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Performance Prediction Methodology of Slow Aging Assets

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Abstract**—**Asset management of urban infrastructures faces a multitude of challenges that need to be overcome to obtain a reliable measurement of performances. Predicting the performance of slowly aging systems is one of those challenges, which helps the asset manager to investigate specific failure modes and to undertake the appropriate maintenance and rehabilitation interventions to avoid catastrophic failures as well as to optimize the maintenance costs. This article presents a methodology for modeling the deterioration of slowly degrading assets based on an operating history. It consists of extracting degradation profiles by grouping together assets that exhibit similar degradation sequences using an unsupervised classification technique derived from artificial intelligence. The obtained clusters are used to build the performance prediction models. This methodology is applied to a sample of a stormwater drainage culvert dataset.

Keywords**—**Artificial intelligence, clustering, culvert, regression model, slow degradation.

I. Introduction

INFRASTRUCTURE systems, such as roads, bridges and drainage systems present slow degradation profiles during their useful life due to regulatory maintenance programs. Culverts represent an essential asset for rural and suburban drainage systems carrying precipitation and runoff water below roads in a safe way. Culvert failure may have catastrophic consequences on people and the environment and can cause significant delays due to road closures. Deterioration of culverts is a major concern for infrastructure managers in maintaining the required performance of drainage systems. According to [1], predicting the condition of culvert degradation is often the main obstacle for an effective maintenance plan encompassing the prevention of major failures, the extension of life service and the optimization of maintenance costs. Degradation models are used at both network and project levels of the asset management system. At the network level, the culvert condition is evaluated using structural measures and converted to an aggregate index variable. At the project level, the culvert condition can be measured at a finer scale, perhaps by estimating the severity and extent of each defect individually in order to provide recommendations for appropriate maintenance.

As culverts deteriorate very slowly over time, the experts conduct systematic inspections of structural and hydraulic defects. The inspection is generally difficult to perform due to narrow culvert shapes, climatic conditions and culvert locations. For example, small diameter culverts are inspected from the ends of the culvert using a torch, giving an inaccurate assessment of certain structural defects. In addition, the inspection has a non-uniform periodicity, depends on the condition of the culvert, requires qualified personnel in order to be performed, and can be expensive. According to culvert experts, the age, the design features, the weather and the traffic conditions have an impact on the culvert degradation profile. Moreover, some culverts have been inspected once, twice or three times over their lifespan. Typically, the databases available for modeling the degradation of slow aging assets are in the form of short sequences of observations of the global performance index or inspection criteria over time. Due to the irregularity of the inspection periodicity, several degradation profiles are identifiable such as sequences with few observations, shifted in time, or even with jumps. An example of these sequences is shown in Fig. 1, where each observation sequence characterizes the performance index of a culvert over time.

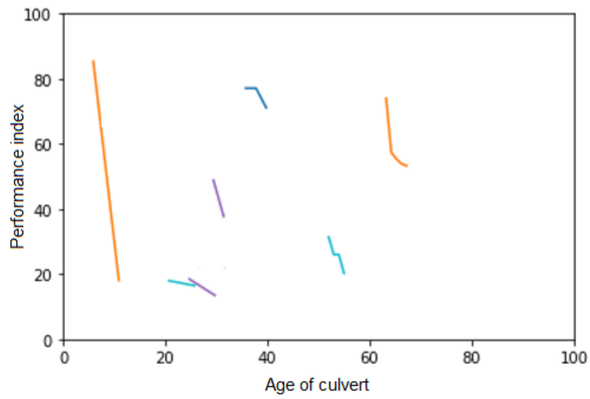

Fig. 1 Mapping nonlinear data to a higher dimensional feature space

As shown Fig. 1, the two circled sequences likely have a similar slope but appear at two different ages. The similarity in degradation profiles despite the difference in age and performance index level is generally due to maintenance interventions and replacements. In order to extract degradation profiles regardless of age and performance level, we propose a clustering technique which classifies similar assets according to their degradation slopes. The age and the performance index are then used to construct a performance forecasting model based on the extracted degradation profiles.

