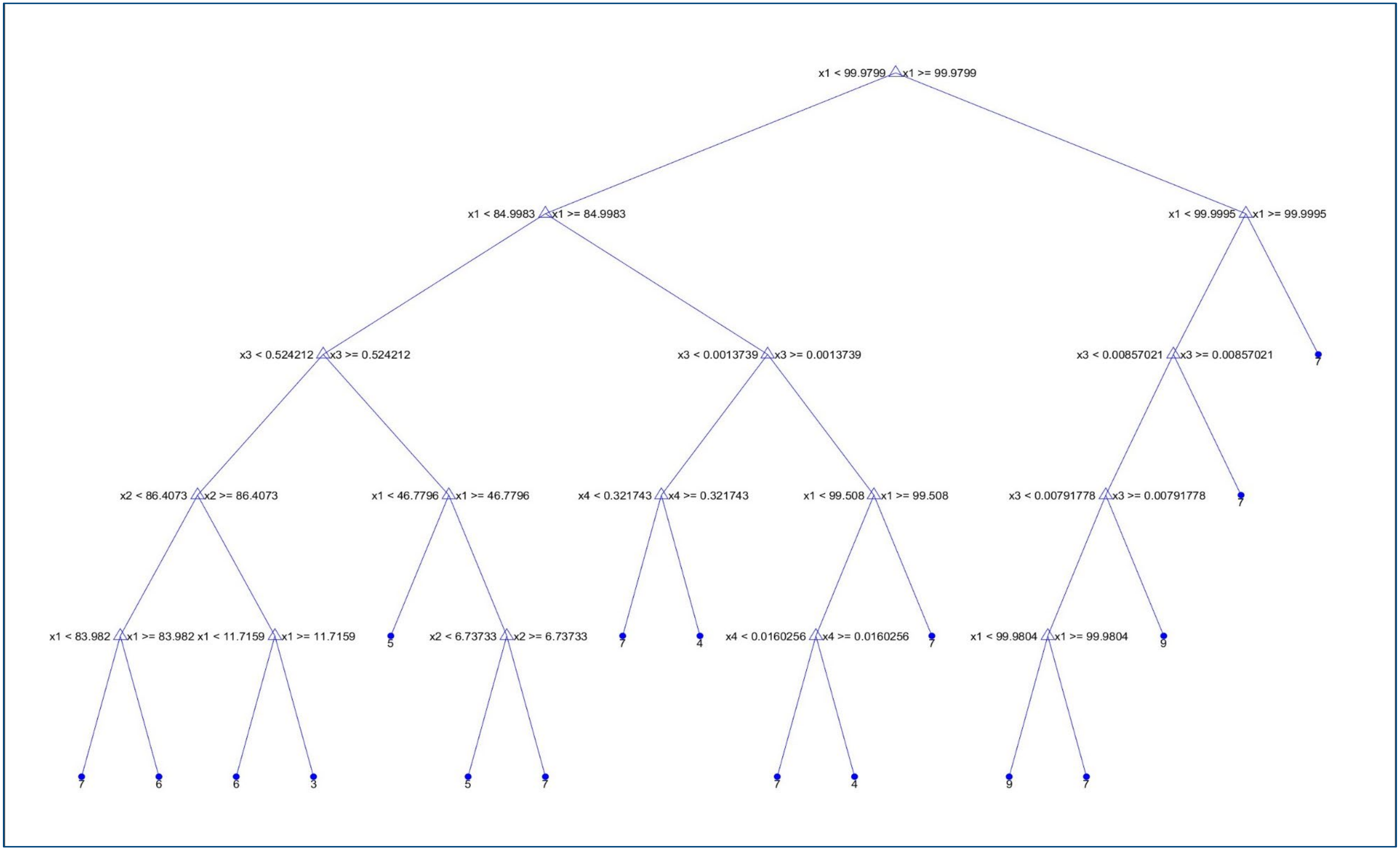
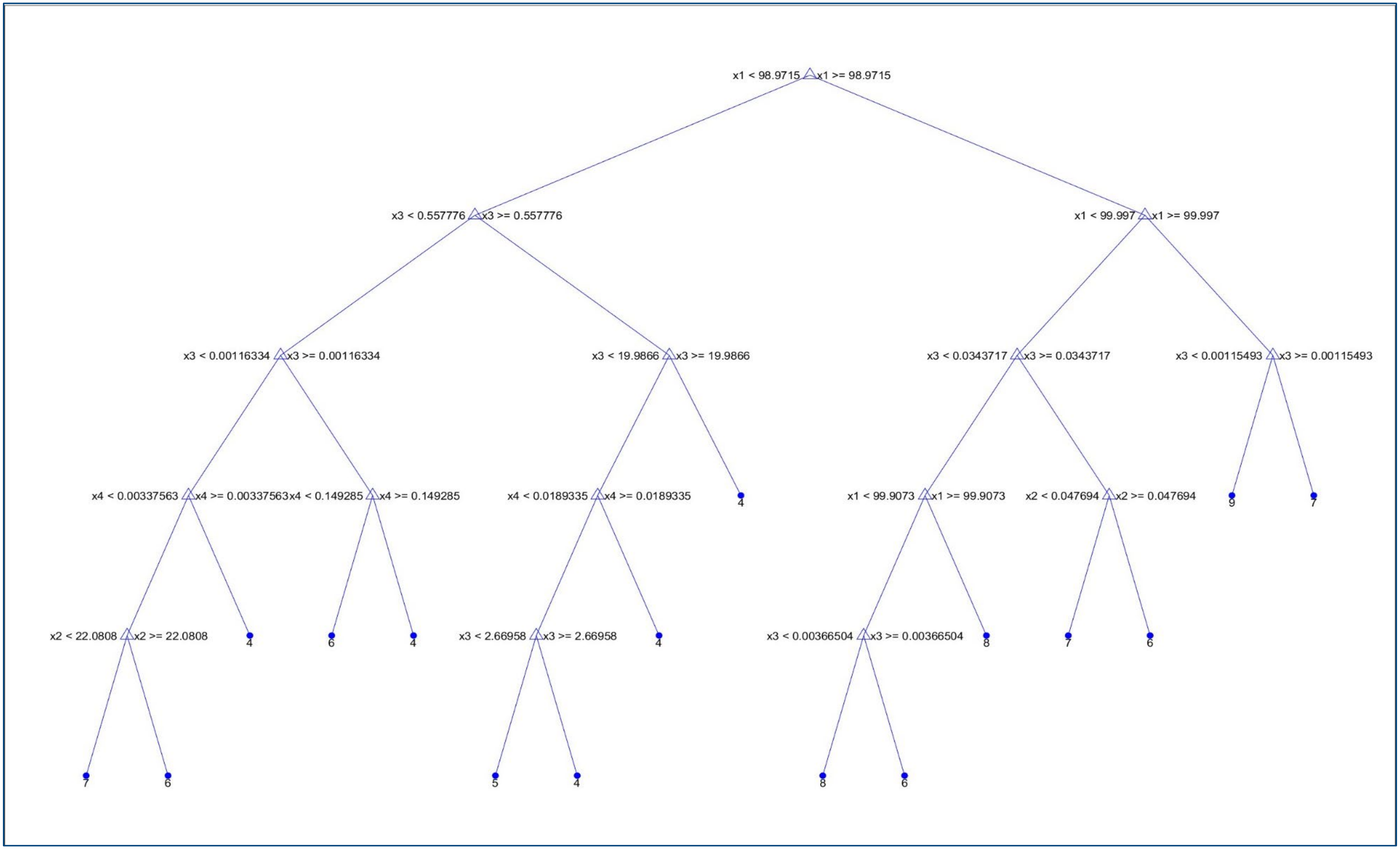


ID#13 (Deck – Reinforced Concrete - Balanced)



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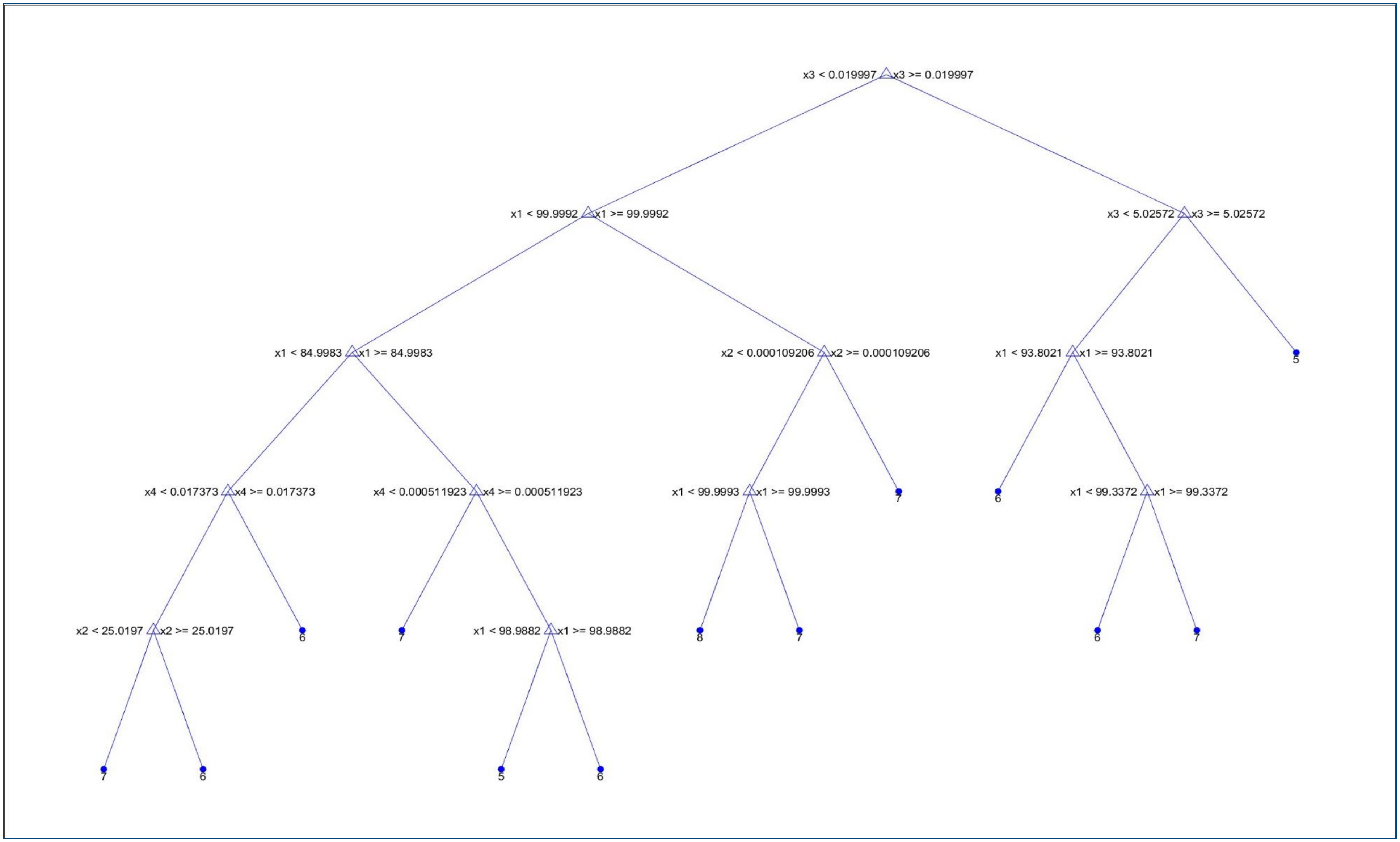
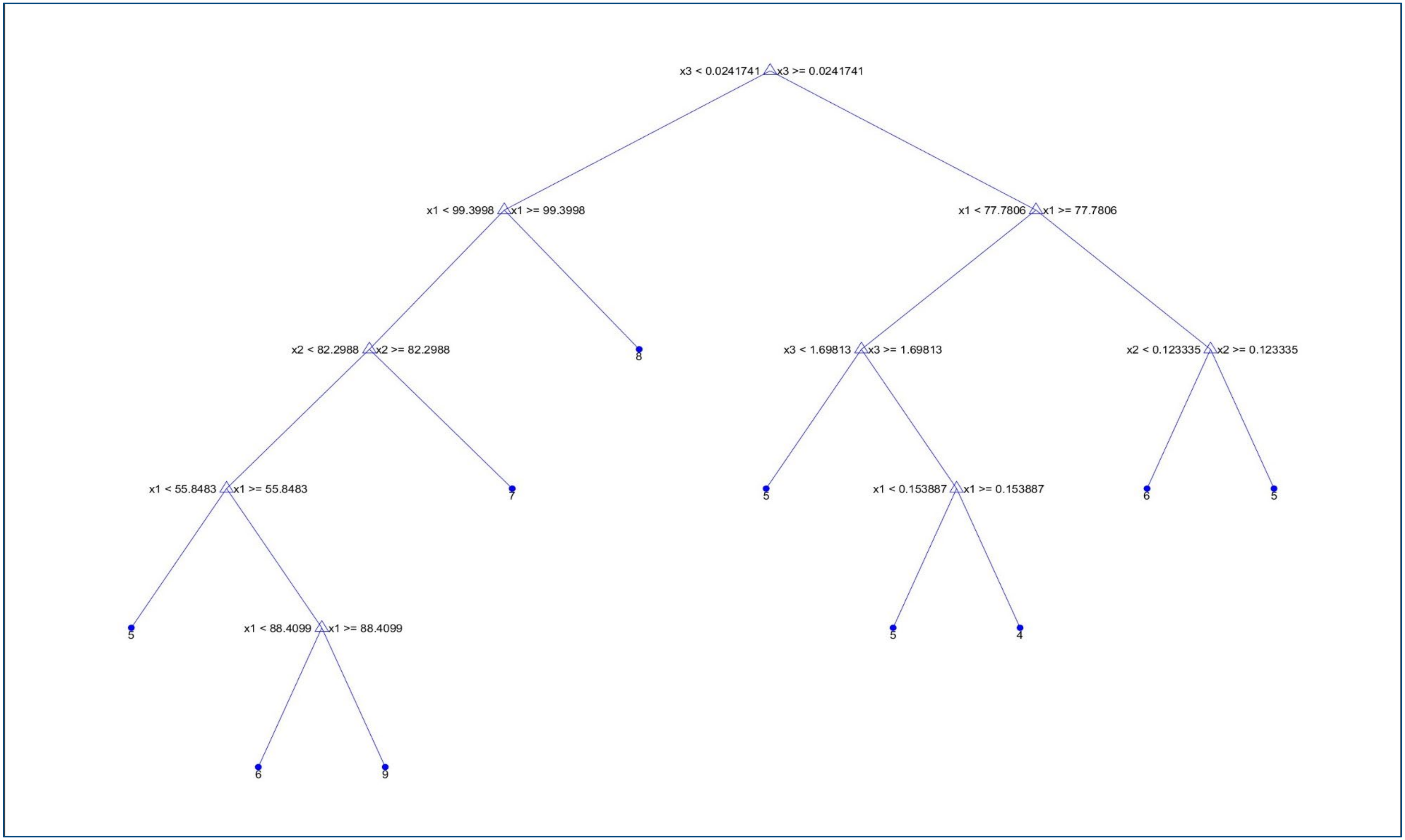


ID#15 (Deck – Steel - Balanced)



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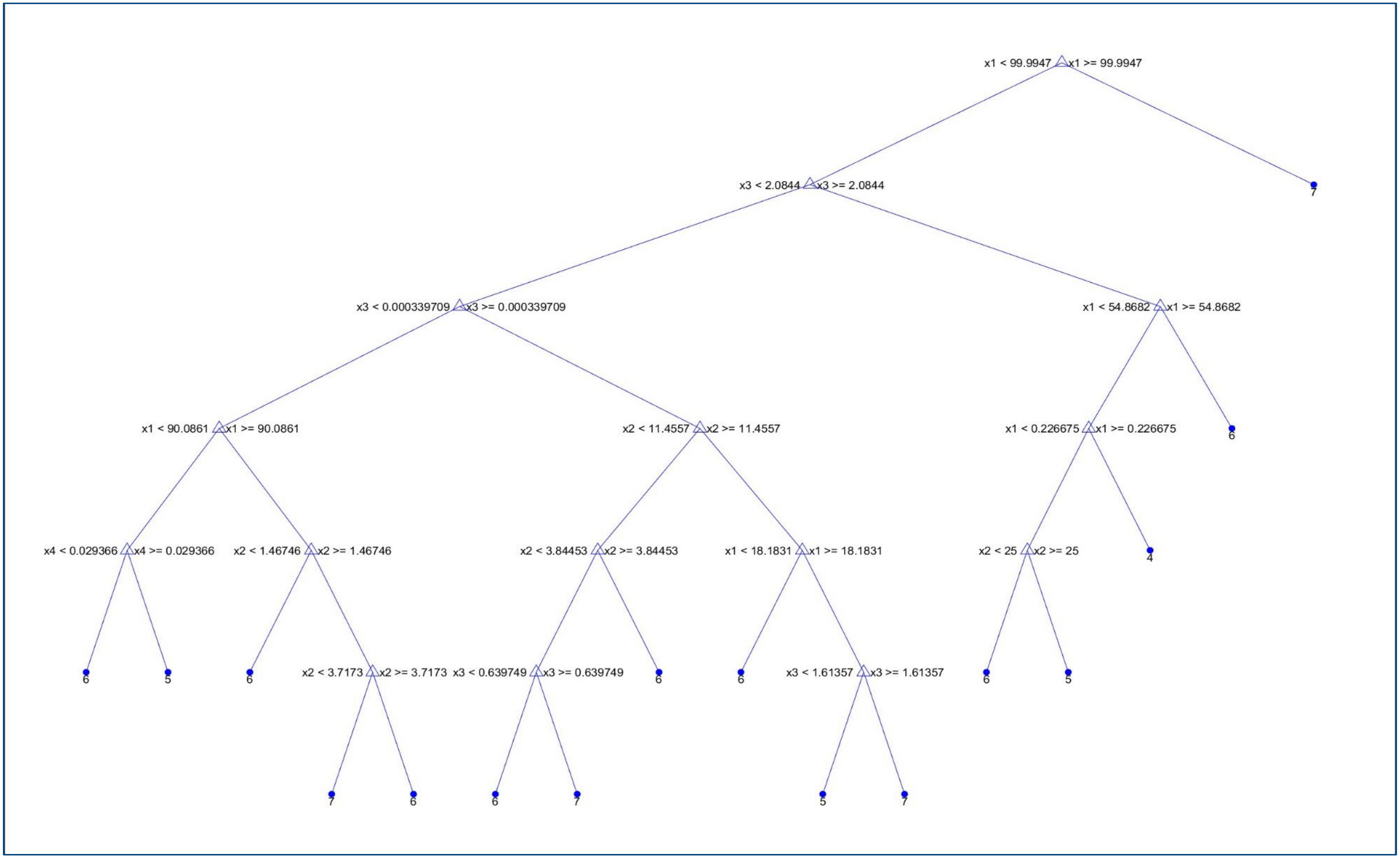

