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Key Points:

- Physical, operational and environmental factors of asset deterioration are discussed and deterioration models are summarized
- Predicted service lives are obtained and the effect of maintenance and rehabilitation interventions on asset service life are analyzed
- The methodology for service life prediction can be applied to other water assets

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Deterioration Models and Service Life Prediction of Vertical Assets of Urban Water Systems

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Abstract This study proposes a methodology for developing deterioration models and predicting the service lives of vertical assets of urban water systems (i.e., water storage tanks and pumping stations) using regression analysis. The main factors contributing to the deterioration of these assets are analyzed. Simple and multiple linear regression models of average and maximum deterioration are calculated for 22 water storage tanks and 17 wastewater pumping stations. Data on a set of four water storage tanks are used to validate the developed deterioration models. Service life prediction is carried out using the developed models and considering two maximum deterioration levels: the maximum recommended and admissible deterioration levels. Two water storage tanks are further studied to illustrate and discuss the effect of maintenance and rehabilitation interventions on asset service life by comparing the asset deterioration before and after the interventions. Results include simple linear regression models of average and maximum deterioration indices as a function of asset age and multiple linear regression models that incorporate other physical, operational and environmental factors. The results show that simple linear regression models of asset deterioration show a better predictive power than multiple regression models. Despite the higher data variability of multiple regression models, these models allow to include the random process of asset deterioration, through the calculation of the standard deviation. This study also shows that periodic interventions are a preferable maintenance and rehabilitation strategy over major sporadic rehabilitation interventions since it allows to maintain assets in good condition and to extend their service life almost indefinitely.

Plain Language Summary Urban water assets are continuously deteriorating and more investments are necessary to maintain adequate levels of service. However, investment budgets are often limited and appropriate deterioration models and reliably predicted service lives are essential for planning and scheduling maintenance actions. This paper develops deterioration models for water storage tanks and wastewater pumping stations based on the identification and classification of anomalies through visual inspection. Additionally, service lives (i.e., the period from the installation until the asset or its components fulfill the service requirements) were obtained and compared with reference values. Finally, the effect of maintenance actions and rehabilitation interventions on the service life of vertical assets was discussed. In order to maintain a good asset condition and extend its service life quasi-indefinitely, periodic and well-established interventions are a preferable maintenance and rehabilitation strategy over major sporadic rehabilitation interventions.

1. Introduction

Assets and components have finite service lives due to the deterioration process caused by chemical, physical or mechanical changes (Masters & Brandt, 1989). Deterioration processes are usually associated with specific physical phenomena that evolve as deterioration progresses, causing a reduction in the performance and in the physical condition of the assets (Elwany & Gebraeel, 2009; Ferreira et al., 2021; Gorjian et al., 2009). Deterioration models used to predict the aging process can focus on asset physical condition (condition-based models) or on asset performance reliability (reliability-based models) (Ugarelli & Bruaset, 2010). The infrastructural condition assessment of urban water asset. allows to obtain an accurate prediction of the residual service life evaluation of its current value, improving the forecast of future rehabilitation capital expenditure needs (Feliciano et al., 2017; Scholten et al., 2014). Furthermore, appropriate deterioration models and reliably predicted service lives are essential for cost-effective and timely maintenance planning and scheduling (EPA, 2013; Scheidegger et al., 2015; Wang & Zhang, 2007).

The asset service life corresponds to the period after the installation during which an asset or its components fulfill the performance requirements (ISO 15686-1, 2011), which depends on the type and nature of the asset. The reference service life is the lifetime of an asset that is known to be expected under a particular set (reference set) of in-use conditions (ISO 15686-9, 2008). Vertical assets and facilities are assets that are not buried and whose condition is likely to be directly assessed by visual inspection (e.g., water storage tanks, pumping stations and treatment plants). Reference service lives that are generally accepted in the United States, Central and Northern Europe and Australia are higher than those considered in Portugal, since the former countries have better operation and maintenance (O&M) practices in their infrastructures (e.g., more frequent maintenance interventions) than those used in Portugal.

Reference service lives are, usually, obtained through informed judgments from experienced experts. These values are only indicative, as this parameter is greatly affected by the quality of production of materials, transport and storage conditions, method of installation, adaptation to local conditions and O&M practices (Cabral et al., 2019; Halcrow, 2007). Reference services lives are useful when no more information is available; however, they have a high level of inherent subjectivity because expert judgments are influenced by their experience and skills, which can, sometimes, result in inconsistent or misleading recommendations (Alegre et al., 2014; Wang & Zhang, 2007).

Different methods can be applied to predict the asset service life, each with a different level of complexity, applicability, and input data. The most common methods are: (a) deterministic; (b) probabilistic; and (c) engineering (Lacasse & Sjöström, 2004; Moser, 2004). Deterministic methods are based on the analysis of asset deterioration factors and their mechanisms to quantify them in terms of deterioration models (Silva, 2015; Tavares et al., 2020). These methods are easy to understand and apply; they can be implemented relatively quickly, avoiding redundancy of information; they maintain their operability even when not all variables of the same problem are known (Gaspar, 2002). Since the service life is a deterministic value, these methods do not allow providing information regarding the deterioration process nor the change from one deterioration state to another and are, therefore, unable to capture the random nature of the assets' deterioration (Hovde, 2000; Mc Duling et al., 2008).