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This paper proposes an efficient performance prediction methodology that takes advantage of unsupervised machine learning to group similar culvert degradation profiles. More specifically, the aim is to develop models for predicting the general condition index of culverts as well as degradation criteria representing hydraulic and structural defects based on the conceptual and environmental characteristics of the various culverts.

The rest of the paper is divided into four sections. Section II reviews the degradation modeling approaches of similar infrastructure systems and presents an overview of the potentially usable unsupervised modeling methods. Section III details the proposed methodology and its constituent steps. Section IV applies the proposed methodology on a real case study and discusses the results. Section V concludes the paper and provides consideration for future work.

II. Review of Modeling Approaches

The deterioration of infrastructure assets raises several interesting problems that are shared between culverts, pavements, bridges, constructions, and water distribution systems to model the degradation based on short sequences of observations made after regulatory inspections. To address this issue, three main approaches were highlighted from the literature review: deterministic, stochastic and supervised learning approaches. The first two approaches use model-based methods. Their aim focuses on the capitation of physical degradation phenomena over time using regression and stochastic models. The supervised learning is a data-driven approach consisting of learning a prediction function from labeled examples. Table I highlights the main advantages and disadvantages in infrastructure degradation modeling.

From a practical point of view, the model-based methods require experimental data to build a deterministic physical model that cannot be useful for prediction if the system conditions and usage change over time. The stochastic models are sensitive to noise, need some simplifying assumptions, do not allow easy interpretability of probabilities and require the availability of lifetime data, which are extremely rare in infrastructure assets. However, the major weakness of the supervised learning methods is related to the model overfitting, which can be verified by cross-validation [2].

Through this literature review, the unsupervised approach has not been tested yet on asset degradation problems.

Technically, the unsupervised learning methods aim to divide a set of data into different homogeneous "packets" so that the data in each subset share common characteristics. These characteristics most often correspond to proximity criteria that are defined by introducing measures of distance or similarity between objects [3]. The development of a time series-clustering algorithm consists of implementing the similarity measure, the prototype and the clustering mechanism.

A. Similarity Measure

The measure of similarity or dissimilarity is the metric that makes it possible to compare two sequences of observations. It is the most critical criterion of clustering that should be chosen carefully. Table II discusses the main characteristics (advantages (+) and limitations (-)) of the most popular metrics used in time series unsupervised clustering problems.

B. Clustering Prototype

A prototype is an element of the data space that represents a group of similar elements. A cluster prototype can be characterized by a Medoid, a single mean vector (Centroid), a distribution law or a density region [16]. Since we are dealing with short time series dispersed in time and value, the most suitable prototype is the Medoid. Thus, each cluster will be presented by the longest element (sequence) whose average similarity to all the elements in the cluster is maximal.

TABLE I
COMPARISON OF ASSET DEGRADATION MODELING APPROACHES

	Methods	Advantages	Disadvantages
Deterministic	Linear regression Exponential regression Nonlinear regression	Provides insight into the factors that most affect the deterioration process. The final form (equation) is very user-friendly. Relatively easy to understand and develop.	The underlying assumptions, which may be difficult to validate, must be satisfied. Not suitable for modeling discrete states with a linear model.
Stochastic	Markov models Logistic regression Multiple discriminant analysis Cohort survival model Proportional risk model	Can be easily integrated into risk models [4]. Discrete data output Models the uncertainty inherent in deterioration processes [2].	May require longitudinal data that are difficult to find [5]. It may be necessary to create cohorts, requiring more data [6]. Difficulty in interpreting transition probabilities [2].
Machine learning (supervised)	Neural network Random Forest Support Vector Machine (SVM) Gradient Boosting	Can model unknown, complex and nonlinear relationships between inputs and outputs. Some underlying assumptions can be used when data are inaccurate, incomplete and subjective [7].	Overfitting problem [2]. The initial configuration can be complicated [8]. "Black box" technique means that the solution path is not transparent. Large amount of data needed for training and calibration. Large amount of data needed for training and calibration [9].