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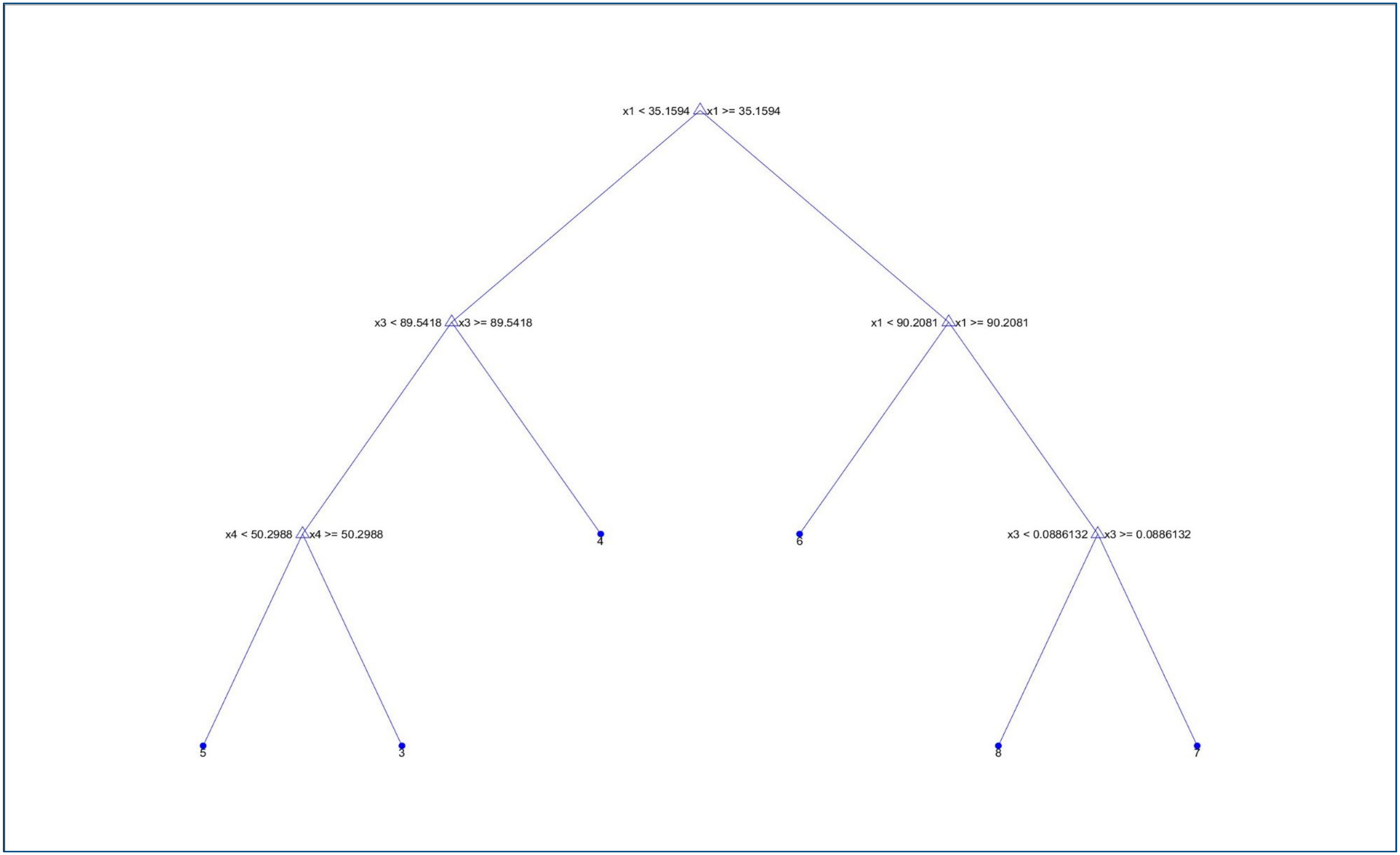

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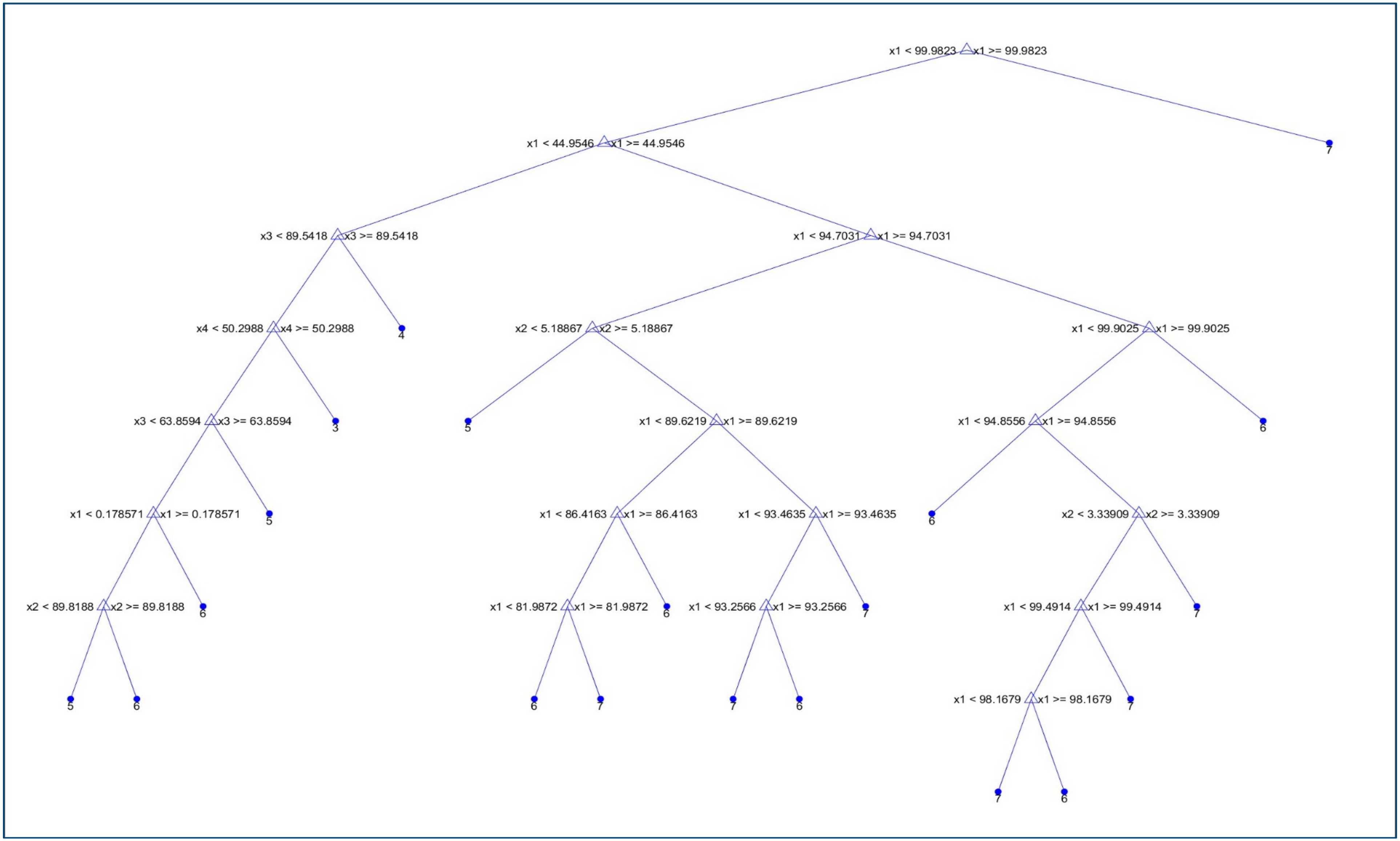
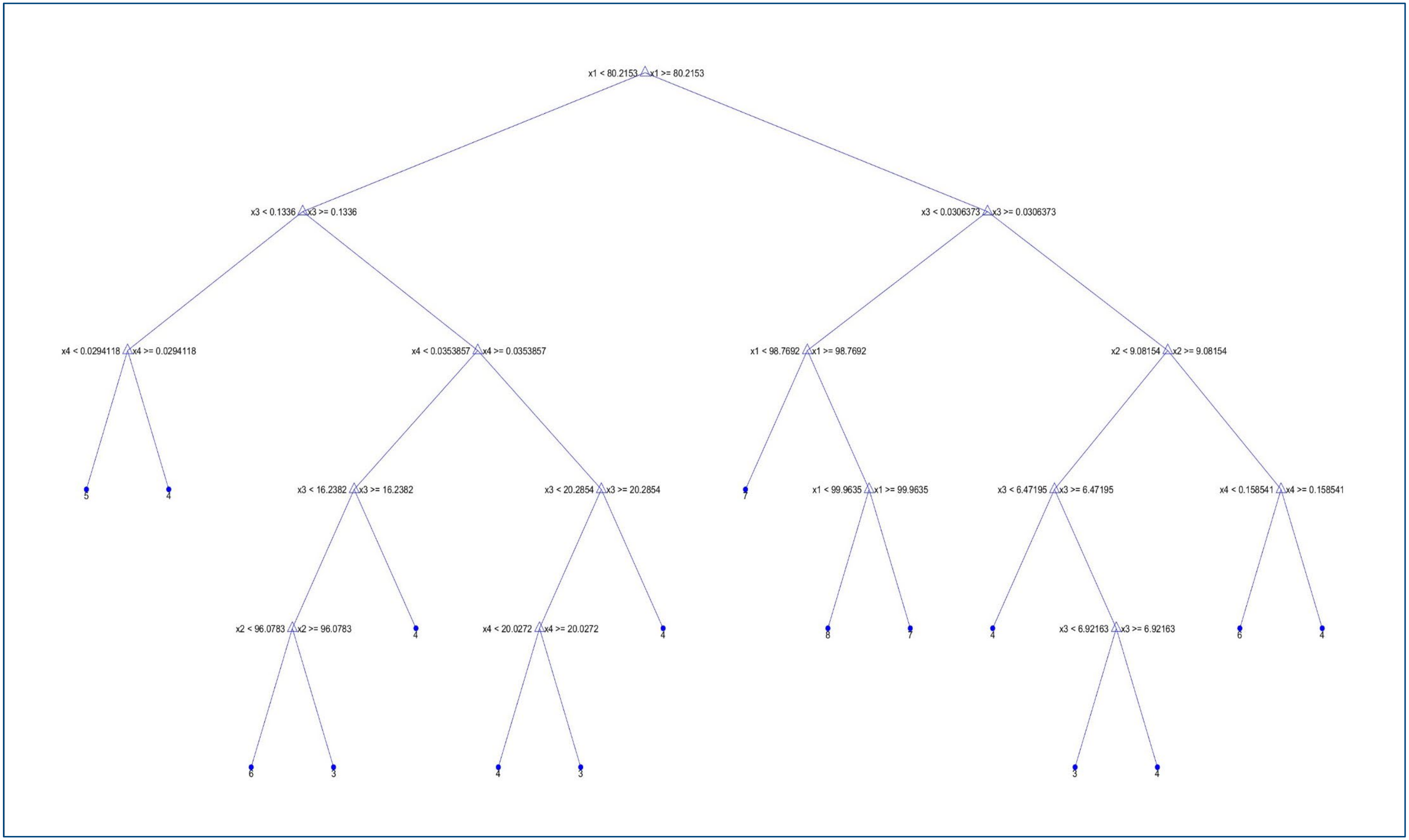


ID#19 (Superstructure – Reinforced Concrete - Balanced)



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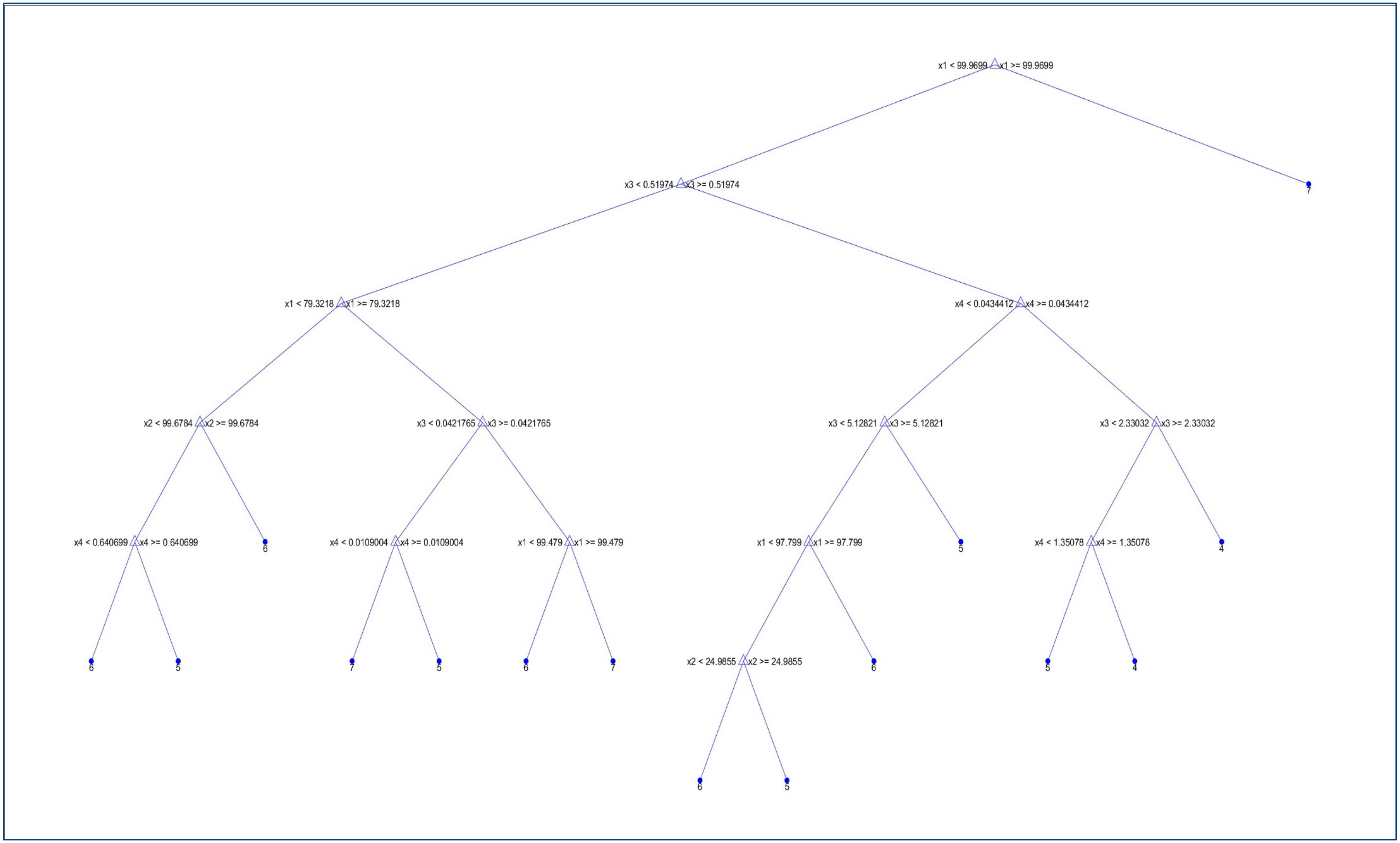
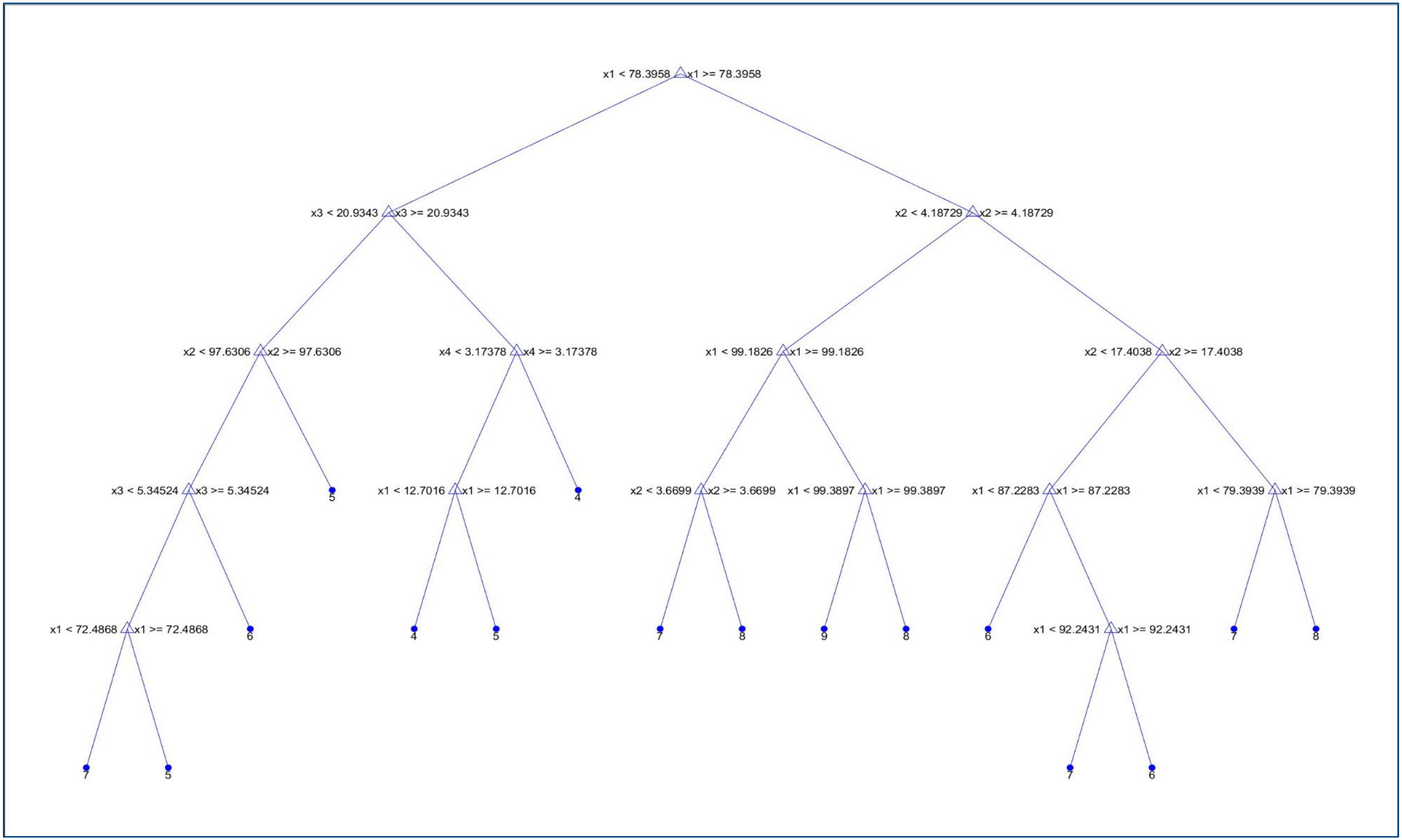


ID#21 (Superstructure – RC Arches - Balanced)