The most widely used deterministic methods for service life prediction are simple or multiple linear regressions and factorial methods. Factorial methods were the main drivers of deterministic methods, being the basis for the international standard for service life planning of buildings and constructed assets (ISO 15686: 2011). Bhadauria and Grupta (2006) developed a bilinear graphical deterioration model of water tanks constructed in India to estimate the average total service life for staging and water retaining components and the overall tank structure. Chughtai and Zayed (2008) developed condition assessment models for sewer pipes using multiple regression techniques and considering different physical, environmental and operational influence factors.

Probabilistic methods can also be used to predict asset deterioration. In these models, asset deterioration is represented as a stochastic process based on random variables that define the probabilistic parameters affecting an average deterioration curve (Moser, 2004). Although these methods contribute to a better understanding of the physical phenomena associated with the deterioration process, it is necessary to use complex mathematical models, a large number of data points and a great dependence on fieldwork (Gaspar, 2002). Sempewo and Kyokaali (2016) proposed a decision support system to predict the future condition of a water distribution network using a Markov-based approach and a case study in Kampala Water, Uganda. Martins et al. (2013) developed a comparative study of three stochastic models for the prediction of pipe failures in water distribution systems: the single-variate Poisson process, the Weibull accelerated lifetime model and the linear-extended Yule process.

The engineering methods present the advantages of the two previous methods; they are easily understood and applied as deterministic methods but describe the deterioration processes probabilistically (Cecconi, 2002). An example of these methods is the probabilistic approach to the factorial method, in which probability density functions are used instead of adopting deterministic values for the variable (Moser, 2004).

Despite several studies of service life prediction through deterioration models of concrete structures and electrical equipment exist (see, for example, Jenberg et al., 2004; Lacasse & Sjöström, 2004; Zhou et al., 2021), very few studies address urban water assets and those developed in this field focus only on pipes and sewers (see, for example, Egger et al., 2014; Jayaram & Srinivasan, 2008; Li & Haimes, 1992a, 1992b; Rajani & Kleiner, 2001;

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Scheidegger et al., 2011; Ugarelli & Bruaset, 2010). The lack of sound methodologies for service life prediction applied to vertical assets in urban water systems using deterioration models leads engineers and decision makers to use reference values of service lives (in Portugal, recommended by the water regulator, ERSAR) to establish the maintenance and rehabilitation plans. These values were defined for a reference set of in-use and O&M conditions, which can result in the under or over-estimation of the real assets' service life, causing errors in intervention scheduling and the prediction of the future rehabilitation capital expenditure needs.

This paper proposes and demonstrates the application of a methodology for service life prediction of vertical urban water assets using deterioration models of asset physical condition. The proposed methodology has several key-novel features in comparison to previous approaches, namely: (a) the establishment of two maximum deterioration levels; (b) the analysis of the main factors that contribute to the deterioration of water storage tanks and wastewater pumping stations and their respective deterioration mechanisms; (c) the development and validation of simple and multiple deterioration models for civil work components and equipment; (d) the service life prediction using deterioration models and their comparison with the reference service lives; and (e) the analysis and discussion of the effect of maintenance interventions on asset service life.

2. Proposed Methodology

The proposed methodology for service life prediction is a four-step procedure: (a) Asset inspection and deterioration indices calculation; (b) Identification of main factors that contribute to asset deterioration; (c) Deterioration models development and validation; and (d) Service life prediction.

In the first step of the proposed methodology, a visual inspection of the selected assets is carried out to identify and classify the anomalies in terms of severity, intensity and extension and results from visual inspections are used to calculate the average and maximum values of deterioration indices proposed by Cabral et al. (2022a): component deterioration index (CDI_{av} and CDI_{max}, respectively for average and maximum values), asset deterioration index (ADI_{av} and ADI_{max}, respectively for average and maximum values) and infrastructure deterioration index (IDI_{av} and IDI_{max}, respectively for average and maximum values). These deterioration indices vary between 0 (the absence of anomalies) and 100 (the component, asset or infrastructure is totally degraded).

The CDI_{av} is calculated taking into consideration the severity, the intensity and the extension of each anomaly in the component and it represents the average component deterioration:

$$CDI_{av}\,(t) = \frac{\sum_{i=1}^{n}(S_i \cdot I_i \cdot E_i)}{n} \tag{1}$$

where t is the reference time when the index is calculated, $CDIav$ is the average component deterioration index at the time t (-), S_i, I_i, E_i are the severity, intensity and extension of the anomaly i (-), respectively, and n is the total number of anomalies identified in the component. The CDI_{max} corresponds to the classification value of the worst anomaly in the inspected component and it is calculated since this anomaly may require urgent intervention and is not reflected in the average index value.