TABLE II
COMPARISON OF SIMILARITY MEASURES FOR TIME SERIES

Metrics	Advantages (+) / Disadvantages (-)
Dynamic Time Warping	(+) Elastic measure (+) Take into account deformation over time (-) Same ends of the two time series [10]
Pearson correlation coefficient	(-) Only processes stationary and synchronized time series [11]
Euclidian distance	(-) Inelastic measure, distance point to point [12]
Probability-based distance	(-) Only processes long time series [13]
Short time-series distance (STSD)	(+) Can deal with short time series (+) Capture time (-) Only processes synchronized series [14]
Longest common sub-sequence (LCSS)	(+) Robust against noise (+) Elastic measure (-) Process sequences (and not time series) [15]

C. Clustering Algorithm

The clustering algorithm represents the data partition mechanism. There are several methods for grouping time series such as hierarchical, partitioning, grid-based, model-based, density-based clustering and multi-step clustering algorithms.

Since we are interested in finding clusters with similar degradation profiles based on medoids, the k-medoid is the most suitable algorithm to extract a number of clusters known a priori by maximizing the similarity between the centers (Medoids) and the elements of each cluster. Partitioning Around Medoids (PAM) algorithm will be used to classify sequences based on similarities between elements. PAM will be adapted to maximize the global sum of similarity instead of minimizing the global sum of distances.

D. Clustering Evaluation

The silhouette coefficient measures the quality of classification [17]. For each element (sequence), the silhouette coefficient calculates the difference between the average similarity with the elements of the other neighboring groups (separation) and the average similarity with the elements of the same group (cohesion). In the case of a negative value of the silhouette, the element is on average closer to the neighboring group than to itself. Therefore, the element is misclassified. If the silhouette is positive; the element is on average closer to its group than to the neighboring groups. It is therefore well classified.

The silhouette coefficient $s(i)$ is defined on an element i belonging to a group C_i of k-medoid.

$$s(i) = \begin{cases} (a(i) - b(i))/a(i) & if \quad a(i) > b(i) \\ 0 & if \quad a(i) = b(i) \\ (a(i) - b(i))/b(i) & if \quad a(i) < b(i) \end{cases} \tag{1}$$

where $a(i)$ measures the average similarity of the element i to its group C_i and $b(i)$ measures the maximum average similarity of the same element with the elements of the other groups. The quantities $a(i)$ and $b(i)$ are calculated as follows:

$$a(i) = \frac{1}{|C(i)|-1} \sum_{j \in Ci, i \neq j} Sim(i,j) \tag{2}$$

$$b(i) = \max \frac{1}{|C(k)|-1} \sum_{j \in Ck} Sim(i,j) \tag{3}$$

where $Sim(i,j)$ corresponds to the similarity measurement between the two sequences *i* and *j*.

The silhouette score $\bar{s}(i) \in [-1,1]$ denotes the average value of all silhouette coefficients of C_i. According to [18], the found partition can be “Strong” $0.7 < \bar{s}(i) \leq 1$; “Reasonable” $0.5 < \bar{s}(i) \leq 0.7$; “Weak” $0.25 < \bar{s}(i) \leq 0.5$ and “Unclassified” if $\bar{s}(i) \leq 0.25$.

III. The Proposed Methodology

The proposed methodology aims to extract knowledge from the history of culvert degradation to build reliable prediction models of the culvert’s state of degradation. It is a hybrid approach that first uses unsupervised learning to group similar degradation profiles based on vectors of slopes and then combines them using a weighted regression method to construct the degradation model of the entire sequence of observations. Note that each sequence of observations is transformed into a vector of slopes. The slope denotes the degradation shape between two consecutive observations.

A. Step 1-Sequence Preparation

This first step concerns the preliminary processing of the sequences. Since the reasoning is based on slopes, it is necessary to eliminate culverts having a single observation. Thereafter, since the sequences have different numbers of observations often spread over distant ages, their lengths are unequal. In addition, some culverts have similar sequences but shifted in time. To reduce this heterogeneity, a linear interpolation is applied to complete the missing values between each pair of consecutive observations. Fig. 2 shows an example of interpolation of a three-observation sequence. The value of the interpolation is replicated on all intermediate ages with a one-unit time.