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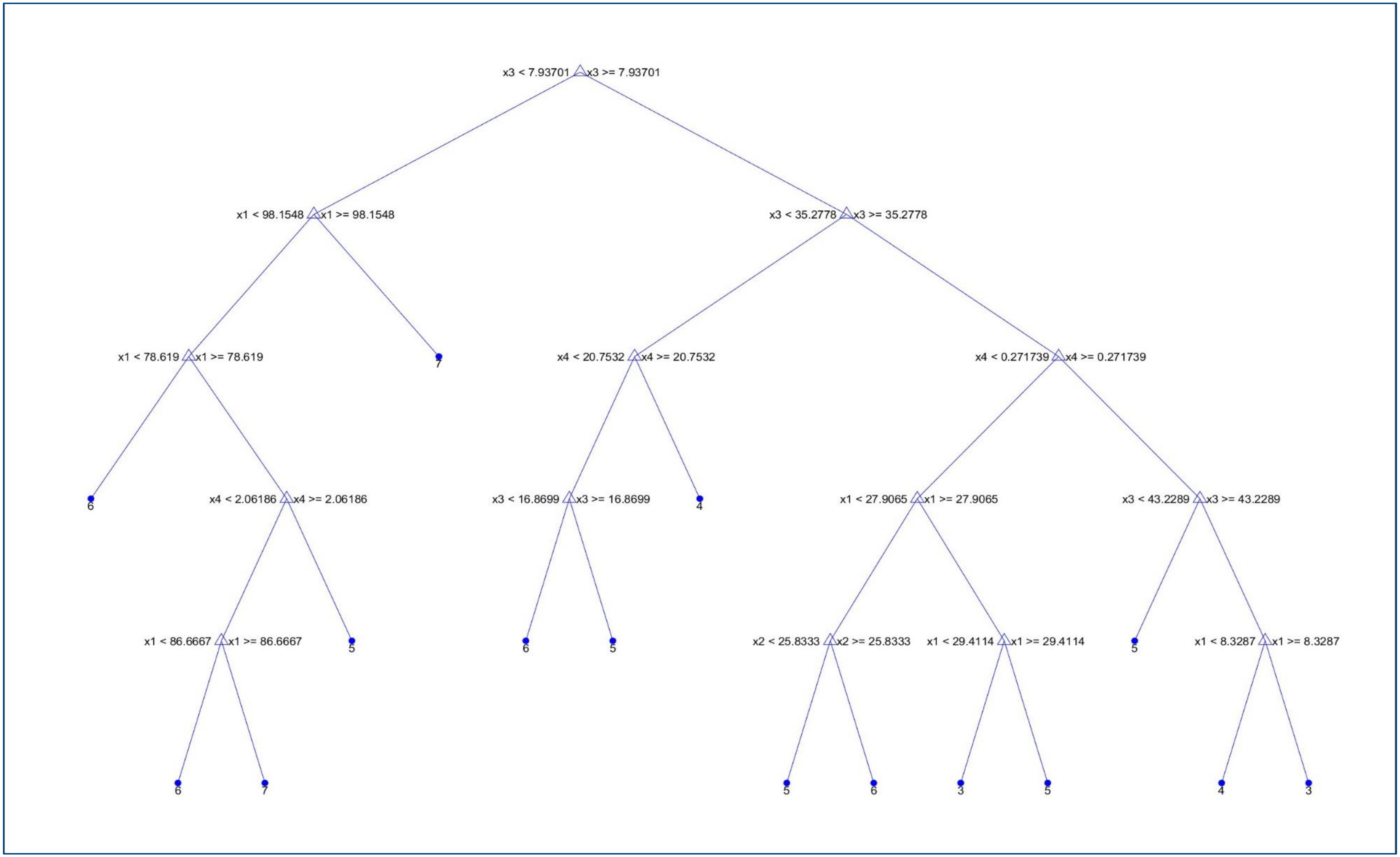
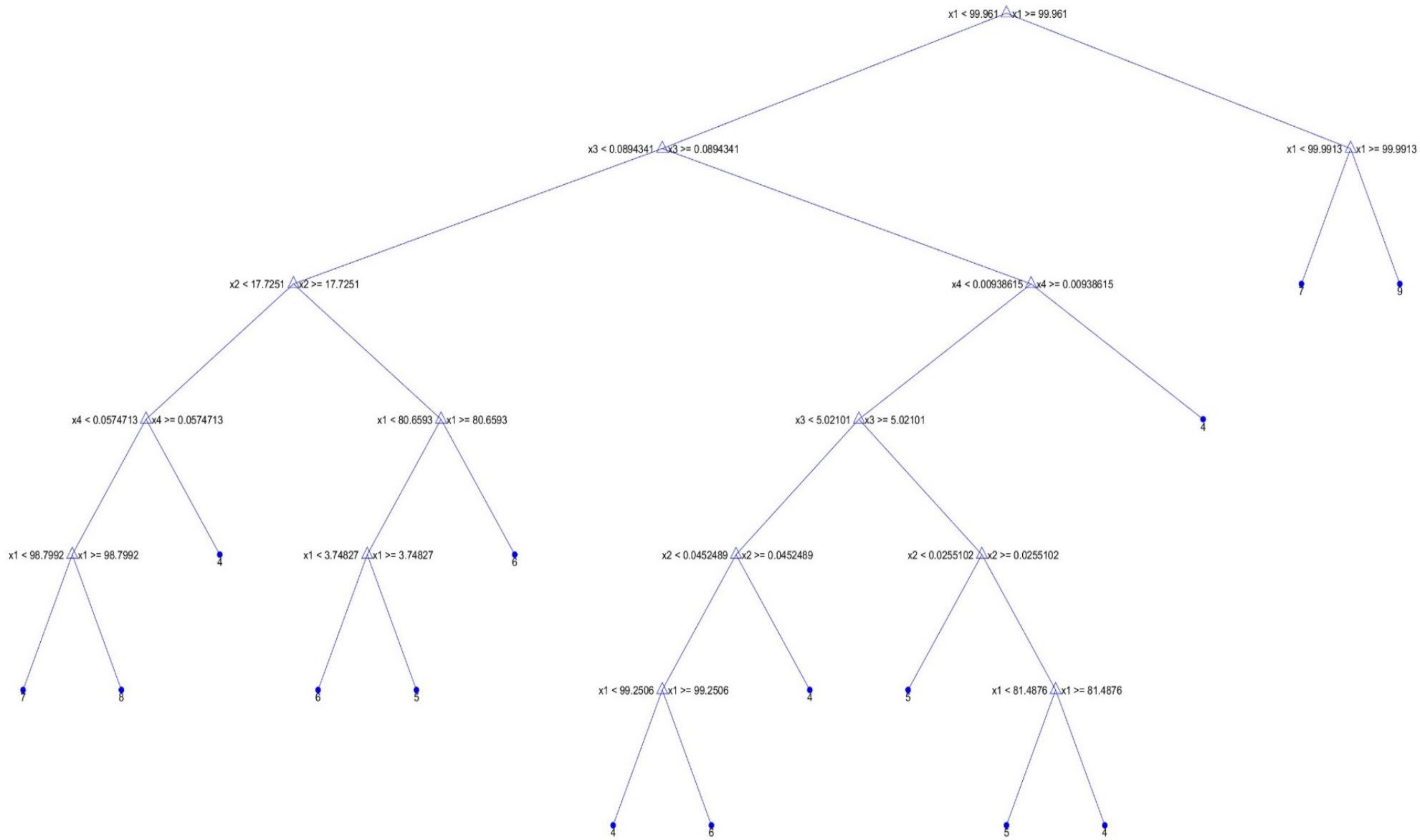


ID#23 (Superstructure – Prestressed Concrete - Balanced)



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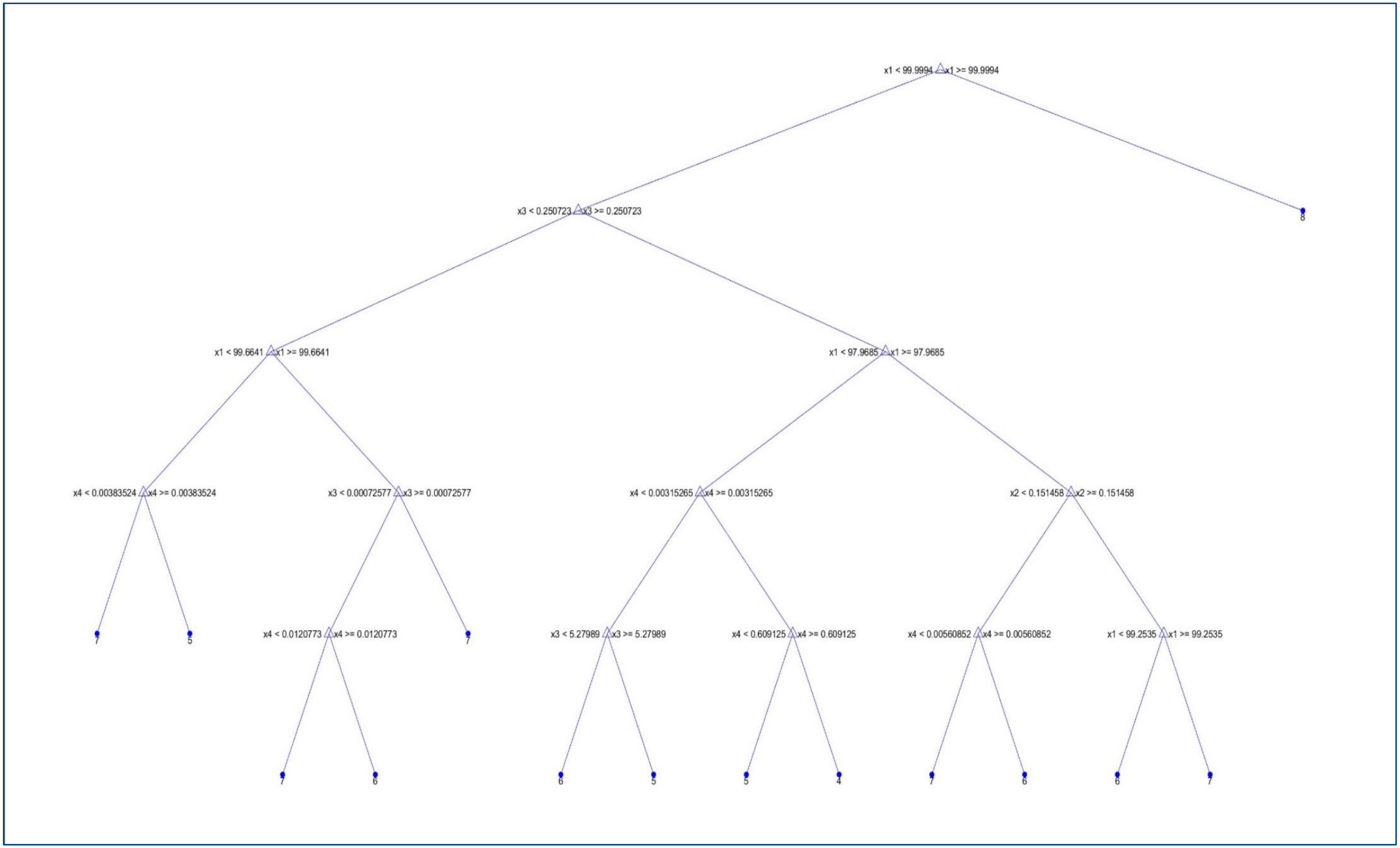

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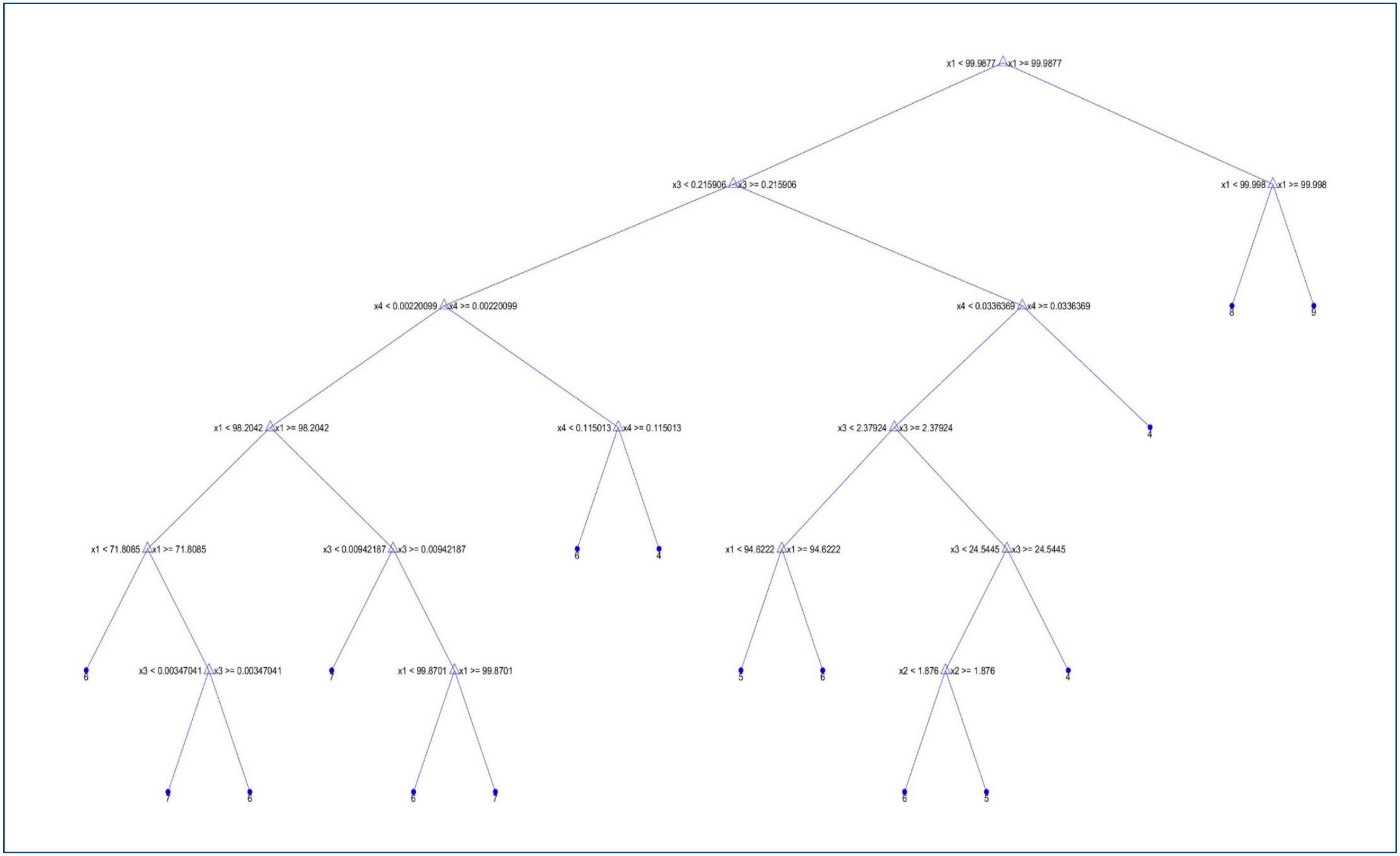
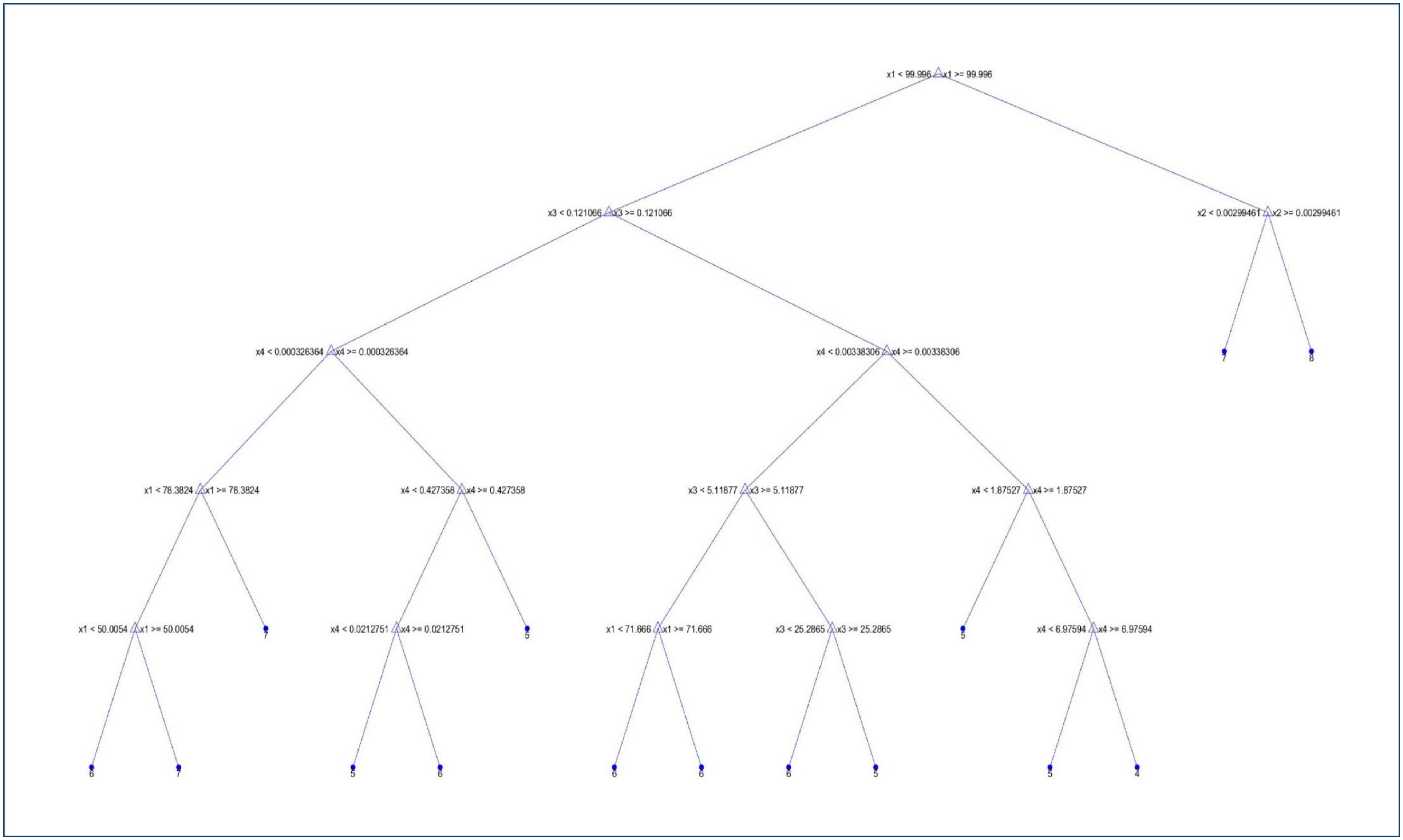


ID#26 (Superstructure – Steel - Imbalanced)