The ADI_{av} indicates a typical value that represents the average deterioration of an asset. It is based on the CDI_{av} of each component weighted by their respective replacement cost or criticality:

$$ADI_{av}(t) = \frac{\sum_{j=1}^{n}(CDI_{j,t\ av} \cdot w_{j,t})}{\sum_{j=1}^{n} w_{j,t}} \tag{2}$$

where ADI_{av} is the average asset deterioration index at time t (-), $CDI_{j,t}\ av$ is the average component deterioration index of component j at time t (-), w_j,t is the weighting factor (replacement cost or criticality) of component j at time t and n is the total number of components presented in the asset. The criticality represents the importance of each component in the asset from the physical condition perspective. The weighting scale from NRAU (2007) proposed for buildings was applied, which varies between 1 (less important finishing components with low impact on asset deterioration) and 6 (very important structural components that significantly contribute to the

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physical deterioration of the asset). The weights assignment was carried out in a brainstorming session between a panel of specialists and water utility engineers.

The ADI_{max} corresponds to the worst anomaly classification of the several components belonging to the asset (i.e., maximum CDI_{max}). It is acknowledged that assets with higher criticality or replacement cost contribute more significantly to the calculated indexes, however, these indexes still rely on the severity, the intensity, and the extension of anomalies for each component, providing a comprehensive description of the condition deterioration for each asset. A similar equation can be used to calculate the IDI_{av}, in which the ADI_{av} of several assets is added, considering a weighting factor that corresponds to the replacement cost or criticality level of each asset in the infrastructure.

In the second step, the most important factors contributing to asset deterioration are identified and the general and technical characteristics of assets are collected. Since asset deterioration is a complex process, influenced by several factors, only the most important ones are considered. In urban water assets, these factors are usually divided into three categories (Barton et al., 2019; Chughtai & Zayed, 2008; FCM & NRC, 2003): physical (i.e., pipe-intrinsic), operational and environmental. Physical factors are associated with asset characteristics, operational aspects deal with the adapted operational and maintenance practices and environmental factors are related to external conditions.

In the third step, deterioration models are developed based on simple linear regression models, with the following general form:

$$Y = \beta_0 + \beta_1 X_1 + \varepsilon \tag{3}$$

where Y is the dependent variable (e.g., ADI_{av}, ADI_{max}), X_1 is the independent variable (deterioration factor), β_0 is the constant term, β_1 is the regression coefficient, and ε is the random component that represents the disturbance or error term. The least-square method is used to obtain the linear parametrical equations (deterioration models).

Simple linear regression models allow an understanding of each identified factor's deterioration mechanisms. Shohet et al. (1999) suggested four typical patterns of deterioration paths in buildings: linear, "convex-shaped", "concave-shaped" and "S-shaped" patterns. The linear pattern is related to factors that cause a permanent deterioration in the asset. The “convex-shaped” pattern is characterized by the physical and chemical phenomena that initially act slowly, but whose action is felt cumulatively. The “concave-shaped” pattern is more related to biological factors that, at an early stage, develop rapidly, but whose potential for deterioration decreases over time (Silva, 2015). The S-shaped pattern is associated with phenomena that change in intensity over time.

Multiple linear regression analysis allows obtaining deterioration models that are explained by more than one independent variable (deterioration factor). Independent variables with a high correlation coefficient for a specific dependent variable should be considered for developing the multiple linear regression model. The general form of these models is the following:

$$Y = \beta_0 + \beta_1 X_1 + \ldots + \beta_p X_p + \varepsilon \tag{4}$$

where $\beta_1, \ldots, \beta_p$ are the regression coefficients and each represents the change in the mean response of the dependent variable, per unit increase in the associated independent variable when all the other independent variables are held constant. The intercept term, β_0, represents the estimated mean response of the dependent variable when all the independent variables are zero.

Once regression models have been developed, it is essential to confirm the goodness-of-fit of the model and the statistical significance of the model and the estimated coefficients. Different measures of goodness-of-fit may be used, namely, the standard deviation/error of the estimator's beta, the r-square, r^2, for simple regression models and the adjusted r-square, r_a^2, for multiple regression models. The adjusted r-square is a modification of the r-square considering the number of existing independent variables. It also represents the quality of the adjustment: a value close to one indicates that the regression adjustment is very good and that the linear regression can explain most of the variation in the dependent variable.

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Assuming the normality of the error terms, it is possible to measure the model significance through the overall F-test. If the p-value of the F-test is less than the significance level (e.g., 0.05), it provides sufficient evidence to conclude that the regression model fits the data better than the model with no independent variables. The study of the serial correlation of error terms is carried out through the Durbin–Watson test, which computes residual autocorrelations, allowing the no correlation of error terms to be concluded (Durbin & Watson, 1950).

The variance inflation factor, *VIF*, is a measure of the degree of multicollinearity between independent variables and it is calculated for all the independent variables of the multiple regression models. This factor is the ratio of the variance of the estimator $\hat{\beta}_i$ ($i = 1,2,\ldots$p) when fitting the full model divided by the variance of $\hat{\beta}_i$ when fitting on its own (James et al., 2013). According to James et al. (2013), the variance inflation factor for each regression coefficient can be calculated by:

$$VIF\left(\hat{\beta}_i\right) = \frac{1}{1 - r^2_{X_i|X_{-i}}} \tag{5}$$

where $r^2_{X_i|X_{-i}}$ is the r-square value associated with the regression model of X_{-i} on other independent variables. The smallest possible value for *VIF* is 1, which indicates the complete absence of collinearity. *VIF* should generally not exceed the value of 10 (Robinson & Schumacker, 2009). A VIF value of 10 indicates that the estimated variance of the regression coefficient is 10 times higher than it would have been if the independent variable had been linearly independent of the other independent variables in the analysis (O'Brien, 2007).