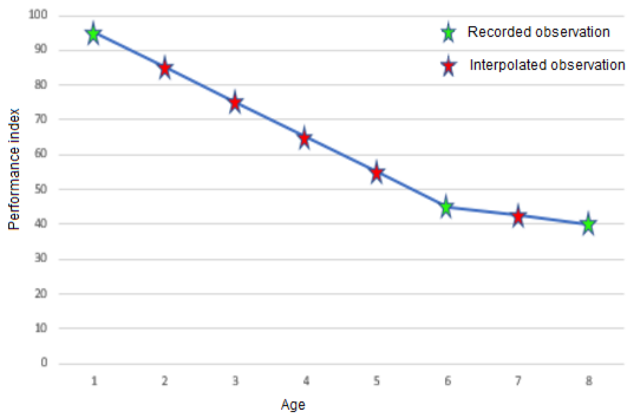

Fig. 2 Interpolation of missing values

Interpolation provides uniform sequences with a one-unit time. It is therefore possible to calculate the degradation slope per unit time between each pair of observations using the formula:

$$P(t) = V(t+1) - V(t) \tag{4}$$

where $P(t)$ denotes the degradation slope at age t and $V(t)$ yields to the value of the performance index at the same age. The result of Step-1 is a single matrix $M(m,n)$ where *m* and *n* denote the number of culverts and the maximum age of culverts respectively. Each line of $M(m,n)$ represents the sequence of slopes of a given culvert and the columns index these slopes by age.

$M(m,n)$ can be written as follows:

$$M = (p_{i,j})_{1 \leq i \leq m, 0 \leq j \leq n} \tag{5}$$

where $p_{ij} = P_i(j)$ if the element *i* is observed at age *j* and $p_{ij} = 1$.

B. Step 2-Clustering

The second step groups culverts whose behavior are similar in the same cluster. As $M(m,n)$ contains both short and time-shifted sequences, none of the reviewed similarity measurement techniques discussed in Table II is suitable for this study.

Therefore, a similarity measure is defined taking into account the short time-distance series and the longest common sub-series. The proposed similarity measurement makes it possible to calculate the length of the longest common subsequence (LCS) between two different sequences. Thus, two observations are considered to be similar when the difference between them is less than a given threshold called Epsilon (ε). The new similarity measure consists of calculating the length of the LCS of slopes between two sequences. The similarity between two sequences $X[1..lx]$ and $Y[1..ly]$ is given by:

$$Sim(X,Y) = \frac{LCS(X,Y)}{Max\,(l_x,l_y)} \tag{6}$$

where l_x and l_y are respectively the lengths of sequences X and Y.

The recurrent relation to calculate the LCS between two prefix sequences $X[1..i]$ and $Y[1..j]$ can be written as [19]:

$$C[i,j] = \begin{cases} 0 & if \quad i = 0 \; or \; j = 0 \\ C[i-1, j-1] + 1 & if \quad |X[i] - Y[j]| \leq \varepsilon \\ \max(C[i-1], C[i, j-1]) & if \quad |X[i] - Y[j]| > \varepsilon \end{cases} \tag{7}$$

The algorithm takes as input the sequences X and Y. It calculates the similarity between $X[1..n]$ and $Y[1..j]$ for all $1 \leq i \leq m$ and $1 \leq j \leq n$ and writes it in $C[i,j]$. $C[l_x, l_y]$ will contain the length of the LCS of X and Y. For example, consider the two slope sequences $X[-1,-5,-6,-8,-2,-3.2,-7.9]$ and $Y[-6,-8,-9,-1.5,-8]$ with a threshold $\varepsilon = 0.2$. The longest common sequence will be $[-6,-8,-8]$ and the similarity will be $Sim(X,Y) = 3/7$. This new similarity measure was integrated in the k-medoid algorithm to classify elements based on degradation slopes and works as follows:

i. Initialization: select k sequences as medoids.
ii. Associate each element to the nearest (most similar) medoid.
iii. While the total similarity of the configuration increases:
   For each medoid "m", for each non-medoidal element "o":
   Swap m and o,
- Associate each element with the nearest medoid,
- Recalculate the objective function (sum of the similarities of the elements with respect to their medoid).
- If the overall similarity of the configuration decreased in the previous step, cancel the exchange.