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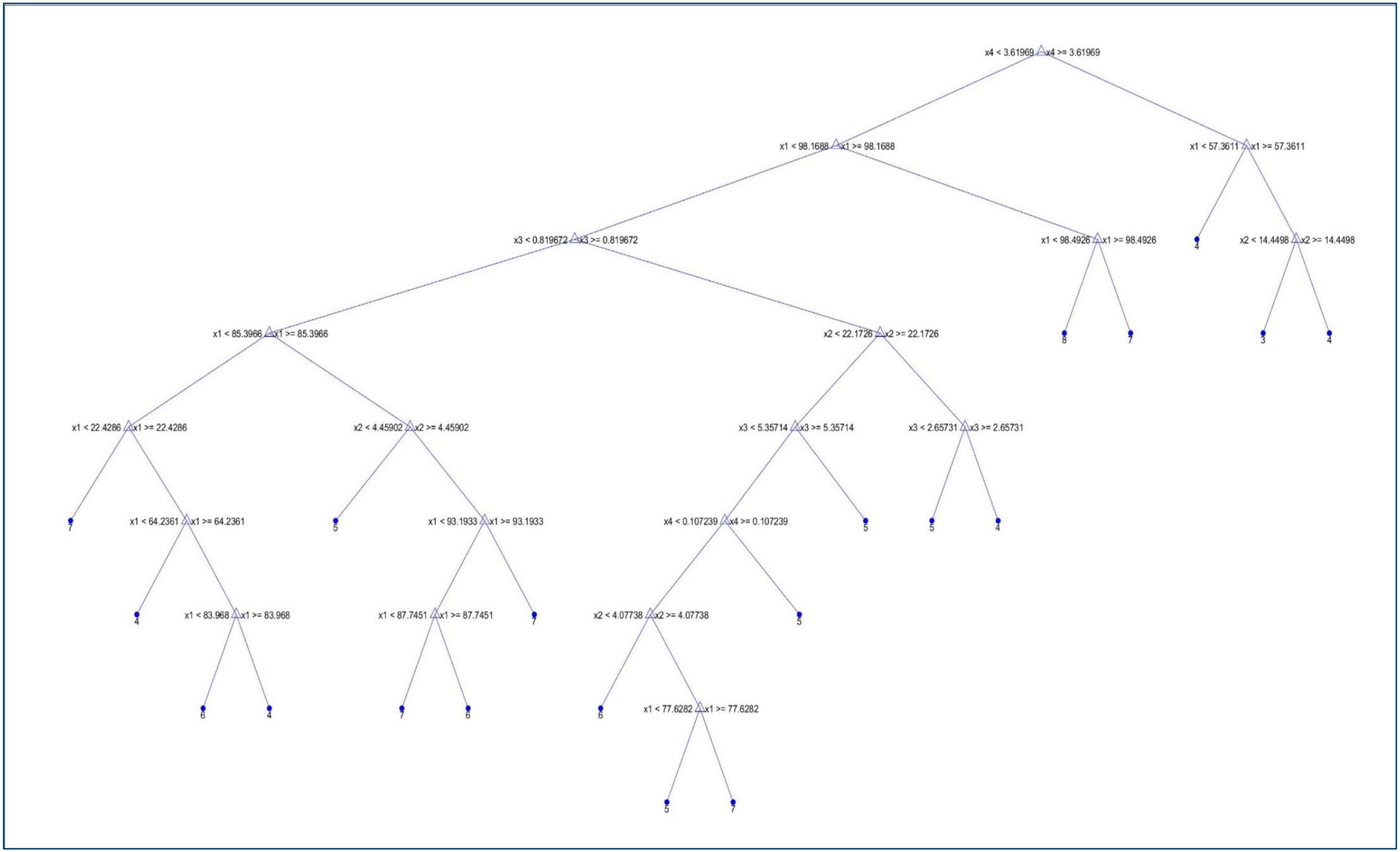

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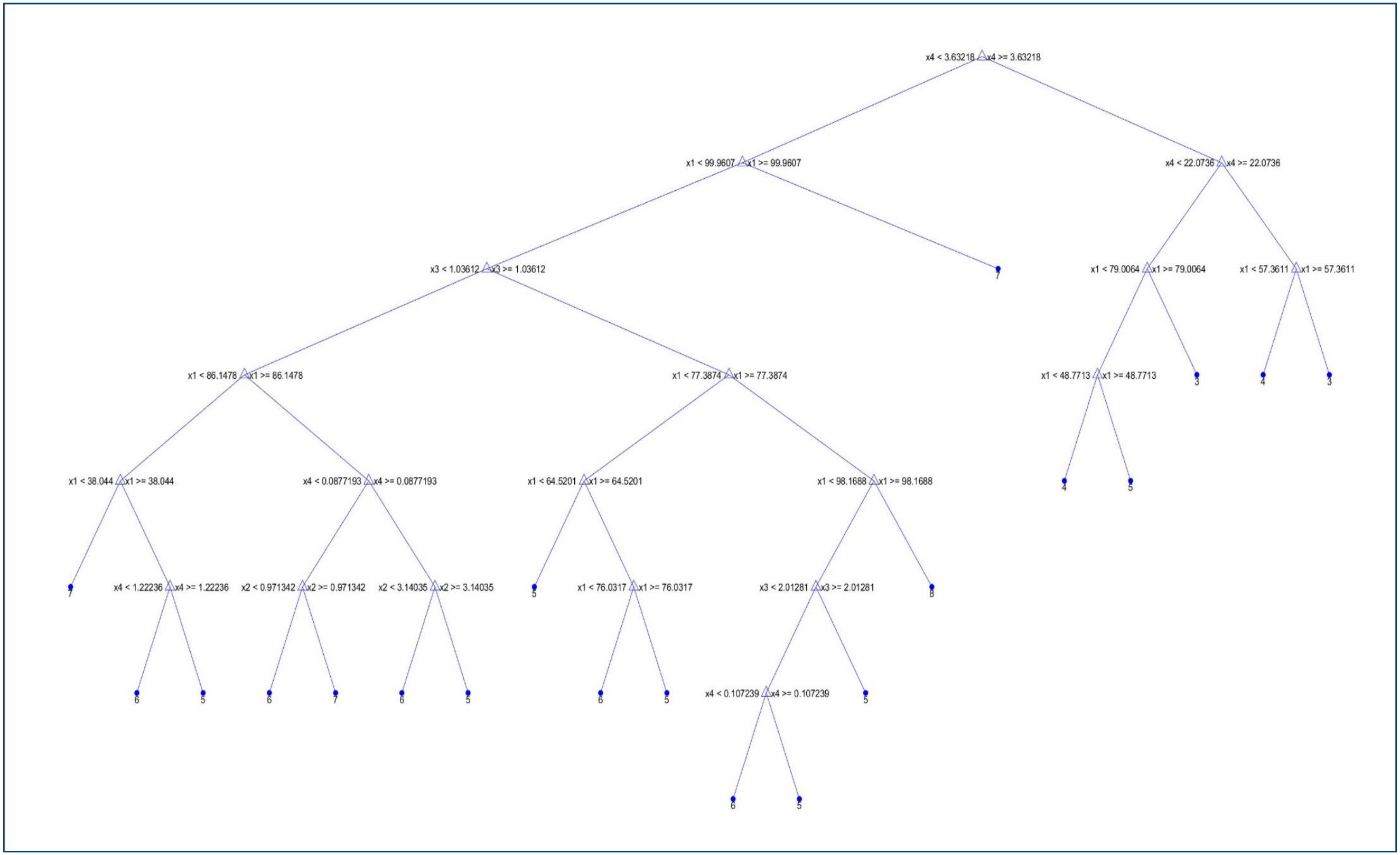
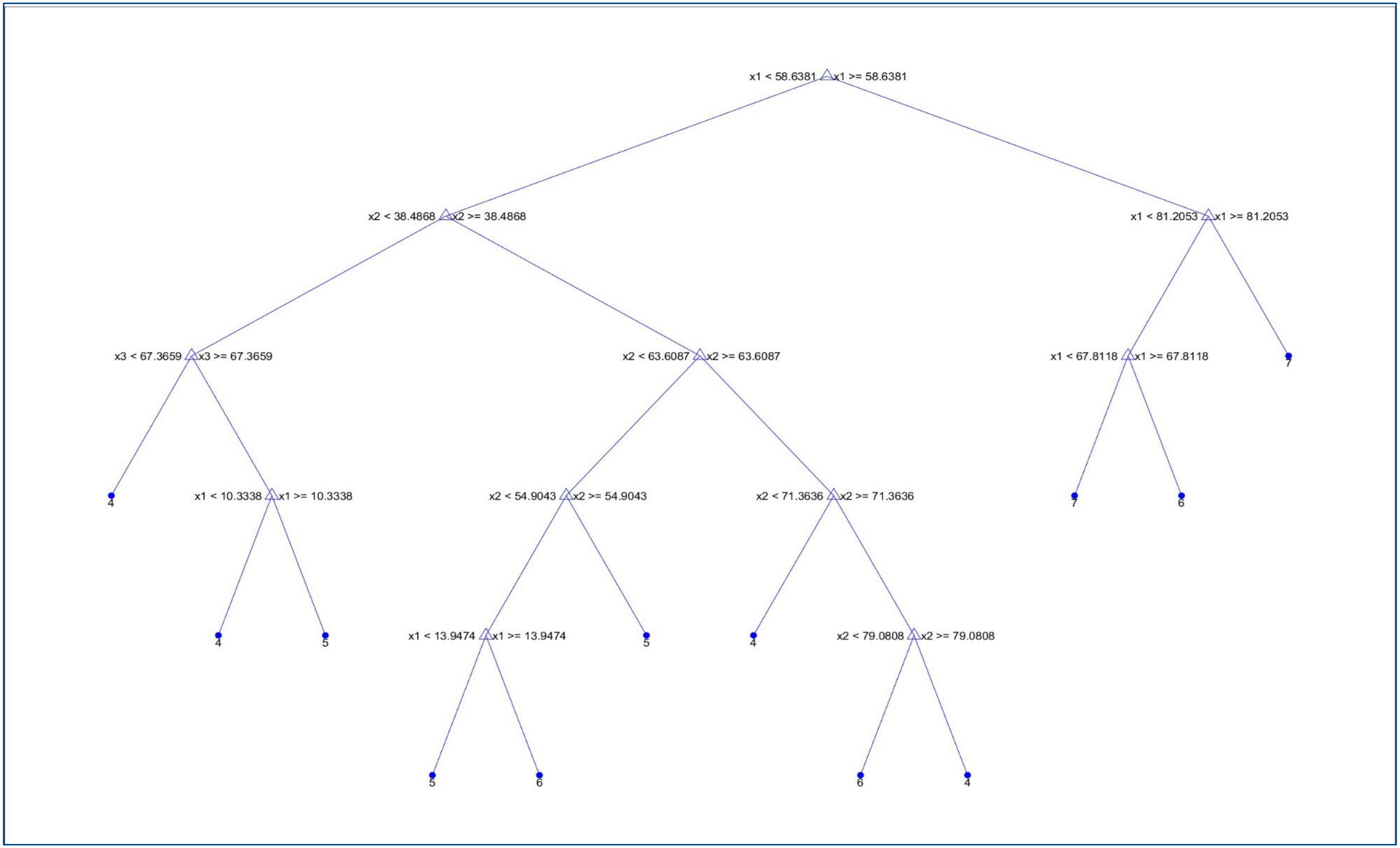


ID#29 (Superstructure – Masonry - Balanced)



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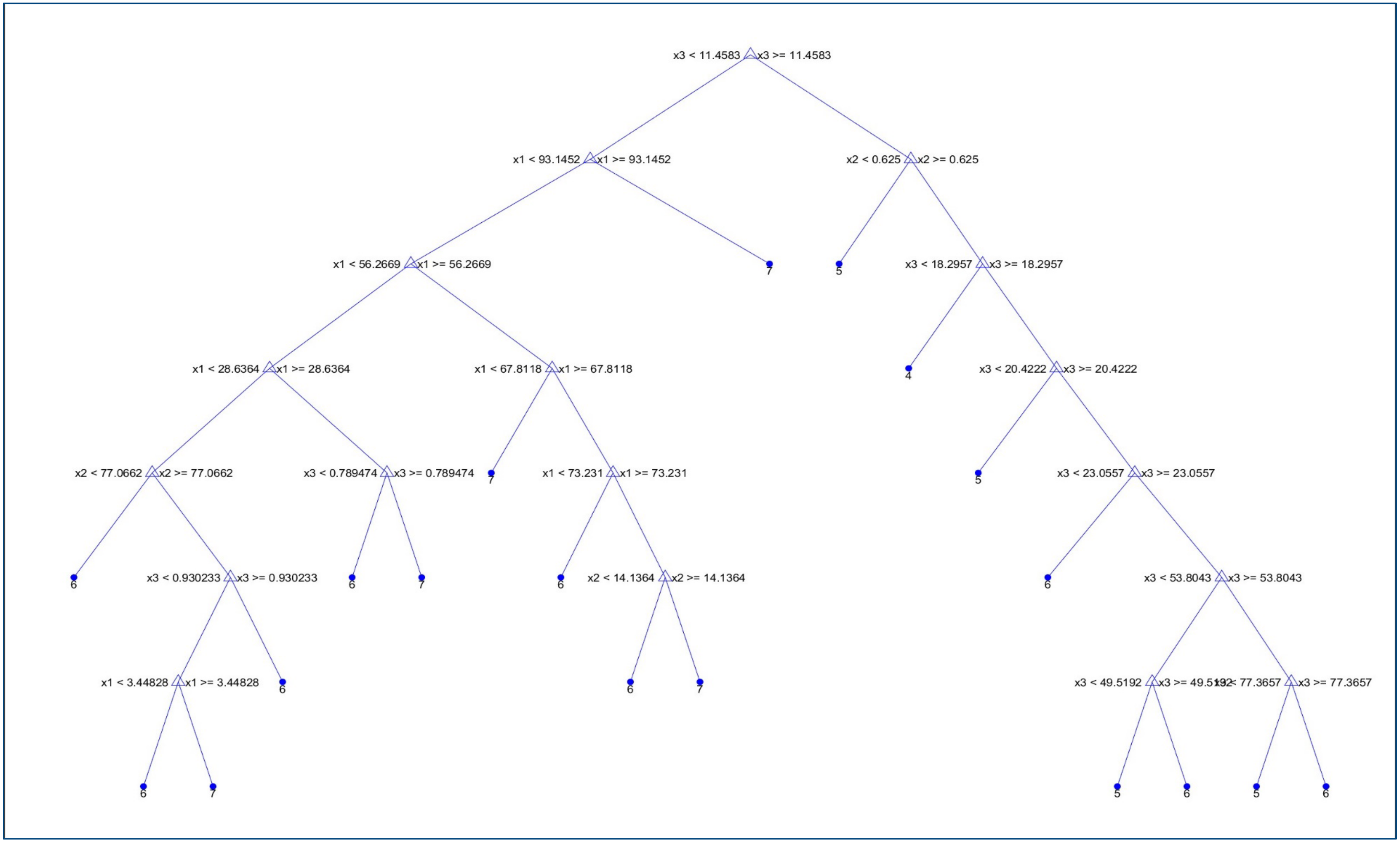
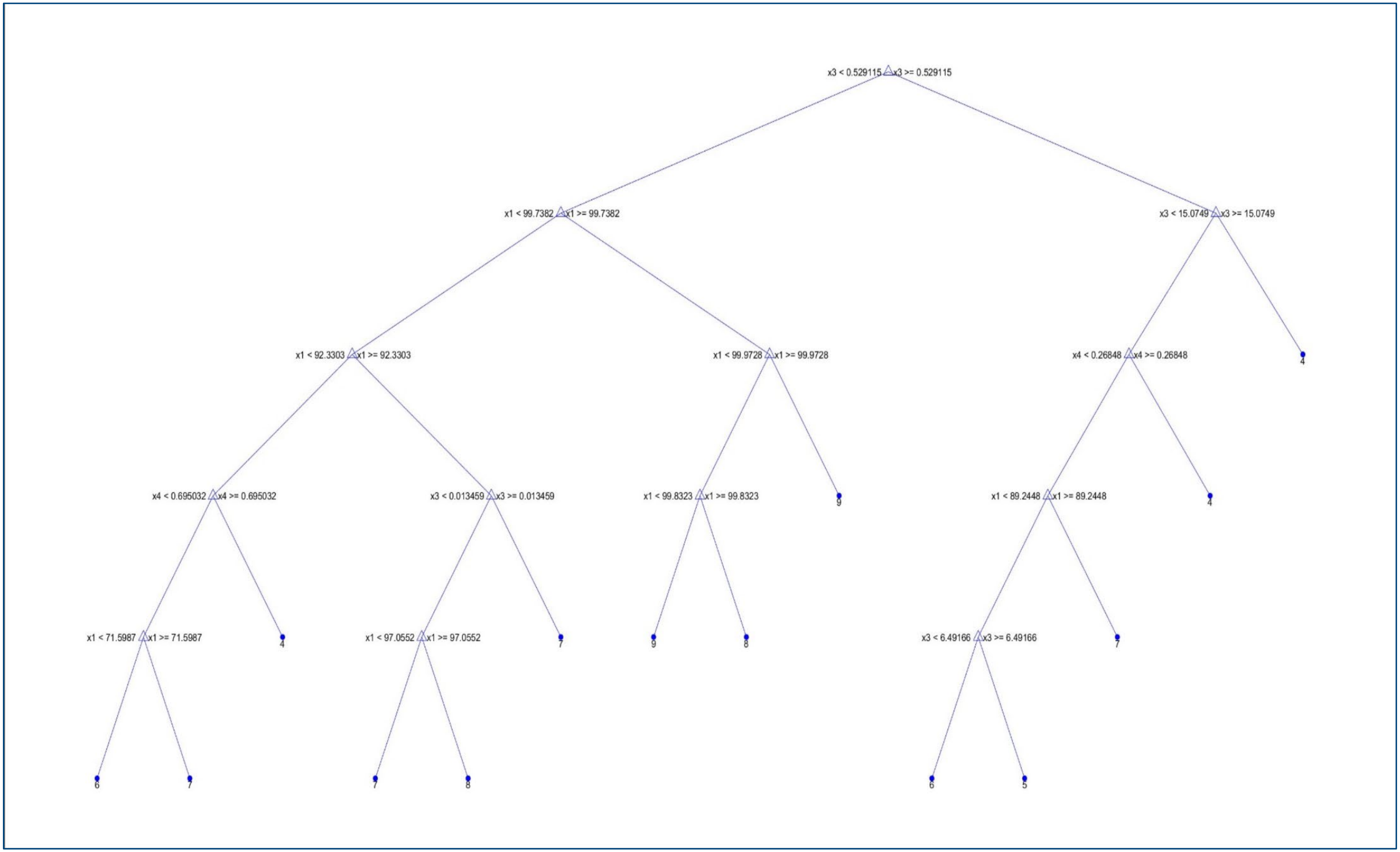


ID#31 (Substructure – Reinforced Concrete - Balanced)