Model validation must be carried out using a different data set from the one used to obtain the simple and multiple linear regression models. The two most common measures used to assess and validate the obtained models comparing the observed values (e.g., ADI_{av} from inspections) and the predicted values (e.g., ADI_{av} from the models) are: the root mean squared error, *RMSE*, and percentage of relative absolute error, RAE. The *RMSE* measures the difference between the real values (ADI_{av_k}) of asset k and estimated values ($\widehat{ADI}_{av_k}$) obtained through the regression model:

$$RMSE = \sqrt{\frac{1}{n}\sum_{k=1}^{n}\left(ADI_{av_k} - \widehat{ADI}_{av_k}\right)^2} \tag{6}$$

The percentage of *RAE* is given by the absolute difference between the real and the estimated value divided by the real value:

$$RAE = \frac{100}{n}\sum_{k=1}^{n}\left|\frac{ADI_{av_k} - \widehat{ADI}_{av_k}}{ADI_{av_k}}\right| \tag{7}$$

In the last and fourth step (Service life prediction), the obtained deterioration models through simple and multiple linear regression analysis are used to predict the service life of urban water assets considering a deterioration level. The maximum deterioration level that establishes the end of the assets' service life is only a theoretical limit, generally difficult to specify (Moser, 2004). The definition of deterioration levels and, consequently, of the assets' end-of-life, may vary over time mainly due to the performance requirements and the utility investment capacity (Silva et al., 2012). Two deterioration levels are proposed herein based on the analysis of deterioration indices and the current condition of the assets: the maximum recommended deterioration level and the maximum admissible deterioration level.

The maximum recommended deterioration level corresponds to an ADI_{av} equal to 40 (assets are, in the worst scenario, in good condition) to ensure that the asset always fulfills its intended purpose. The maximum admissible deterioration level corresponds to an ADI_{av} equal to 60 (assets are, in the worst scenario, in reasonable condition), from which the asset may not fulfill the function for which it was intended, causing a peak investment in the short-term. These values resulted from a comprehensive brainstorming between a panel of specialists and water utility engineers allowing to establish a five level-scale for condition rating (Cabral et al., 2022a).

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Table 1
General Characteristics of the Three Data Sets

Data sets	Assets	General characteristics
1	22 water storage tanks	Tank capacity (m^3): 100–14,000
		Number of units: 1–4
		Construction year: 1960–2009
	17 wastewater pumping stations	Flow rate (l/s): 3.7–222
		Head (m): 2.2–80
		Total hydraulic power (kW): 0.15–28
		Construction year: 1975–2016
2	4 water storage tanks	Tank capacity (m^3): 100–10,000
		Number of units: 1–2
		Construction year: 1986–2009
3	2 water storage tanks	Tank capacity (m^3): 800, 150
		Number of units: 1–2
		Construction year: 1987, 1990
		Rehabilitation year: 2015, 2019

- Rating-level 5 | ADI_{av} [0; 10]: New asset or asset in excellent condition or asset recently fully rehabilitated.
- Rating-level 4 | ADI_{av}]10; 40]: Asset in good condition ensured by regular maintenance.
- Rating-level 3 | ADI_{av}]40; 60]: Asset in a reasonable condition requiring exceptional intervention beyond the regular maintenance plan.
- Rating-level 2 | ADI_{av}]60; 90]: Asset in poor condition endangering its functionality and requiring deep intervention in the short-term.
- Rating-level 1 | ADI_{av}]90; 100]: Asset in an unsatisfactory condition not meeting component functionality requirement.

3. Case Studies

Three data sets are considered to demonstrate the proposed methodology for service life prediction. Each data set is composed of different vertical urban water assets located in Portugal that were inspected in the scope of the present study to assess their physical condition and to calculate their average and maximum asset deterioration index.

- Data set one is used to analyze factors that contribute to asset deterioration, to develop simple and multiple deterioration models using linear regression analysis and to predict assets service life (results will be presented in Sections 4.1, 4.2 and 4.4).
- Data set 2 is used to validate the obtained simple and multiple deterioration models of water storage tanks (results will be presented in Section 4.3).
- Data set 3 is used to discuss the effect of maintenance interventions in improving the service life of vertical assets and to provide recommendations on the adjustment of deterioration models when applied to assets with intervention works (results will be presented in Section 4.5).

Table 1 presents the general characteristics of the three data sets. The first comprises 22 water storage tanks and 17 wastewater pumping stations, the second comprises four water storage tanks, and the third comprises two storage tanks with interventions during their service life.