Applying the K-Medoid algorithm requires the determination of the most appropriate number of clusters. In order to do this, we have drawn the curve of the average silhouette according to the number of clusters. This curve allows for identifying the most interesting number of clusters which thereby yields the best average silhouette. Obtaining an overall silhouette maximum is not always possible, which is why we chose the number corresponding to the first local silhouette maximum. The evaluation of clustering quality is based on the measurement of the average silhouette of all the sequences. Thus, to improve this score, we have isolated culverts with a negative silhouette in a new cluster called "Others".

C. Step 3-Interpretability of Degradation Profiles

Random Forests method is used to identify the factors that differentiate one degradation profile from the other profiles. It is one of the most popular machine learning algorithms. It is very successful due to its capability to generally provide good predictive performance and ease of interpretation [20]. This interpretability is given by the most important factor that discriminates each degradation profile from the others in the decision tree. Thus, Random Forest will be used to interpret clustering by evaluating the key variables in the differentiation of clusters.

The idea of this method is simple. We use the conceptual, climatic and management variables of each culvert to predict its cluster by the Random Forest. In other words, we will reclassify the culverts (sequences) in a supervised manner to assess the percentage contribution of each variable in the classification obtained a priori.

D. Step 4: Construction of Degradation Models

The proposed clustering algorithm is used to form groups of culverts whose degradation behavior of a specific criterion is similar, while exploiting the characteristics of these structures to explain the difference between the clusters. Each grouping can be represented by the average slope of its elements. The proposed degradation model corresponds to a combination of similar slopes by age zone and by state. It is a question of subdividing the plan (age, index) into small areas (zones) by constructing a grid as shown in Fig. 3.

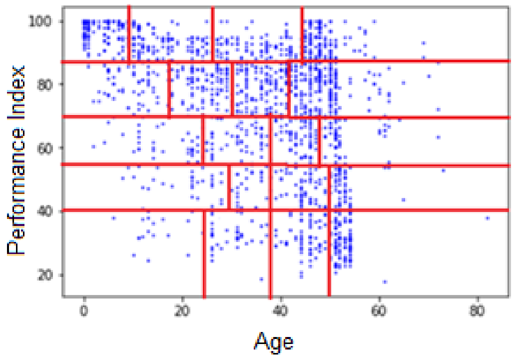

Fig. 3 Prediction grid

The dots represent the beginning of the observation sequences of the culvert's population studied. As an example, the grid can be constructed as follows: (1) the ordinate axis may be subdivided into five degradation states (40, 55, 70, 88, 100) and (2) the age may be subdivided according to 25th, 50th, 75th and 100th quantiles of the density of the start of the sequences. The idea allows assigning a model (slope) to each of the zones which includes several degradation profiles. These zones can be represented by the weighted average of the slopes of the clusters present in the zone as well as the standard deviation, which describes the dispersion of these slopes. As each beginning of a sequence corresponds to a cluster, the calculation of the frequencies of the groups in each zone can be based only on these beginnings. The following formula predicts the degradation slope at age $t+\Delta t$ based on observation at age t:

$$PS_{t+\Delta t} = \sum_{z\in Z}\sum_{k\in K} f_{kz}\, S_k\, 1_z(Ind_t) \tag{8}$$

where $PS_{t+\Delta t}$: Predicted degradation slope at age $t+\Delta t$, S_k: Mean slope of the medoid of cluster k, $Z = \{z_h, h = 1..20\}$: All grid zones, K: all clusters, f_{kz} : frequency of series classified in cluster k which start in zone $z = 1..20$, Ind_t: Degradation index value at age t

$$1_z(Ind_t) = \begin{cases} 1 & if\ (Ind_t, t) \in z\ zone \\ 0 & else \end{cases} \tag{9}$$

Point by point prediction is used to obtain degradation curves with multiple slopes. For a given age and value of the performance criterion, the algorithm predicts the value of the degradation indices in a recursive manner using the following loop:

For each year on the horizon:

i. Find the zone corresponding to the age and the state of estimated value.
ii. Subtract the slope of the zone from the value of the criterion.
iii. Zone the estimated value (the estimated value ± 2σ).