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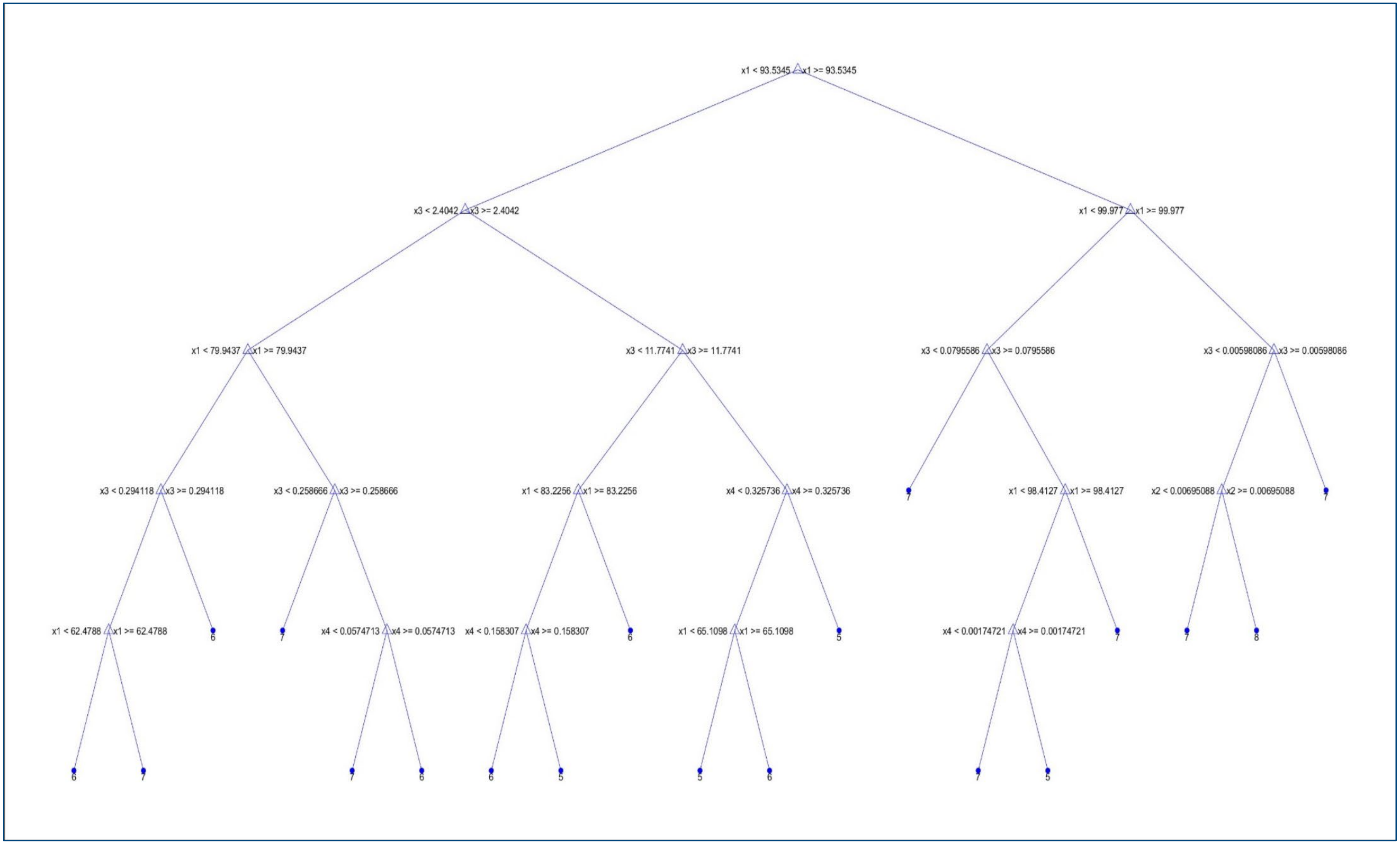

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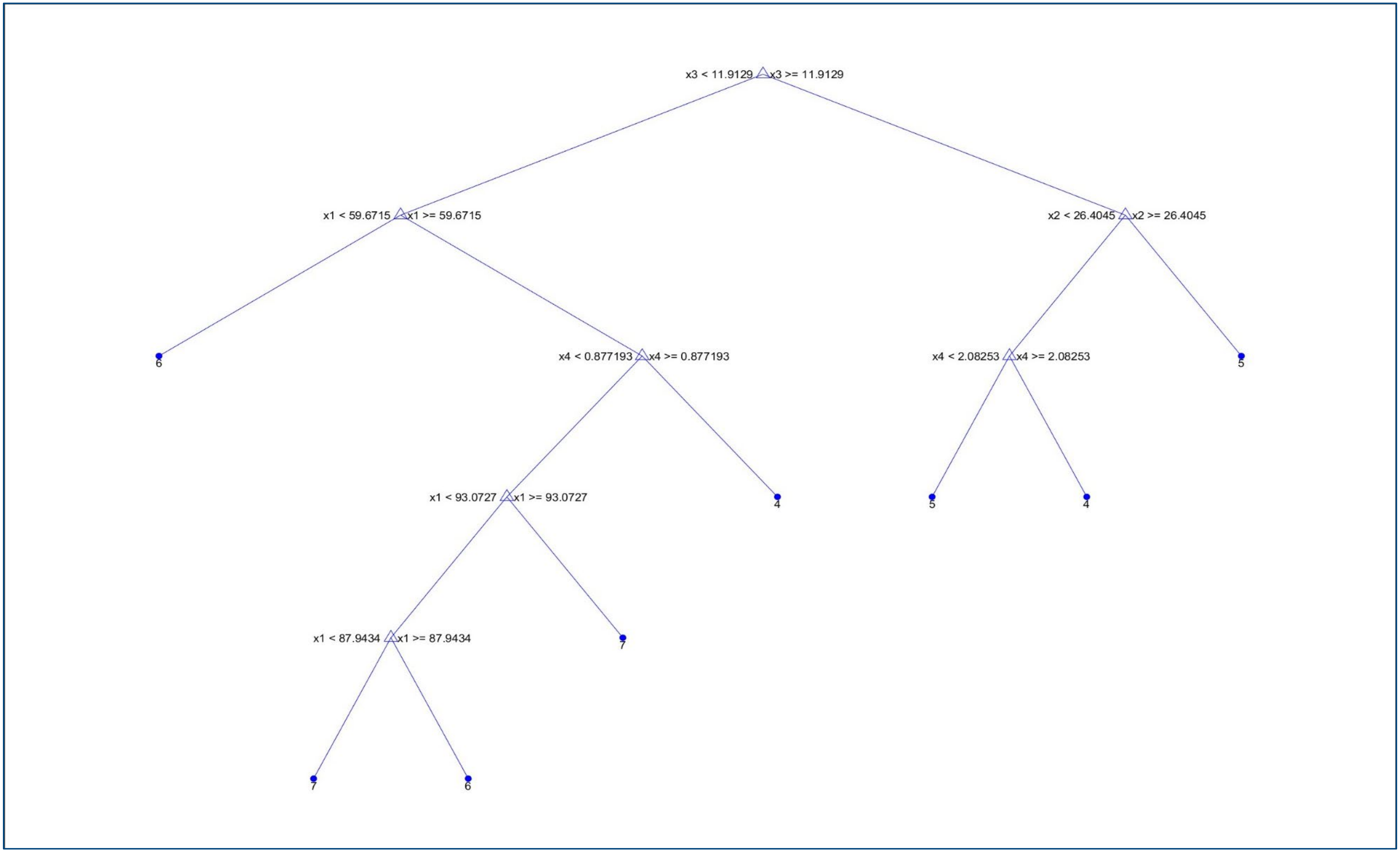

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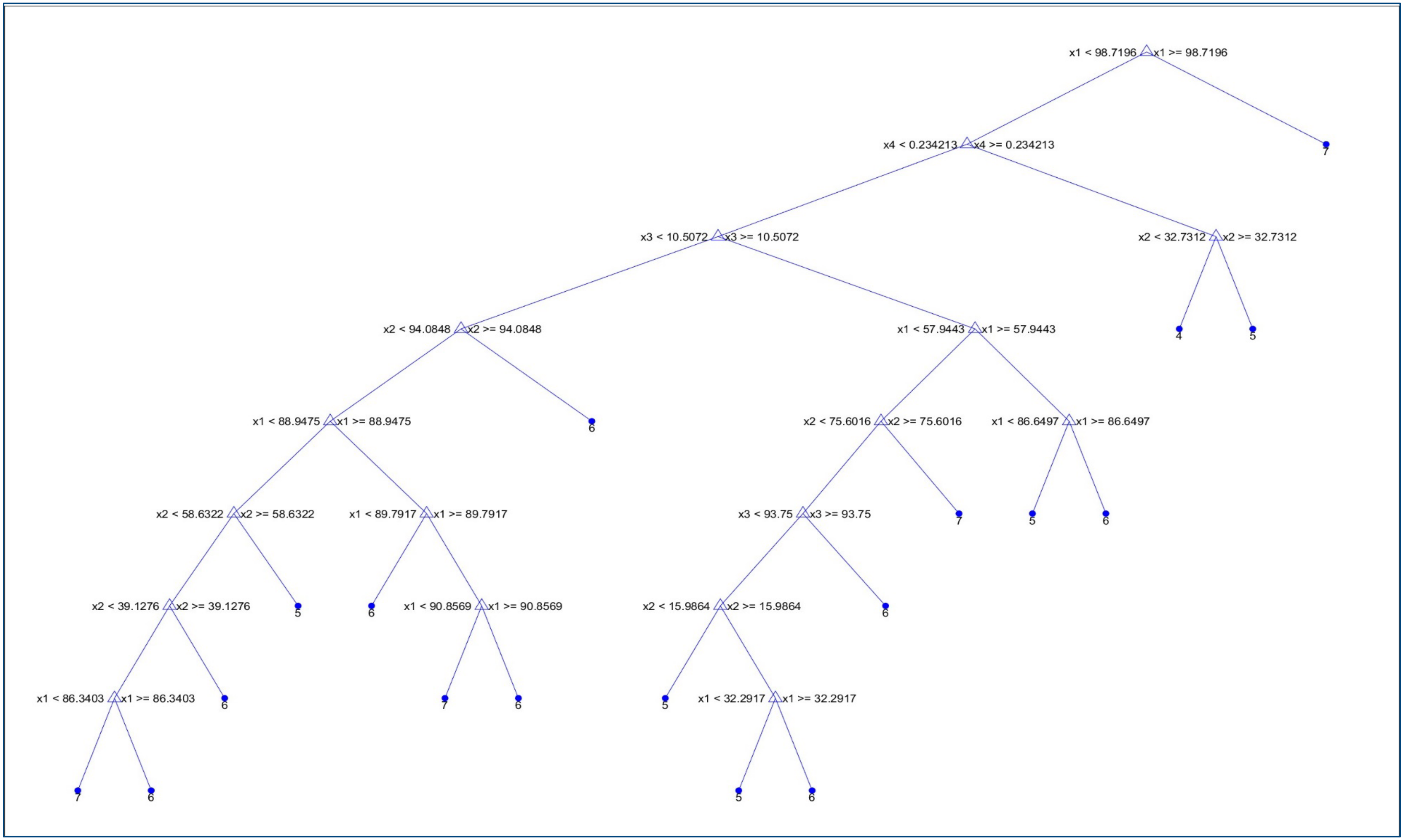

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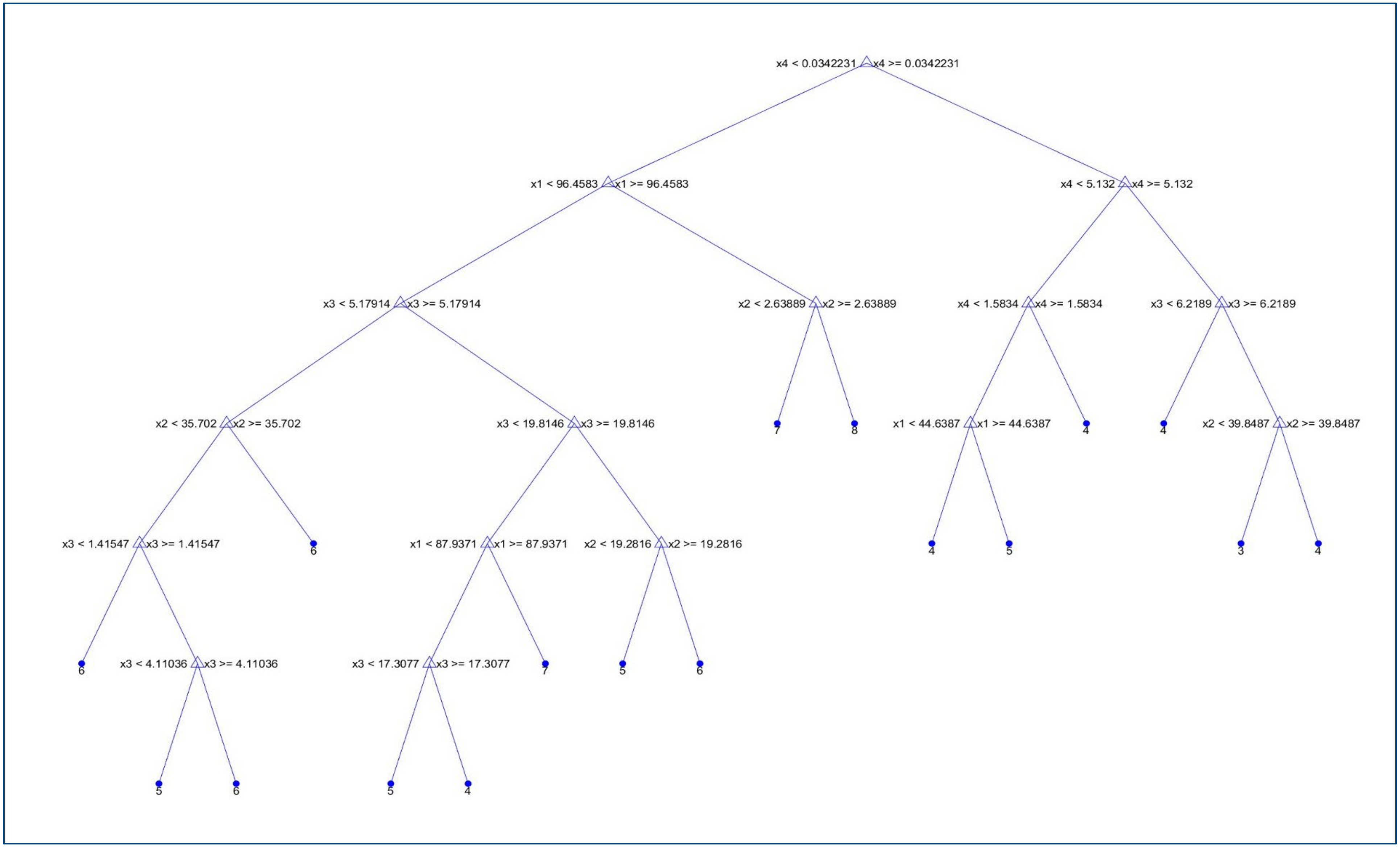

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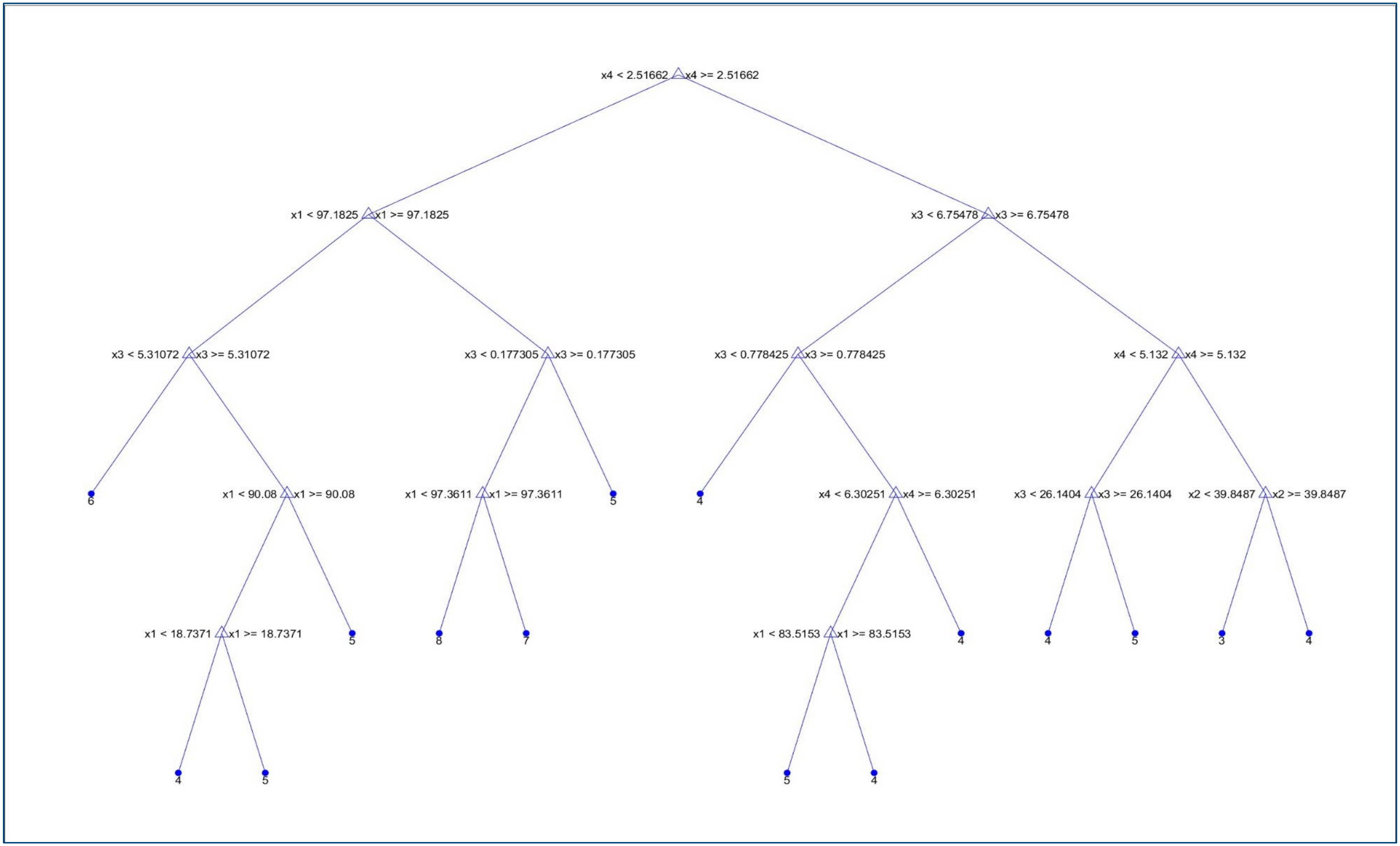
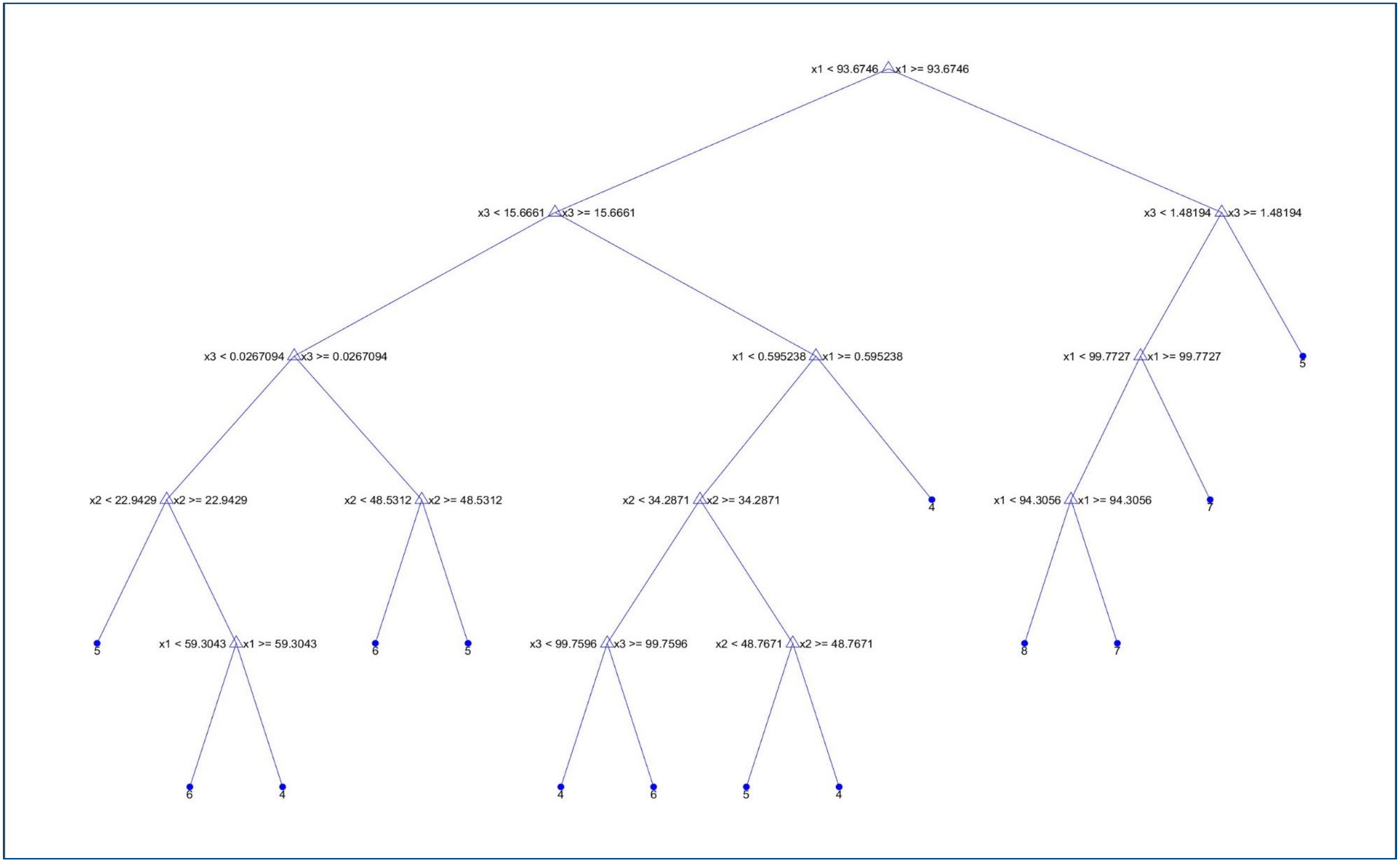
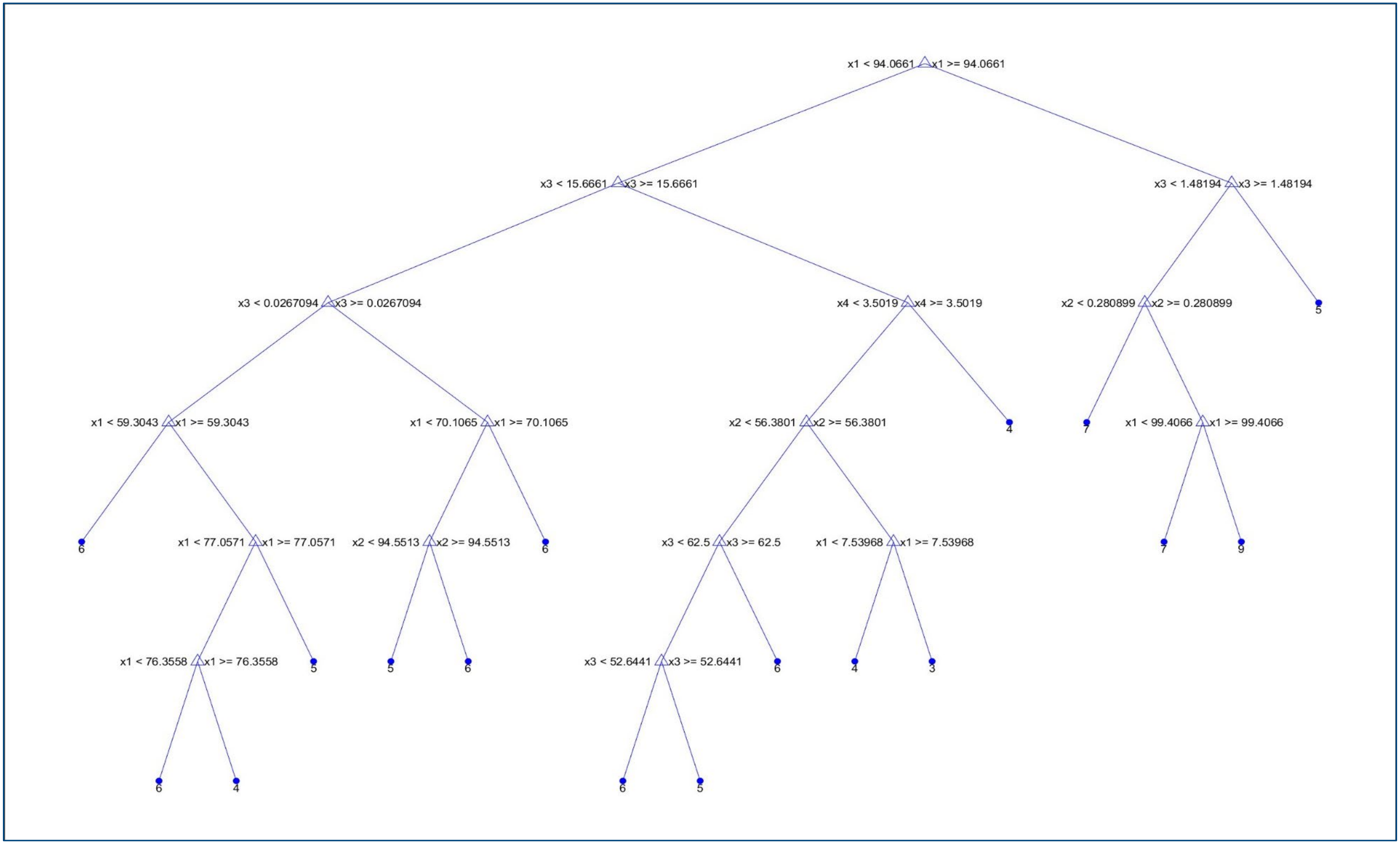