4. Results

4.1. Analysis of the Factors That Contribute to Asset Deterioration

The factors contributing to the deterioration of water storage tanks and wastewater pumping stations are divided herein into physical, operational and environmental, following the approach proposed by FCM and NRC (2003) and Chughtai and Zayed (2008) to describe deterioration factors of water mains and sewer pipes, respectively and

Table 2
Description of Factors That Contribute to Water Storage Tank Deterioration in Data Set 1

Factors		Explanation	Range in the data set	% of assets from data set 1 (absolute number)
Physical	Civil work components age (years)	The effects of deterioration become more evident over time	11–60	100% (22)
	Equipment age (years)	The effects of deterioration become more evident over time	5–50	100% (22)
	Typology	More difficulty in inspecting semi-buried tanks and some anomalies may not be detected	Ground	41% (9)
			Semi-buried	59% (13)
	Number of units	A higher number of units is usually associated with critical tanks	1	32% (7)
			2	55% (12)
			4	14% (3)
	Construction material	Prefabricated tanks require good practices to maintain structural integrity	Reinforced concrete/ Masonry	91% (20)
			Prefabricated	9% (2)
	Total volume (m3)	Higher volumes are usually associated with critical tanks	100–14,000	100% (22)
Operational	O&M practice level	Insufficient practices can enhance asset deterioration	Good	18% (4)
			Reasonable	50% (11)
			Insufficient	32% (7)
Environmental	Distance from the sea (km)	Coastal zones are more susceptible to biodeterioration due to the presence of salts	≤5	45% (10)
			>5	55% (12)
	Traffic	Traffic represents a source of pollution that influences asset deterioration	Low	68% (15)
			Medium	32% (7)
			High	0% (0)

Table 3
Description of Factors That Contribute to Wastewater Pumping Station Deterioration in Data Set 1

Factors		Explanation	Range in the data set	% of assets from data set 1 (absolute number)
Physical	Civil work components age (years)	The effects of deterioration become more evident over time	4–40	100% (17)
	Equipment age (years)	The effects of deterioration become more evident over time	0–20	100% (17)
	Pump group installation	Wet pump groups are more prone to deterioration	Wet	76% (13)
			Dry	24% (4)
	Number of pump groups	A higher number of pump groups is usually associated with critical pumping stations	1	76% (13)
			2	24% (4)
	Flow rate (m^3/s)	Higher flow rates are usually associated with critical pumping stations	0.0037–0.22	100% (17)
	Head (m)	Higher heads are usually associated with critical pumping stations	2.2–80	100% (17)
	Total hydraulic power (kW)	Higher total hydraulic powers are usually associated with critical pumping stations	0.15–27.6	100% (17)
Operational	O&M practice level	Insufficient practices can enhance asset deterioration	Good	59% (10)
			Reasonable	41% (7)
			Insufficient	0% (0)
Environmental	Distance from the sea (km)	Coastal zones are more susceptible to biodeterioration due to the presence of salts	≤5	59% (10)
			>5	41% (7)
	Traffic	Traffic represents a source of pollution that influences asset deterioration	Low	71% (12)
			Medium	29% (5)
			High	0% (0)

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Table 4
Restricted Simple Linear Regression Deterioration Models for ADI_{av} and ADI_{max} With the Asset Age of Water Storage Tanks and Wastewater Pumping Stations: Model Parameters and Goodness-Of-Fit

Asset		Dependent variable (-)	Independent variable	Regression coefficient	Standard error	r^2
Water storage tanks ($n = 22$)	Civil work components	ADI_{av}	Constant (-)	$\beta_0 = 11$	-	0.67
			Age (Years)	$\hat{\beta}_1 = 0.704$	0.04	
		ADI_{max}	Constant (-)	$\beta_0 = 19$	-	0.34
			Age (Years)	$\hat{\beta}_1 = 1.00$	0.11	
	Equipment	ADI_{av}	Constant (-)	$\beta_0 = 0$	-	0.82
			Age (Years)	$\hat{\beta}_1 = 1.17$	0.05	
		ADI_{max}	Constant (-)	$\beta_0 = 0$	-	0.69
			Age (Years)	$\hat{\beta}_1 = 1.45$	0.10	
Wastewater pumping stations ($n = 17$)	Civil work components	ADI_{av}	Constant (-)	$\beta_0 = 11$	-	0.68
			Age (Years)	$\hat{\beta}_1 = 0.96$	0.09	
		ADI_{max}	Constant (-)	$\beta_0 = 19$	-	0.48
			Age (Years)	$\hat{\beta}_1 = 1.16$	0.18	
	Equipment	ADI_{av}	Constant (-)	$\beta_0 = 0$	-	0.84
			Age (Years)	$\hat{\beta}_1 = 3.09$	0.15	
		ADI_{max}	Constant (-)	$\beta_0 = 0$	-	0.67
			Age (Years)	$\hat{\beta}_1 = 4.00$	0.32	

Note. r^2—Coefficient of determination.

by Silva and Pietro (2021) to describe deterioration environmental factors (distance from the sea and traffic) of facade claddings. Table 4 presents the main deterioration factors identified for water storage tanks and their explanation.