E. Step 5: Anomaly Detection and Model Evaluation

The last step of this approach concerns the exploitation of the models found to detect noise and the evaluation of the efficiency of the regression method.

- Anomaly Detection

Clustering allows for the standardization of the degradation slopes to facilitate the identification of anomalies. In order to do this, we have proposed a way to detect noise. By analyzing the results of the clustering, we noted the presence of extreme slopes which do not translate into a physical degradation phenomenon but rather accidents or transcription errors. In order to isolate these abnormal slopes at the level of each zone, we have removed the slopes which satisfy the following condition:

$$|P_i - P_{pz}| > 2\sigma_{pz} \tag{10}$$

where P_i denotes the slope of observation i, P_{pz} is the weighted average slope of the zone, σ_{pz}: is the weighted standard deviation of the zone and P_{mz} denotes the average slope in the zone where observation i is located. Fig. 4 describes the method of isolating anomalies using the law of distribution of the slope in a well-defined box.

The abnormal slopes are those found in the circled part. The slope P_{mz} is the average slope in the area and P_{pz} corresponds to the average slope after standardization by clustering. The limits of the two eliminated parts depend on the difference between the slopes P_{mz} and P_{pz}.

- Model Evaluation

The evaluation of the models by the coefficient of determination (adjusted R^2) and the mean square error MSE allows for the evaluation of the efficiency of the forecast. Cross Validation is used to make sure that this new method has solved the problem of Overfitting.

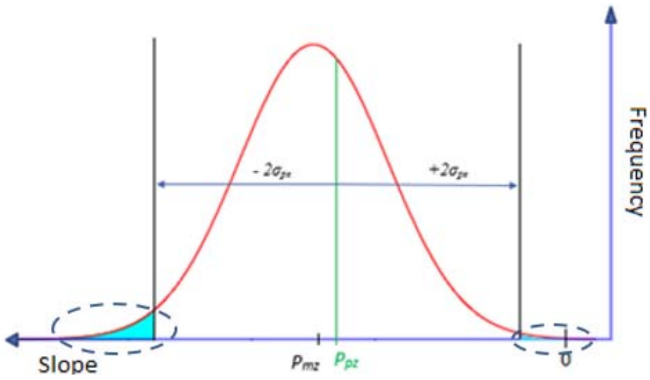

Fig. 4 Anomaly detection

IV. Application Example

The proposed methodology was applied on a sample of the dataset of culverts provided by the Ministère des Transports du Québec. The dataset counts a few thousand culverts with an opening of less than 3 m divided into eight subtypes (concrete, corrugated sheet pipe, PVC, etc.). The condition of the culverts is established by a rigorous periodic inspection program defined in the Culvert Inspection Manual [21]. Mainly, the inspection assesses 7 criteria to characterize the most important defects that affect the culvert performance. These criteria consist of structural defects D1 (Movement and deformation), D2 (Material defects) and D3 (Cracking and assembly) and hydraulic defects D4 (Sedimentation), D5 (Scour), D6 (Infiltration) and D7 (Accumulation of debris). Each criterion is evaluated on a decreasing scale from 5 (good condition, absence of defects) to 1 (bad condition, presence of a major defect). These criteria are combined into a weighted formula to calculate a Culvert State Index (CSI). The scale of CSI varies from 100 (good state) to 0 (worst state). It is divided into 5 state classes, from A to E. Culverts of class A, B or C are considered to be in good condition, while culverts of classes D and E are classified to be in poor condition. Other than the columns of the CSI, the inspection criteria and the age of the culvert, the other columns contain design factors (diameter, length, height of the embankment, etc.), environmental (geographic position, sump, type of roadway, etc.) as well as usage factors (daily vehicle flow, percentage of trucks, etc.).

A. Preliminary Modeling Tests

In order to verify the applicability of commonly used modeling methods, some preliminary tests are performed on a witness subtype. Assuming that the observations of a sequence are independent, we applied Linear Regression (LR), Artificial Neural Network (ANN), Random Forests (RF), Support Vector Machine (SVM), Extra Trees (ET), Gradient Boosting (GB) and Gaussian Process (GP) to extract the degradation models of the CSI and its seven criteria.