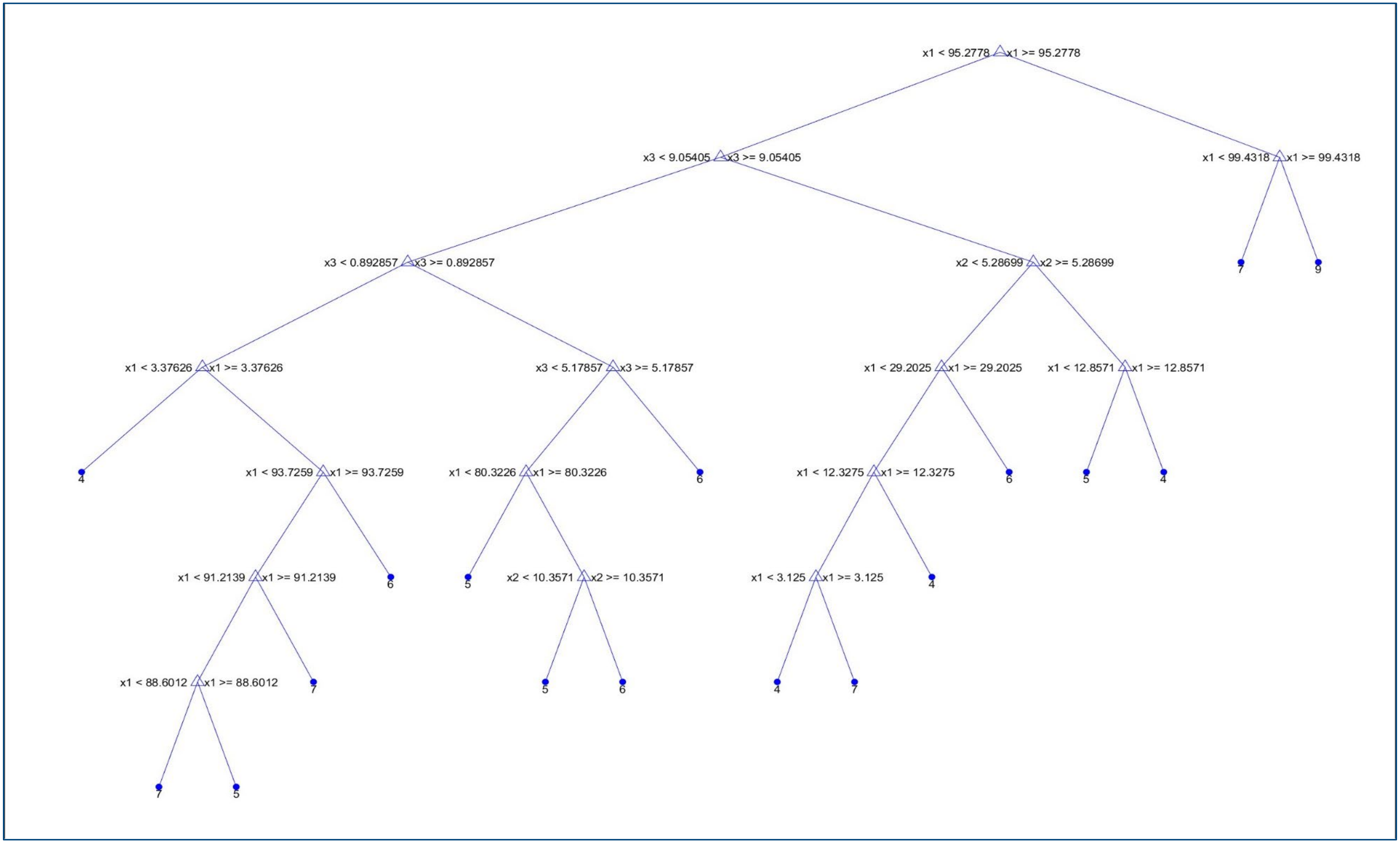
ID#37 (Substructure – Masonry - Balanced)



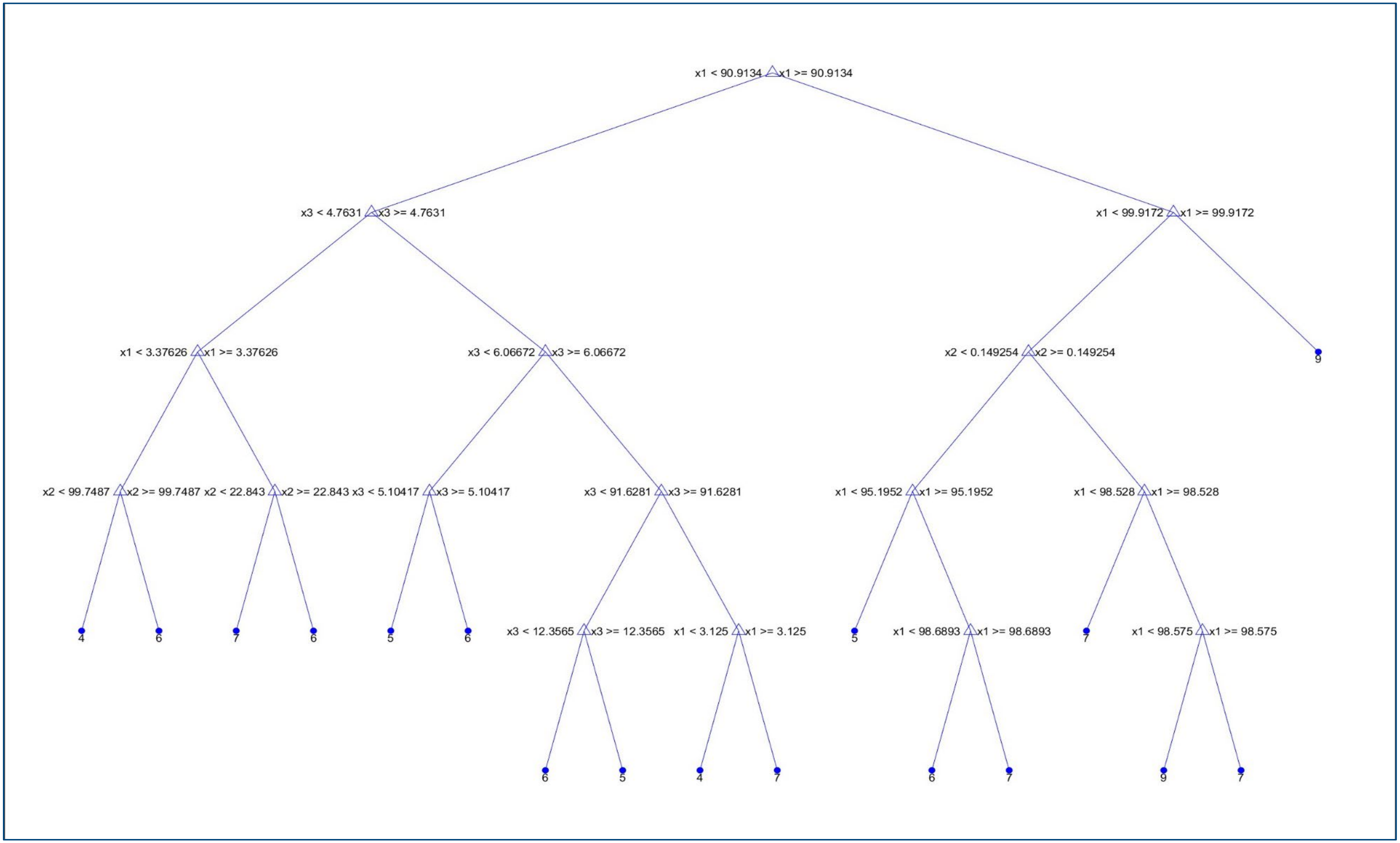
ID#38 (Substructure – Masonry - Imbalanced)



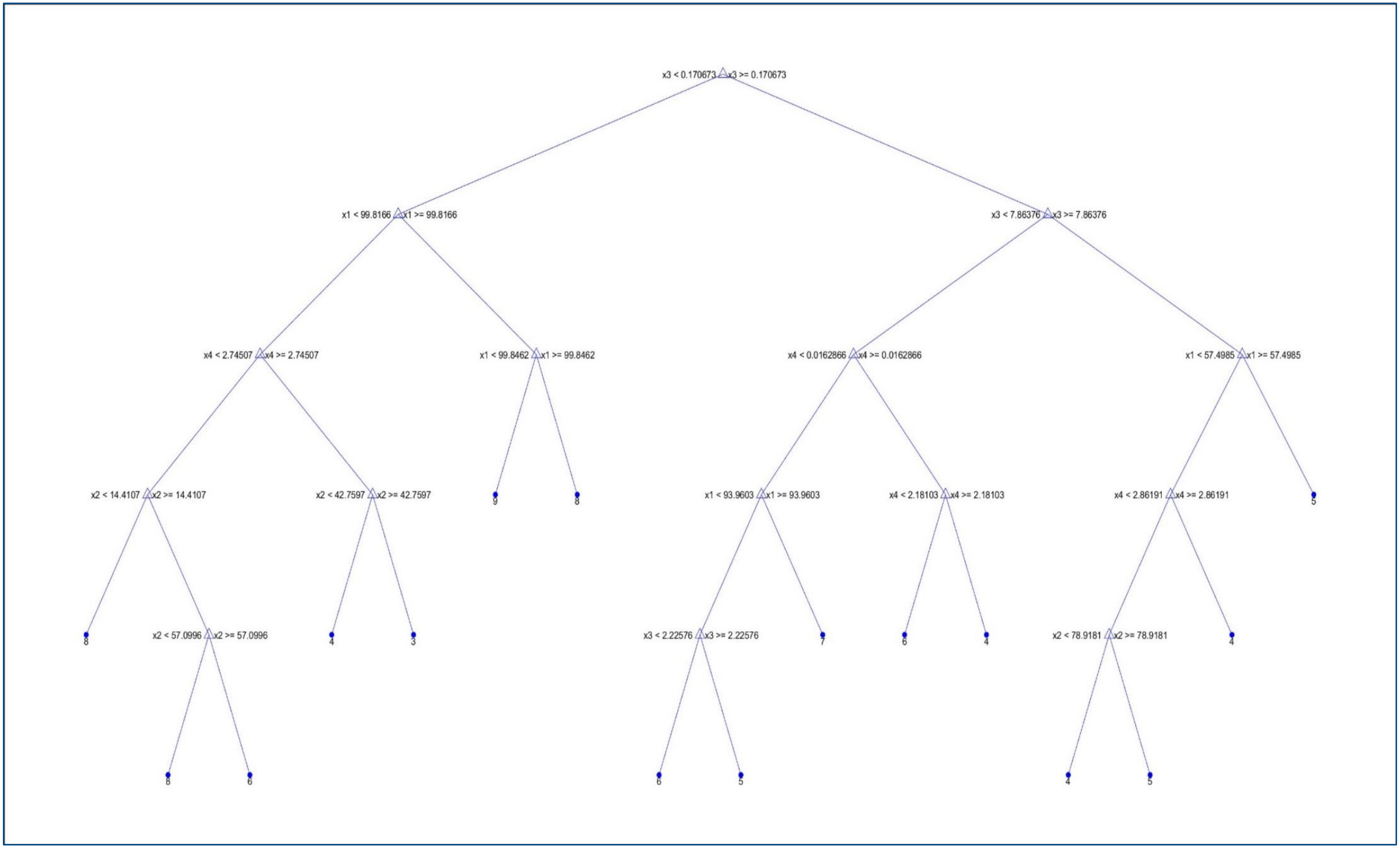
ID#39 (Substructure – Other - Balanced)



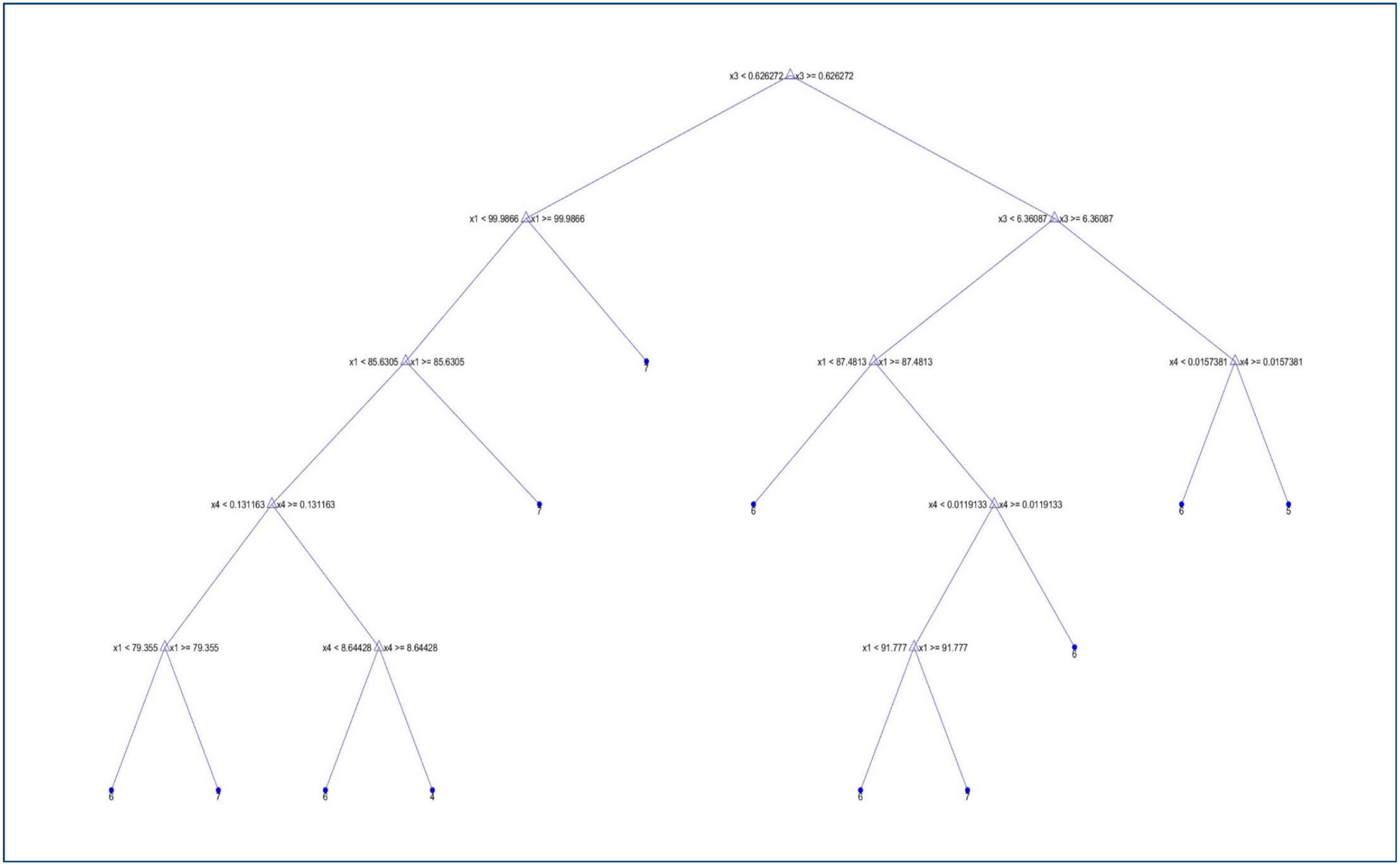
ID#40 (Substructure – Other - Imbalanced)