A description of each factor based on Data set one is also presented in Table 4. Each factor can be represented by a discrete variable (e.g., civil work components and equipment age) or a categorical variable (e.g., typology of the storage tank and O&M practice level). The relative and absolute frequency of the 22 water storage tanks (Data set 1) are also presented. For instance, the age of civil work components of storage tanks varies between 11 and 60 years representing 100% of studied tanks (i.e., 22 water storage tanks). Regarding the typology, 41% of storage tanks (i.e., 9 tanks) are ground tanks and the remaining 59% (i.e., 13 tanks) are semi-buried tanks.

Physical factors are associated with the characteristics of the water storage tanks, including the age of civil work components and equipment, typology (e.g., ground and semi-buried), number of units, construction material (e.g., reinforced concrete/masonry and prefabricated) and total volume. The operational factors are related to the O&M practices in water storage tanks, which are divided into three levels, according to Cabral et al. (2022b): good, reasonable and insufficient. *Good practices* are related to periodic inspections, cleaning and sanitization at intervals less than or equal to 1 year, periodic preventive interventions, adequate ventilation and monitoring of water retention time and chlorine decay. *Reasonable practices* are associated with a periodicity of inspections, cleaning and sanitization between two and 3 years, reasonable ventilation and thermal insulation and only sporadic control of water retention time and chlorine decay. *Insufficient practices* are related to a periodicity of inspections, cleaning and sanitization higher than 3 years, no guarantee of adequate ventilation and thermal insulation and no control of water retention time and chlorine decay.

Environmental factors include two different variables, distance from the sea and traffic. The distance from the sea is divided into locations in coastal areas (with a distance lower or equal to 5 km) and in inland areas (with a distance from the sea higher than 5 km). The traffic can be classified into: (a) low traffic, usually related to rural areas; (b) medium traffic, related to urban areas near major cities; and (c) higher traffic, related to urban areas with intensive traffic. No inspected water storage tanks were classified with high traffic.

Table 5 describes factors contributing to the deterioration of wastewater pumping stations and the frequency of inspected assets in which category of different factors. Factors are also divided into the categories of physical,

Table 5
MLR Models for ADI_{av} and ADI_{max} of Water Storage Tanks and Wastewater Pumping Stations

Asset		Dependent variable (-)	Independent variable	Regression coefficient	Standard error	r^2	r^2_{adj}
Water storage tanks (n = 22)	Civil work components	ADI_{av}	Constant (-)	$\hat{\beta}_0 = 21.104$	2.430	0.90	0.87
			Age (Years)	$\hat{\beta}_1 = 0.619$	0.071		
			Volume (m^3)	$\hat{\beta}_2 = 0.00003$	0.0002		
			Material (1: Prefabricated; 0: Reinforced concrete/masonry)	$\hat{\beta}_3 = -7.872$	3.154		
			Good practices (1: Yes; 0: No)[a]	$\hat{\beta}_4 = -10.238$	2.794		
			Reasonable practices (1: Yes; 0: No)[a]	$\hat{\beta}_5 = -8.670$	2.048		
		ADI_{max}	Constant (-)	$\hat{\beta}_0 = 38.75$	9.133	0.60	0.49
			Age (Years)	$\hat{\beta}_1 = 0.671$	0.267		
			Volume (m^3)	$\hat{\beta}_2 = 0.0007$	−0.0008		
			Material (1: Prefabricated; 0: Reinforced concrete/masonry)	$\hat{\beta}_3 = -21.82$	11.85		
			Good practices (1: Yes; 0: No)[a]	$\hat{\beta}_4 = -30.23$	10.50		
			Reasonable practices (1: Yes; 0: No)[a]	$\hat{\beta}_5 = -10.61$	7.698		
	Equipment	ADI_{av}	Constant (-)	$\hat{\beta}_0 = 1.349$	4.032	0.87	0.84
			Age (Years)	$\hat{\beta}_1 = 0.999$	0.110		
			Units (-)	$\hat{\beta}_2 = 2.744$	1.519		
			Good practices (1: Yes; 0: No)[a]	$\hat{\beta}_3 = -4.228$	3.983		
			Reasonable practices (1: Yes; 0: No) [a]	$\hat{\beta}_4 = -2.103$	3.110		
		ADI_{max}	Constant (-)	$\hat{\beta}_0 = -7.425$	7.110	0.81	0.76
			Age (Years)	$\hat{\beta}_1 = 1.237$	0.195		
			Units (-)	$\hat{\beta}_2 = 7.979$	2.678		
			Good practices (1: Yes; 0: No)[a]	$\hat{\beta}_3 = -8.304$	7.023		
			Reasonable practices (1: Yes; 0: No)[a]	$\hat{\beta}_4 = -2.714$	5.484		
Wastewater pumping stations (n = 17)	Civil work components	ADI_{av}	Constant (-)	$\hat{\beta}_0 = 6.830$	3.432	0.72	0.67
			Age (Years	$\hat{\beta}_1 = 1.001$	0.204		
			Power (kW)	$\hat{\beta}_2 = 0.113$	0.222		
			Building (1: Yes; 0: No)	$\hat{\beta}_3 = 3.887$	3.595		
		ADI_{max}	Constant (-)	$\hat{\beta}_0 = 9.191$	6.062	0.65	0.57
			Age (Years)	$\hat{\beta}_1 = 1.187$	0.359		
			Power (kW)	$\hat{\beta}_2 = 0.235$	0.393		
			Building (1: Yes; 0: No)	$\hat{\beta}_3 = 11.835$	6.351		
	Equipment	ADI_{av}	Constant (-)	$\hat{\beta}_0 = 3.103$	10.349	0.85	0.81
			Age (Years)	$\hat{\beta}_1 = 3.171$	0.397		
			Power (kW)	$\hat{\beta}_2 = 0.056$	0.456		
			Number of pumps (-)	$\hat{\beta}_3 = -3.756$	8.080		
		ADI_{max}	Constant (-)	$\hat{\beta}_0 = 5.280$	22.543	0.68	0.61
			Age (Years)	$\hat{\beta}_1 = 4.244$	0.865		
			Power (kW)	$\hat{\beta}_2 = 0.057$	0.949		
			Number of pumps (-)	$\hat{\beta}_3 = -7.487$	17.600		