Table III summarizes the performance of the adjustment of each of these methods using the measure of R^2 adjusted by the cross-validation method. The ANN yielded negative adjusted R^2 for the CSI and all the criteria. The best models are given by RF, ET and GB. However, their coefficients of determination are under 70% and do not allow for validation of the models. These results are obtained by the Cross-validation technique. To ensure that this is an Overfitting, we have recalculated the coefficient of determination on the training data. The adjusted R^2 values are greater than 90% for all models. Since RF presents the best performance, we tried to optimize its number of estimators (trees) and to carry out a variable selection. However, it did not improve the prediction efficiency.

Since the methods of supervised learning have shown their limits, we have tried the methods of unsupervised learning, notably clustering, by always considering the observations of a sequence as independent of each other. In order to do this, we applied some classic clustering algorithms. The K-means and hierarchical clustering made it possible to group similar elements into a number of clusters fixed a priori. The other techniques made it possible to find the optimal number of clusters according to their principles. The density-based clustering DBSCAN grouped all the observations in a single cluster (-1) devoted to noise. The other two algorithms Mean Shift and Affinity spread formed hundreds or thousands of small groupings of 1 to 3 elements.

TABLE III
QUALITY OF COMMON MACHINE-LEARNING METHODS

Adj.R^2	LR	ANN	RFs	SVM	ET	GB	GP
CSI	46.2	-	64.37	39.9	63	51.1	19.9
D1	18.4	-	43.32	10.3	43.8	20.5	-
D2	38.1	-	62.23	31.5	62.2	42.3	-
D3	27.4	-	50.26	20.9	51.3	298	-
D4	15.1	-	38.34	5.6	34.6	16.2	-
D5	12.3	-	33.94	3.4	33.7	16.5	-
D6	35.9	-	55.43	28.2	53.7	37.8	-
D7	4.1	-	18.94	-	3.8	7.1	-

The testing of different clustering algorithms highlighted the heterogeneity of the data and showed that the data have enormous noise, which can affect the quality of the prediction models. We have chosen the K-means algorithm to assess the impact of clustering on forecast quality because this is the most effective technique for this kind of data. The idea was to apply K-means clustering several times with different numbers of clusters and to train RF method on each of these classes. Although we tried to assign a model to each group of similar culverts, the quality of the models is still poor. Other methods of cluster wise regression can be applied such as Branch and Bound regression and Späth algorithm. However, they require more resources for computation.

B. Application of the Methodology

Tests of the various regression and clustering models have shown that conventional artificial intelligence methods are not effective to model infrastructure degradation. The methodology was applied on eight subtypes of culverts to extract the prediction models of the CSI and its seven criteria. The methodology is very efficient in terms of extracting degradation profiles with a mean silhouette superior to 80%. The proposed classification made it possible to extract different degradation profiles. Figs. 5 and 6 depict the obtained clusters related to two different degradation profiles (a) and (b).

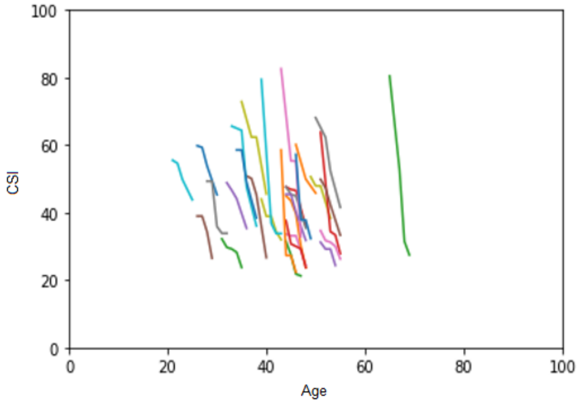

Fig. 5 Sequences of profile (a)