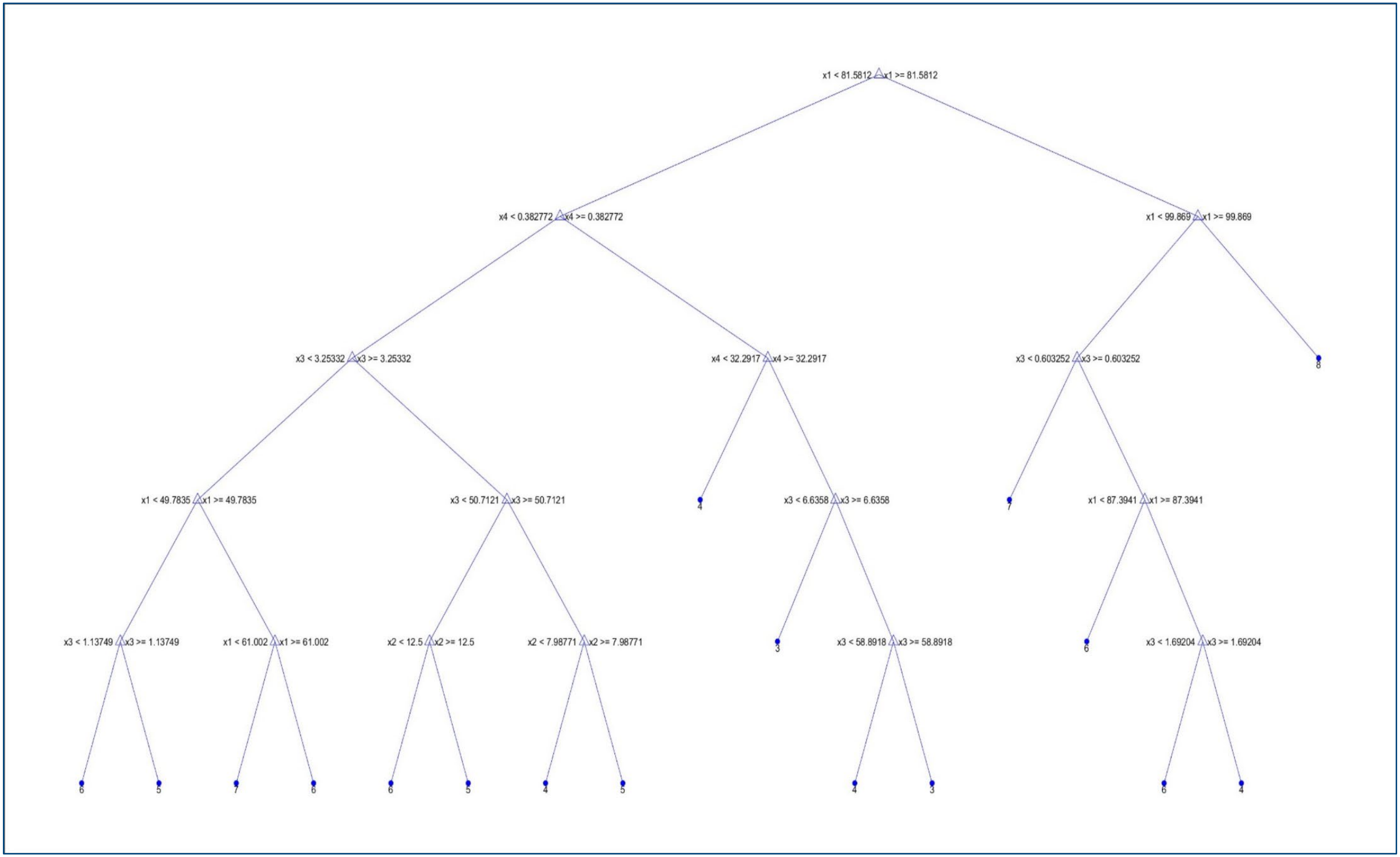
ID#41 (Culvert – Reinforced Concrete - Balanced)



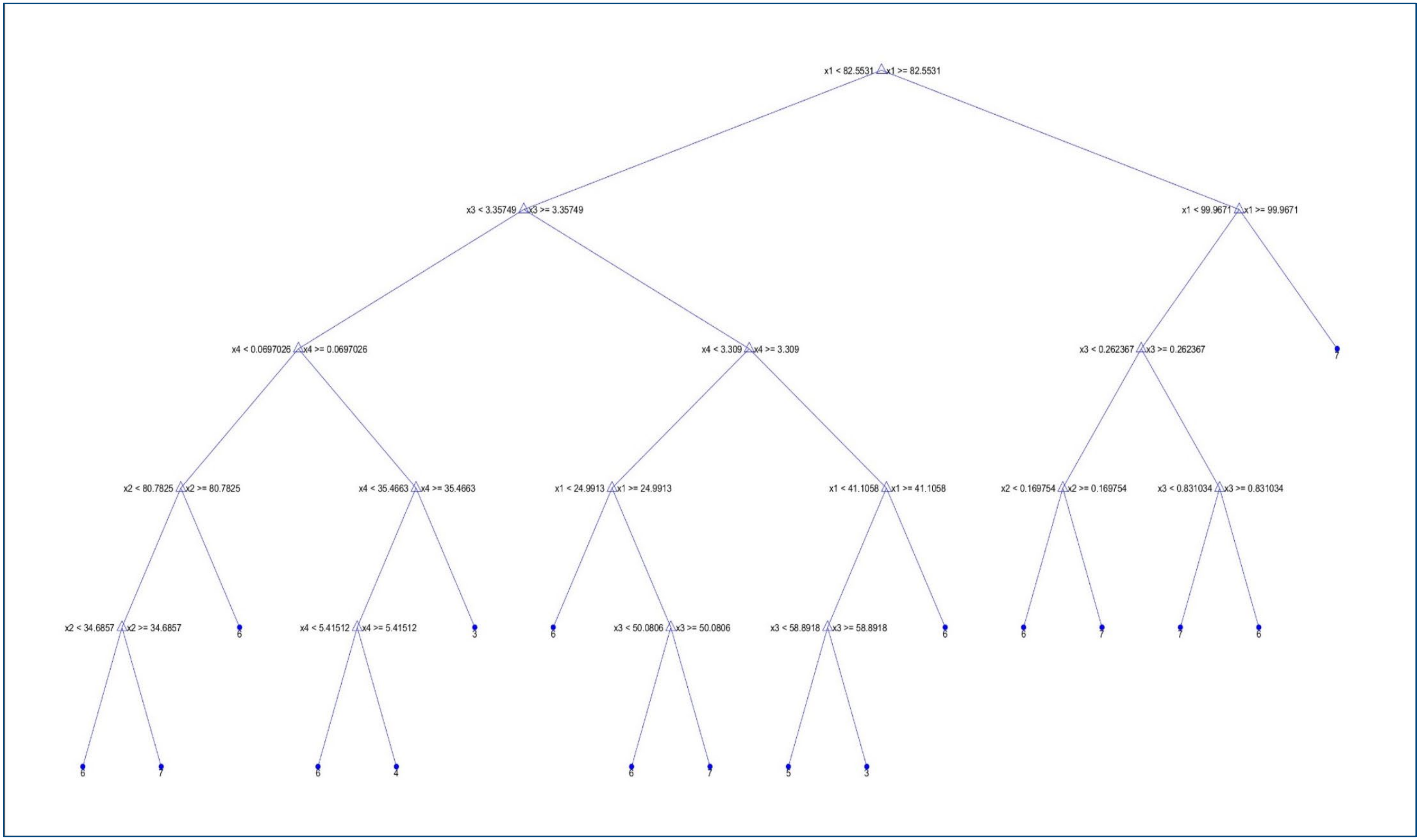
ID#42 (Culvert – Reinforced Concrete - Imbalanced)



ID#43 (Culvert – Steel - Balanced)



ID#44 (Culvert – Steel - Imbalanced)



APPENDIX IV – ACCURACY FOR FINALIZED CONVERSION PROFILES

Total accuracies and individual condition rating accuracies for margin of errors ±0 CR, ±1 CR, and ±2 CR for the finalized models summarized in Table 27.

Table 29. Detailed Accuracy Percentages for the Model ID#1 (Universal - Balanced).

Margin of Error	Individual Condition Rating							Total (%)
	CR3	CR4	CR5	CR6	CR7	CR8	CR9	
				Training				
±0	0%	61%	8%	69%	33%	15%	77%	43%
±1	74%	68%	89%	88%	77%	93%	85%	83%
±2	78%	96%	98%	100%	99%	99%	98%	98%
				Testing				
±0	0%	60%	8%	69%	33%	15%	77%	43%
±1	75%	67%	88%	87%	75%	94%	85%	83%
±2	82%	96%	98%	100%	99%	100%	98%	98%

Table 30. Detailed Accuracy Percentages for the Model ID#2 (Universal - Imbalanced).

Margin of Error	Individual Condition Rating							Total (%)
	CR3	CR4	CR5	CR6	CR7	CR8	CR9	
				Training				
±0	0%	9%	28%	55%	79%	0%	0%	53%
±1	26%	63%	85%	100%	99%	95%	0%	94%
±2	72%	95%	100%	100%	100%	100%	99%	100%
				Testing				
±0	0%	9%	28%	55%	79%	0%	0%	53%
±1	22%	62%	85%	100%	99%	95%	0%	94%
±2	71%	94%	100%	100%	100%	100%	99%	100%

Table 31. Detailed Accuracy Percentages for the Model ID#3 (Component - Deck - Balanced).

Margin of Error	Individual Condition Rating							**Total (%)**
	CR3	**CR4**	**CR5**	**CR6**	**CR7**	**CR8**	**CR9**	
				Training				
±0	0%	73%	43%	27%	36%	8%	78%	43%
±1	81%	92%	88%	80%	51%	95%	81%	81%
±2	93%	96%	99%	99%	96%	97%	97%	97%
				Testing				
±0	0%	76%	44%	27%	35%	10%	78%	44%
±1	89%	94%	89%	79%	49%	95%	80%	81%
±2	97%	97%	99%	99%	96%	97%	98%	97%

Table 32. Detailed Accuracy Percentages for the Model ID#4 (Component - Deck - Imbalanced).

Margin of Error	Individual Condition Rating							**Total (%)**
	CR3	**CR4**	**CR5**	**CR6**	**CR7**	**CR8**	**CR9**	
				Training				
±0	0%	0%	35%	52%	77%	0%	0%	55%
±1	0%	67%	87%	100%	98%	93%	0%	94%
±2	78%	95%	100%	100%	100%	99%	98%	100%
				Testing				
±0	0%	0%	35%	52%	76%	0%	0%	54%
±1	0%	70%	87%	100%	98%	92%	0%	94%
±2	82%	96%	100%	100%	100%	99%	98%	100%

Table 33. Detailed Accuracy Percentages for the Model ID#5 (Component - Superstructure - Balanced).

Margin of Error	Individual Condition Rating							**Total (%)**
	CR3	**CR4**	**CR5**	**CR6**	**CR7**	**CR8**	**CR9**	
				Training				
±0	0%	71%	58%	24%	26%	11%	93%	46%
±1	77%	92%	91%	82%	34%	93%	97%	81%
±2	93%	97%	98%	100%	99%	97%	99%	98%
				Testing				
±0	0%	71%	60%	22%	26%	11%	92%	46%
±1	76%	92%	90%	82%	34%	93%	96%	81%
±2	89%	97%	97%	100%	99%	95%	99%	98%

Table 34. Detailed Accuracy Percentages for the Model ID#6 (Component - Superstructure - Imbalanced).

Margin of Error	Individual Condition Rating							Total (%)
	CR3	CR4	CR5	CR6	CR7	CR8	CR9	
				Training				
±0	0%	12%	20%	57%	84%	0%	0%	51%
±1	20%	56%	85%	100%	100%	97%	0%	94%
±2	66%	95%	100%	100%	100%	100%	99%	100%
				Testing				
±0	0%	11%	20%	57%	84%	0%	0%	51%
±1	18%	59%	86%	100%	100%	97%	0%	94%
±2	64%	96%	100%	100%	100%	100%	99%	100%

Table 35. Detailed Accuracy Percentages for the Model ID#7 (Component - Substructure - Balanced).

Margin of Error	Individual Condition Rating							Total (%)
	CR3	CR4	CR5	CR6	CR7	CR8	CR9	
				Training				
±0	0%	68%	16%	58%	37%	22%	73%	45%
±1	84%	78%	91%	86%	77%	93%	88%	86%
±2	89%	96%	99%	100%	98%	100%	99%	99%
				Testing				
±0	0%	71%	18%	58%	34%	22%	77%	46%
±1	82%	81%	92%	87%	79%	92%	92%	87%
±2	94%	95%	99%	100%	99%	99%	99%	99%

Table 36. Detailed Accuracy Percentages for the Model ID#8 (Component - Substructure - Imbalanced).

Margin of Error	Individual Condition Rating							Total (%)
	CR3	CR4	CR5	CR6	CR7	CR8	CR9	
				Training				
±0	0%	0%	33%	46%	87%	0%	0%	56%
±1	0%	65%	82%	100%	99%	98%	0%	95%
±2	80%	93%	100%	100%	100%	100%	99%	100%
				Testing				
±0	0%	0%	33%	46%	87%	0%	0%	56%
±1	0%	66%	82%	100%	99%	98%	0%	95%
±2	82%	93%	100%	100%	100%	100%	99%	100%

Table 37. Detailed Accuracy Percentages for the Model ID#9 (Component - Culvert - Balanced).

Margin of Error	Individual Condition Rating							**Total (%)**
	CR3	**CR4**	**CR5**	**CR6**	**CR7**	**CR8**	**CR9**	
Training								
±0	33%	64%	32%	28%	55%	82%	0%	48%
±1	80%	84%	75%	86%	89%	93%	96%	86%
±2	87%	93%	99%	100%	98%	99%	100%	98%
Testing								
±0	29%	59%	23%	24%	55%	79%	0%	44%
±1	76%	76%	71%	79%	90%	91%	100%	83%
±2	76%	91%	99%	100%	99%	99%	100%	97%

Table 38. Detailed Accuracy Percentages for the Model ID#10 (Component - Culvert - Imbalanced).

Margin of Error	Individual Condition Rating							**Total (%)**
	CR3	**CR4**	**CR5**	**CR6**	**CR7**	**CR8**	**CR9**	
Training								
±0	0%	6%	6%	75%	67%	0%	0%	58%
±1	29%	25%	90%	100%	100%	92%	0%	97%
±2	36%	98%	100%	100%	100%	100%	99%	100%
Testing								
±0	0%	9%	6%	75%	66%	0%	0%	58%
±1	18%	32%	89%	100%	100%	93%	0%	97%
±2	29%	97%	100%	100%	100%	100%	97%	100%

Table 39. Detailed Accuracy Percentages for the Model ID#11 (Deck – Prestressed Concrete - Balanced).

Margin of Error	Individual Condition Rating							**Total (%)**
	CR3	**CR4**	**CR5**	**CR6**	**CR7**	**CR8**	**CR9**	
Training								
±0	86%	74%	85%	41%	85%	15%	96%	67%
±1	86%	89%	93%	89%	85%	89%	96%	90%
±2	100%	96%	100%	96%	100%	93%	100%	98%
Testing								
±0	86%	74%	85%	41%	85%	15%	96%	67%
±1	86%	89%	93%	89%	85%	89%	96%	90%
±2	100%	96%	100%	96%	100%	93%	100%	98%

Table 40. Detailed Accuracy Percentages for the Model ID#12 (Deck – Prestressed Concrete - Imbalanced).

Margin of Error	Individual Condition Rating							Total (%)
	CR3	CR4	CR5	CR6	CR7	CR8	CR9	
				Training				
±0	17%	36%	35%	12%	99%	0%	3%	67%
±1	17%	41%	48%	99%	100%	98%	3%	94%
±2	100%	45%	100%	100%	100%	100%	100%	100%
				Testing				
±0	0%	0%	19%	16%	99%	0%	0%	66%
±1	0%	50%	31%	98%	100%	99%	0%	94%
±2	100%	50%	100%	100%	100%	99%	100%	100%

Table 41. Detailed Accuracy Percentages for the Model ID#13 (Deck – Reinforced Concrete - Balanced).

Margin of Error	Individual Condition Rating							Total (%)
	CR3	CR4	CR5	CR6	CR7	CR8	CR9	
				Training				
±0	0%	79%	16%	46%	35%	21%	74%	44%
±1	86%	88%	88%	74%	69%	96%	87%	84%
±2	91%	96%	98%	100%	92%	99%	98%	97%
				Testing				
±0	0%	80%	17%	48%	35%	19%	74%	45%
±1	85%	90%	87%	78%	67%	95%	87%	84%
±2	90%	97%	97%	100%	92%	99%	97%	97%

Table 42. Detailed Accuracy Percentages for the Model ID#14 (Deck – Reinforced Concrete - Imbalanced).

Margin of Error	Individual Condition Rating							Total (%)
	CR3	CR4	CR5	CR6	CR7	CR8	CR9	
				Training				
±0	0%	0%	35%	53%	76%	0%	0%	54%
±1	0%	67%	87%	100%	98%	92%	0%	94%
±2	74%	96%	100%	100%	100%	99%	98%	100%
				Testing				
±0	0%	0%	35%	52%	76%	0%	0%	54%
±1	0%	71%	86%	100%	98%	92%	0%	94%
±2	72%	95%	100%	100%	100%	99%	98%	100%

Table 43. Detailed Accuracy Percentages for the Model ID#15 (Deck – Steel - Balanced).

Margin of Error	Individual Condition Rating							Total (%)
	CR3	CR4	CR5	CR6	CR7	CR8	CR9	
				Training				
±0	0%	94%	100%	47%	65%	71%	67%	74%
±1	0%	100%	100%	88%	100%	88%	83%	93%
±2	100%	100%	100%	88%	100%	100%	100%	98%
				Testing				
±0	0%	94%	100%	47%	65%	71%	67%	74%
±1	0%	100%	100%	88%	100%	88%	83%	93%
±2	100%	100%	100%	88%	100%	100%	100%	98%

Table 44. Detailed Accuracy Percentages for the Model ID#16 (Deck – Steel - Imbalanced).