[a]To consider insufficient practices, it should be used the value zero in good and reasonable practices.

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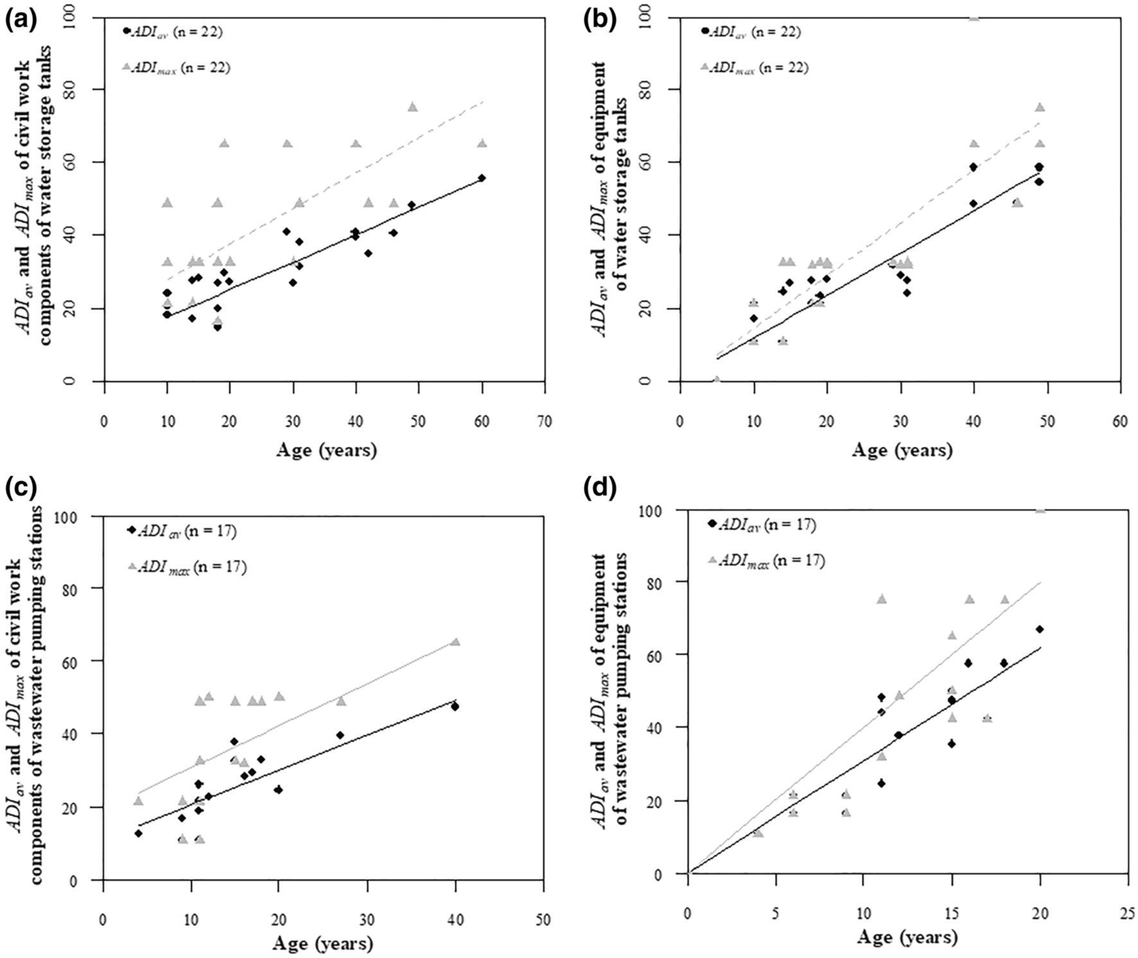

Figure 1. Restricted deterioration models for ADI_{av} and ADI_{max} with the asset age: (a) civil work components of water storage tanks; (b) equipment of water storage tanks; (c) civil work components of wastewater pumping stations; and (d) equipment of wastewater pumping stations.

operational and environmental and their explanation is also based on the referred three studies, that is, FCM and NRC (2003), Chughtai and Zayed (2008) and Silva and Pietro (2021). Physical factors are associated with the characteristics of the wastewater pumping stations, including the age of civil work components and equipment, type of pump group installation (e.g., wet or dry), number of pump groups, flow rate, head and total hydraulic power. Operation and environmental factors present the same categories as water storage tanks. None of the inspected pumping stations was classified with insufficient O&M practices nor high traffic.