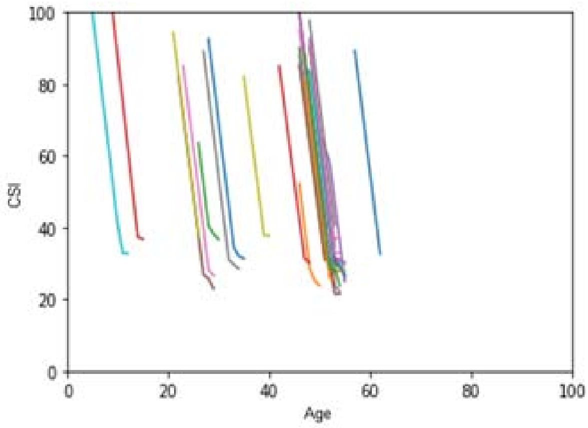

Fig. 6 Sequences of profile (b)

The method has been implemented using Python. The main program takes as input the file containing the observations of the criterion studied and the factors relating to each culvert in order to automatically generate an Excel file containing: the model, the quality of clustering and forecasting, the histogram of importance of the variables in the clustering as well as the description of the clusters. Table IV contains the Adjusted R^2 of the obtained prediction models.

TABLE IV
QUALITY OF THE 64 PREDICTION MODELS

Subtype	1	2	3	4	5	6	7	8
CSI	96.6	97.9	93.8	89.9	98.2	91.7	97.0	90.2
D1	91.9	96.4	84.9	70.8	47.1	74.5	87.2	80.4
D2	93.8	100	95.3	12.6	98.5	27.2	93.1	85.5
D3	92.2	93.8	71.1	93	94.2	78.2	88.1	84.3
D4	87.7	98.2	90.7	84.5	67.8	94.7	87.3	81.6
D5	90.9	99.7	86.9	76.2	9.5	93.5	8.2	83.7
D6	41.7	76.3	92.2	100	97.6	67	94.7	85.8
D7	79.7	79	75.6	81.7	79.8	85.7	86.4	72.3

As shown in Table IV, the algorithm succeeded in validating 60 models out of 64 expected by considering a minimum threshold of 70% for the adjusted R^2. These results prove the ability of this methodology to capture the physical phenomenon of slow culvert degradation. It outperforms conventional artificial intelligence methods. The independent variables contribute with different influences in the 64 clustering. Fig. 7 illustrates the average contribution by category of factors in the classifications made.

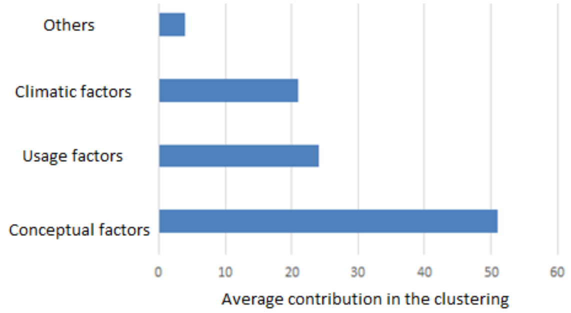

Fig. 7 Average contribution of factors

By analyzing the influence of the variables in the clustering of subtypes according to the CSI and the different criteria, we found that the design characteristics are the factors that contribute the most in the classification. The culvert length is the most important contributor for the 64 models with an average influence of 20%, followed by the fill height and the diameter width with a total contribution of 30%. This study showed the remarkable influence of the operating factors of the pavement above the culverts. Indeed, the daily flow of vehicles and the percentage of trucks represent on average 24% of this importance. Climatic factors relating to temperature and precipitation have a contribution of 21%. This category represents the degradation caused by the environment.

V. Conclusion

This paper presents a methodology that predicts the state of culvert degradation. Based on the interpretable artificial intelligence method, the methodology first extracts the degradation slopes using efficient similarity measurement then estimates the value of the degradation indexes by merging the extracted profiles into regression models. The proposed methodology is validated using a sample of culverts degradation dataset. The obtained results show that the proposed approach offers superior performance compared to the conventional methods in addition to the interpretability of the models.

The proposed methodology can be applied to other infrastructure assets such as pavement and bridges. In addition to this adaptability, the models can be used to estimate and optimize the maintenance budget for these structures. Despite the proven effectiveness of this methodology, it is possible to improve it in particular by optimizing the construction of the zone-state grid (or age range and the initial state of the culvert) and by making it compatible with other industrial degradation phenomena.

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