Margin of Error	Individual Condition Rating							Total (%)
	CR3	CR4	CR5	CR6	CR7	CR8	CR9	
				Training				
±0	0%	88%	50%	93%	69%	0%	0%	68%
±1	0%	88%	93%	100%	100%	78%	0%	95%
±2	0%	100%	100%	100%	100%	94%	50%	98%
				Testing				
±0	0%	88%	50%	93%	69%	0%	0%	68%
±1	0%	88%	93%	100%	100%	78%	0%	95%
±2	0%	100%	100%	100%	100%	94%	50%	98%

Table 45. Detailed Accuracy Percentages for the Model ID#17 (Deck – Timber - Balanced).

Margin of Error	Individual Condition Rating							Total (%)
	CR3	CR4	CR5	CR6	CR7	CR8	CR9	
				Training				
±0	100%	80%	100%	40%	20%	100%	0%	68%
±1	100%	100%	100%	100%	100%	100%	100%	100%
±2	100%	100%	100%	100%	100%	100%	100%	100%
				Testing				
±0	100%	80%	100%	40%	20%	100%	0%	68%
±1	100%	100%	100%	100%	100%	100%	100%	100%
±2	100%	100%	100%	100%	100%	100%	100%	100%

Table 46. Detailed Accuracy Percentages for the Model ID#18 (Deck – Timber – Imbalanced).

Margin of Error	Individual Condition Rating							**Total (%)**
	CR3	**CR4**	**CR5**	**CR6**	**CR7**	**CR8**	**CR9**	
				Training				
±0	100%	80%	35%	73%	96%	0%	0%	78%
±1	100%	80%	100%	100%	100%	100%	0%	99%
±2	100%	100%	100%	100%	100%	100%	100%	100%
				Testing				
±0	100%	80%	35%	73%	96%	0%	0%	78%
±1	100%	80%	100%	100%	100%	100%	0%	99%
±2	100%	100%	100%	100%	100%	100%	100%	100%

Table 47. Detailed Accuracy Percentages for the Model ID#19 (Superstructure – Reinforced Concrete - Balanced).

Margin of Error	Individual Condition Rating							**Total (%)**
	CR3	**CR4**	**CR5**	**CR6**	**CR7**	**CR8**	**CR9**	
				Training				
±0	30%	78%	76%	34%	89%	20%	0%	64%
±1	91%	81%	99%	84%	94%	99%	0%	90%
±2	91%	96%	100%	99%	95%	99%	90%	98%
				Testing				
±0	43%	80%	82%	38%	86%	17%	0%	66%
±1	93%	83%	100%	86%	91%	98%	20%	90%
±2	93%	100%	100%	100%	94%	98%	100%	98%

Table 48. Detailed Accuracy Percentages for the Model ID#20 (Superstructure – Reinforced Concrete - Imbalanced).

Margin of Error	Individual Condition Rating							**Total (%)**
	CR3	**CR4**	**CR5**	**CR6**	**CR7**	**CR8**	**CR9**	
				Training				
±0	0%	28%	32%	51%	87%	0%	0%	63%
±1	18%	72%	88%	100%	99%	99%	0%	96%
±2	82%	96%	100%	100%	100%	99%	90%	100%
				Testing				
±0	0%	22%	29%	53%	85%	0%	0%	62%
±1	14%	69%	89%	99%	99%	100%	0%	96%
±2	50%	98%	100%	100%	100%	100%	100%	100%

Table 49. Detailed Accuracy Percentages for the Model ID#21 (Superstructure – RC Arches - Balanced).

Margin of Error	Individual Condition Rating							**Total (%)**
	CR3	**CR4**	**CR5**	**CR6**	**CR7**	**CR8**	**CR9**	
				Training				
±0	0%	88%	41%	51%	55%	71%	3%	55%
±1	45%	93%	92%	89%	99%	81%	84%	90%
±2	100%	95%	100%	100%	100%	94%	88%	97%
				Testing				
±0	0%	88%	41%	51%	55%	71%	3%	55%
±1	45%	93%	92%	89%	99%	81%	84%	90%
±2	100%	95%	100%	100%	100%	94%	88%	97%

Table 50. Detailed Accuracy Percentages for the Model ID#22 (Superstructure – RC Arches - Imbalanced).

Margin of Error	Individual Condition Rating							**Total (%)**
	CR3	**CR4**	**CR5**	**CR6**	**CR7**	**CR8**	**CR9**	
				Training				
±0	67%	30%	49%	71%	58%	0%	0%	56%
±1	67%	75%	98%	100%	97%	74%	0%	94%
±2	100%	100%	100%	100%	100%	100%	88%	100%
				Testing				
±0	0%	45%	41%	71%	60%	0%	0%	54%
±1	0%	75%	100%	100%	94%	92%	0%	95%
±2	100%	100%	100%	100%	100%	100%	86%	100%

Table 51. Detailed Accuracy Percentages for the Model ID#23 (Superstructure – Prestressed Concrete - Balanced).

Margin of Error	Individual Condition Rating							**Total (%)**
	CR3	**CR4**	**CR5**	**CR6**	**CR7**	**CR8**	**CR9**	
				Training				
±0	0%	82%	86%	6%	41%	15%	93%	53%
±1	92%	96%	99%	70%	54%	96%	97%	85%
±2	98%	96%	99%	100%	95%	97%	99%	98%
				Testing				
±0	0%	80%	87%	1%	39%	18%	94%	52%
±1	92%	90%	100%	73%	52%	96%	96%	85%
±2	100%	92%	100%	100%	95%	97%	100%	97%

Table 52. Detailed Accuracy Percentages for the Model ID#24 (Superstructure – Prestressed Concrete - Imbalanced).

Margin of Error	Individual Condition Rating							Total (%)
	CR3	CR4	CR5	CR6	CR7	CR8	CR9	
				Training				
±0	0%	26%	26%	28%	55%	84%	0%	57%
±1	71%	65%	69%	100%	99%	99%	92%	98%
±2	90%	89%	100%	100%	100%	100%	100%	100%
				Testing				
±0	0%	23%	27%	28%	55%	85%	0%	58%
±1	83%	59%	69%	100%	99%	99%	92%	98%
±2	100%	91%	100%	100%	100%	100%	100%	100%

Table 53. Detailed Accuracy Percentages for the Model ID#25 (Superstructure – Steel - Balanced).

Margin of Error	Individual Condition Rating							Total (%)
	CR3	CR4	CR5	CR6	CR7	CR8	CR9	
				Training				
±0	0%	62%	47%	40%	43%	0%	92%	46%
±1	70%	84%	89%	94%	61%	98%	92%	86%
±2	87%	97%	100%	100%	99%	100%	98%	99%
				Testing				
±0	0%	61%	47%	35%	46%	0%	94%	46%
±1	71%	86%	92%	91%	61%	98%	94%	86%
±2	87%	97%	100%	100%	100%	100%	98%	99%

Table 54. Detailed Accuracy Percentages for the Model ID#26 (Superstructure – Steel - Imbalanced).

Margin of Error	Individual Condition Rating							Total (%)
	CR3	CR4	CR5	CR6	CR7	CR8	CR9	
				Training				
±0	0%	8%	26%	59%	79%	0%	0%	50%
±1	18%	62%	88%	100%	100%	95%	0%	93%
±2	67%	96%	100%	100%	100%	100%	99%	100%
				Testing				
±0	0%	9%	26%	58%	79%	0%	0%	50%
±1	10%	59%	88%	100%	100%	95%	0%	93%
±2	61%	96%	100%	100%	100%	100%	98%	100%

Table 55. Detailed Accuracy Percentages for the Model ID#27 (Superstructure – Timber - Balanced).

Margin of Error	Individual Condition Rating							**Total (%)**
	CR3	**CR4**	**CR5**	**CR6**	**CR7**	**CR8**	**CR9**	
				Training				
±0	100%	88%	70%	76%	91%	27%	0%	77%
±1	100%	100%	91%	85%	100%	82%	0%	93%
±2	100%	100%	100%	100%	100%	100%	100%	100%
				Testing				
±0	100%	88%	70%	76%	91%	27%	0%	77%
±1	100%	100%	91%	85%	100%	82%	0%	93%
±2	100%	100%	100%	100%	100%	100%	100%	100%

Table 56. Detailed Accuracy Percentages for the Model ID#28 (Superstructure – Timber - Imbalanced).

Margin of Error	Individual Condition Rating							**Total (%)**
	CR3	**CR4**	**CR5**	**CR6**	**CR7**	**CR8**	**CR9**	
				Training				
±0	100%	58%	77%	59%	78%	27%	0%	67%
±1	100%	82%	96%	100%	88%	73%	0%	93%
±2	100%	100%	100%	100%	100%	100%	100%	100%
				Testing				
±0	100%	58%	77%	59%	78%	27%	0%	67%
±1	100%	82%	96%	100%	88%	73%	0%	93%
±2	100%	100%	100%	100%	100%	100%	100%	100%

Table 57. Detailed Accuracy Percentages for the Model ID#29 (Superstructure – Masonry - Balanced).

Margin of Error	Individual Condition Rating							**Total (%)**
	CR3	**CR4**	**CR5**	**CR6**	**CR7**	**CR8**	**CR9**	
				Training				
±0	0%	95%	62%	81%	62%	0%	0%	71%
±1	100%	95%	100%	90%	67%	100%	0%	88%
±2	100%	100%	100%	100%	71%	100%	100%	93%
				Testing				
±0	0%	95%	62%	81%	62%	0%	0%	71%
±1	100%	95%	100%	90%	67%	100%	0%	88%
±2	100%	100%	100%	100%	71%	100%	100%	93%

Table 58. Detailed Accuracy Percentages for the Model ID#30 (Superstructure – Masonry - Imbalanced).

Margin of Error	Individual Condition Rating							**Total (%)**
	CR3	**CR4**	**CR5**	**CR6**	**CR7**	**CR8**	**CR9**	
Training								
±0	0%	14%	81%	82%	80%	0%	0%	70%
±1	50%	76%	93%	98%	96%	100%	0%	92%
±2	100%	100%	100%	100%	100%	100%	100%	100%
Testing								
±0	0%	14%	81%	82%	80%	0%	0%	70%
±1	50%	76%	93%	98%	96%	100%	0%	92%
±2	100%	100%	100%	100%	100%	100%	100%	100%

Table 59. Detailed Accuracy Percentages for the Model ID#31 (Substructure – Reinforced Concrete - Balanced).

Margin of Error	Individual Condition Rating							**Total (%)**
	CR3	**CR4**	**CR5**	**CR6**	**CR7**	**CR8**	**CR9**	
Training								
±0	0%	71%	21%	36%	48%	24%	75%	45%
±1	84%	84%	82%	84%	76%	97%	91%	86%
±2	94%	93%	99%	100%	98%	99%	100%	98%
Testing								
±0	0%	72%	20%	35%	43%	23%	74%	44%
±1	85%	85%	82%	88%	75%	98%	89%	86%
±2	89%	94%	99%	100%	98%	100%	100%	98%

Table 60. Detailed Accuracy Percentages for the Model ID#32 (Substructure – Reinforced Concrete - Imbalanced).

Margin of Error	Individual Condition Rating							**Total (%)**
	CR3	**CR4**	**CR5**	**CR6**	**CR7**	**CR8**	**CR9**	
Training								
±0	0%	0%	33%	46%	87%	0%	0%	56%
±1	0%	64%	82%	100%	99%	98%	0%	95%
±2	79%	93%	100%	100%	100%	100%	99%	100%
Testing								
±0	0%	0%	33%	46%	88%	0%	0%	56%
±1	0%	67%	82%	100%	99%	98%	0%	95%
±2	83%	94%	100%	100%	100%	100%	99%	100%

Table 61. Detailed Accuracy Percentages for the Model ID#33 (Substructure – Steel - Balanced).

Margin of Error	Individual Condition Rating							**Total (%)**
	CR3	**CR4**	**CR5**	**CR6**	**CR7**	**CR8**	**CR9**	
				Training				
±0	0%	73%	100%	82%	100%	0%	0%	71%
±1	0%	100%	100%	100%	100%	100%	0%	96%
±2	0%	100%	100%	100%	100%	100%	100%	98%
				Testing				
±0	0%	73%	100%	82%	100%	0%	0%	71%
±1	0%	100%	100%	100%	100%	100%	0%	96%
±2	0%	100%	100%	100%	100%	100%	100%	98%

Table 62. Detailed Accuracy Percentages for the Model ID#34 (Substructure – Steel - Imbalanced).

Margin of Error	Individual Condition Rating							**Total (%)**
	CR3	**CR4**	**CR5**	**CR6**	**CR7**	**CR8**	**CR9**	
				Training				
±0	0%	73%	87%	77%	77%	0%	0%	75%
±1	100%	100%	91%	100%	100%	89%	0%	96%
±2	100%	100%	100%	100%	100%	100%	100%	100%
				Testing				
±0	0%	73%	87%	77%	77%	0%	0%	75%
±1	100%	100%	91%	100%	100%	89%	0%	96%
±2	100%	100%	100%	100%	100%	100%	100%	100%

Table 63. Detailed Accuracy Percentages for the Model ID#35 (Substructure – Timber - Balanced).

Margin of Error	Individual Condition Rating							**Total (%)**
	CR3	**CR4**	**CR5**	**CR6**	**CR7**	**CR8**	**CR9**	
				Training				
±0	100%	76%	65%	89%	44%	40%	0%	71%
±1	100%	96%	98%	94%	82%	100%	0%	94%
±2	100%	100%	100%	100%	100%	100%	100%	100%
				Testing				
±0	100%	76%	65%	89%	44%	40%	0%	71%
±1	100%	96%	98%	94%	82%	100%	0%	94%
±2	100%	100%	100%	100%	100%	100%	100%	100%

Table 64. Detailed Accuracy Percentages for the Model ID#36 (Substructure – Timber - Imbalanced).

Margin of Error	Individual Condition Rating							Total (%)
	CR3	CR4	CR5	CR6	CR7	CR8	CR9	
				Training				
±0	100%	59%	56%	80%	29%	40%	0%	64%
±1	100%	91%	99%	99%	88%	100%	0%	97%
±2	100%	100%	100%	100%	100%	100%	100%	100%
				Testing				
±0	100%	59%	56%	80%	29%	40%	0%	64%
±1	100%	91%	99%	99%	88%	100%	0%	97%
±2	100%	100%	100%	100%	100%	100%	100%	100%

Table 65. Detailed Accuracy Percentages for the Model ID#37 (Substructure – Masonry - Balanced).

Margin of Error	Individual Condition Rating							Total (%)
	CR3	CR4	CR5	CR6	CR7	CR8	CR9	
				Training				
±0	0%	83%	74%	80%	61%	9%	0%	69%
±1	100%	89%	100%	87%	70%	100%	0%	86%
±2	100%	100%	100%	100%	89%	100%	100%	97%
				Testing				
±0	0%	83%	74%	80%	61%	9%	0%	69%
±1	100%	89%	100%	87%	70%	100%	0%	86%
±2	100%	100%	100%	100%	89%	100%	100%	97%

Table 66. Detailed Accuracy Percentages for the Model ID#38 (Substructure – Masonry - Imbalanced).

Margin of Error	Individual Condition Rating							Total (%)
	CR3	CR4	CR5	CR6	CR7	CR8	CR9	
				Training				
±0	100%	46%	64%	78%	57%	0%	67%	65%
±1	100%	52%	99%	98%	86%	100%	67%	90%
±2	100%	100%	100%	100%	100%	100%	100%	100%
				Testing				
±0	100%	46%	64%	78%	57%	0%	67%	65%
±1	100%	52%	99%	98%	86%	100%	67%	90%
±2	100%	100%	100%	100%	100%	100%	100%	100%

Table 67. Detailed Accuracy Percentages for the Model ID#39 (Substructure – Other - Balanced).

Margin of Error	Individual Condition Rating							Total (%)
	CR3	CR4	CR5	CR6	CR7	CR8	CR9	
				Training				
±0	0%	87%	70%	61%	74%	0%	96%	64%
±1	100%	96%	87%	83%	78%	96%	96%	89%
±2	100%	100%	100%	100%	87%	100%	100%	98%
				Testing				
±0	0%	87%	70%	61%	74%	0%	96%	64%
±1	100%	96%	87%	83%	78%	96%	96%	89%
±2	100%	100%	100%	100%	87%	100%	100%	98%

Table 68. Detailed Accuracy Percentages for the Model ID#40 (Substructure – Other - Imbalanced).

Margin of Error	Individual Condition Rating							Total (%)
	CR3	CR4	CR5	CR6	CR7	CR8	CR9	
				Training				
±0	0%	35%	73%	59%	65%	0%	96%	56%
±1	100%	70%	91%	97%	77%	99%	96%	88%
±2	100%	100%	100%	100%	98%	100%	100%	99%
				Testing				
±0	0%	35%	73%	59%	65%	0%	96%	56%
±1	100%	70%	91%	97%	77%	99%	96%	88%
±2	100%	100%	100%	100%	98%	100%	100%	99%

Table 69. Detailed Accuracy Percentages for the Model ID#41 (Culvert – Reinforced Concrete - Balanced).

Margin of Error	Individual Condition Rating							Total (%)
	CR3	CR4	CR5	CR6	CR7	CR8	CR9	
				Training				
±0	5%	53%	64%	30%	21%	87%	0%	46%
±1	20%	86%	97%	82%	66%	92%	97%	85%
±2	70%	96%	99%	100%	99%	96%	99%	98%
				Testing				
±0	0%	60%	67%	26%	19%	89%	0%	47%
±1	40%	89%	96%	82%	66%	94%	97%	86%
±2	80%	96%	100%	100%	99%	96%	98%	98%

Table 70. Detailed Accuracy Percentages for the Model ID#42 (Culvert – Reinforced Concrete - Imbalanced).

Margin of Error	Individual Condition Rating							**Total (%)**
	CR3	**CR4**	**CR5**	**CR6**	**CR7**	**CR8**	**CR9**	
				Training				
±0	0%	3%	7%	68%	73%	0%	0%	58%
±1	20%	31%	86%	100%	100%	94%	0%	97%
±2	35%	92%	100%	100%	100%	100%	99%	100%
				Testing				
±0	0%	4%	7%	68%	71%	0%	0%	58%
±1	0%	26%	85%	100%	100%	94%	0%	97%
±2	20%	98%	100%	100%	100%	100%	100%	100%

Table 71. Detailed Accuracy Percentages for the Model ID#43 (Culvert – Steel - Balanced).

Margin of Error	Individual Condition Rating							**Total (%)**
	CR3	**CR4**	**CR5**	**CR6**	**CR7**	**CR8**	**CR9**	
				Training				
±0	52%	64%	50%	53%	45%	69%	0%	55%
±1	97%	99%	100%	90%	91%	87%	100%	94%
±2	98%	99%	100%	100%	96%	99%	100%	99%
				Testing				
±0	52%	64%	50%	53%	45%	69%	0%	55%
±1	97%	99%	100%	90%	91%	87%	100%	94%
±2	98%	99%	100%	100%	96%	99%	100%	99%

Table 72. Detailed Accuracy Percentages for the Model ID#44 (Culvert – Steel - Imbalanced).

Margin of Error	Individual Condition Rating							**Total (%)**
	CR3	**CR4**	**CR5**	**CR6**	**CR7**	**CR8**	**CR9**	
				Training				
±0	76%	8%	7%	80%	74%	0%	0%	57%
±1	76%	26%	90%	100%	100%	91%	0%	93%
±2	82%	100%	100%	100%	100%	100%	100%	100%
				Testing				
±0	83%	3%	1%	72%	73%	0%	0%	53%
±1	83%	16%	86%	99%	100%	87%	0%	91%
±2	83%	97%	100%	99%	100%	100%	100%	99%