Other important factors contributing to the deterioration of the studied urban water assets were not included herein due to the lack of available information, such as water quality, soil properties and climate conditions. Aggressive waters can promote the corrosion of materials, and specific properties of soils can also make them corrosive, namely the presence of hydrocarbons and solvents in the soil. Climate factors, such as wind and rain, are also relevant to asset deterioration.

4.2. Development of Simple and Multiple Linear Regression Models

Simple linear regression (SLR) models were developed, using Data set 1, to understand the deterioration mechanism of civil work components (e.g., walls, mortar, columns, beams, stairs, roof slabs, and expansion joints) and equipment (e.g., pipes, fittings, valves, pump groups, flowmeters, pressure gauges and transducers), of water storage tanks and wastewater pumping stations as a function of the asset age. Age is the literature's most cited and also widely considered deterioration factor of constructed assets (see, for example, Barton et al., 2019). Figure 1

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presents the deterioration lines for ADI_{av} and ADI_{max} of civil work components and equipment of water storage tanks and wastewater pumping stations.

Different factors can affect the initial asset deterioration, contributing to anomalies in the early years of the asset life, such as the quality of production of materials, conditions of transport and storage or construction practices. The initial asset deterioration is represented by the intercept regression coefficient (β_0), which represents the value of the dependent variable (ADI_{av} or ADI_{max}) when the independent variable (age) is zero. All the obtained deterioration lines correspond to restricted models, in which the intercept regression coefficient (β_0) is predefined (a known value), as opposed to the original models in which the regression corresponds to the best fit of the sample data (i.e., all regression coefficients are estimated). The restricted models are developed to ensure the physical significance of the models. Considered β_0 values will be discussed further on.

The asset age has a negative effect on the asset deterioration indices by increasing their value, that is, higher deterioration is observed for older assets. As expected, the line for ADI_{max} presents higher values of asset deterioration than that of ADI_{av}. Furthermore, the line for ADI_{max} has also a higher slope indicating that maximum deterioration evolves faster than average deterioration and that the difference between the two models increases with the asset age. These results will influence the predicted asset service life.

Table 4 presents the obtained statistics and SLR (simple linear regression) results of restricted deterioration models of civil work components and equipment of water storage tanks and wastewater pumping stations for ADI_{av} and ADI_{max}. These models correspond to the best-fitted models in terms of goodness-of-fit, statistical significance, and estimated coefficients.

The intercept regression coefficients (β_0) of obtained restricted models were calculated by considering the average value of estimated regression coefficients obtained in the original models for the same dependent variables and the same component categories. For instance, the estimated β_0 of the ADI_{av} original model was 14 and 8 for civil work components of water storage tanks and wastewater pumping stations, respectively; allowing to calculate an average value of 11 which was considered as the β_0 of the ADI_{av} restricted models for the same asset components. Regarding the SLR model for the dependent variable of ADI_{max}, the calculated regression coefficient β_0 was 19 for both assets. In the case of equipment of water storage tanks and wastewater pumping stations, the regression coefficients related to the intercept (β_0) are 0, for both dependent variables (ADI_{av} and ADI_{max}). Results show that the asset deterioration of civil work components of storage tanks and wastewater pumping stations is not zero in the first year of asset operation (age equal to zero); however, more assets need to be inspected to increase the data set and to obtain more reliable models.

The restricted models modify the estimation procedure, in which the calculation of the coefficient of determination and the test of significance should not be equal to the original models. The use of restricted models resulted in a higher residual sum of squares, and in this case, Kozak and Kozak (1985) suggested the use of the following equation for calculating the coefficient of determination:

$$r^2 = 1 - \frac{\sum\left(Y - \hat{Y}_r\right)^2}{\sum\left(Y - \overline{Y}\right)^2} \tag{8}$$

where r^2 is the coefficient of determination, $\hat{Y}_r$ is the predicted values from the restricted models, and $\overline{Y}$ is the mean of the Y observations.

Despite using restricted models, all models present r^2 values close to or higher than 0.50 and p-values approximately close to zero (overall F-test). The model with the highest determination coefficient corresponds to the ADI_{av} of equipment of wastewater pumping stations, in which 84 percent of the variations of equipment of deterioration index are explained by the independent variable (equipment age), since $r^2 = 0.84$. In general, the models associated with the ADI_{max} have low r^2 values when compared to the ADI_{av} since the former dependent variable presents high variability, as shown in, for example, Figure 1a. The study of the serial correlation of error terms was carried out through the Durbin–Watson test, whose p-value is higher than 0.05, corresponding to the value at which the null hypothesis is not rejected.

Multiple linear regression models consider more than one independent variable to explain the ADI_{av} and ADI_{max} (dependent variables). Table 5 presents the multiple linear regression models for civil work components and

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equipment of water storage tanks and wastewater pumping stations. The obtained models correspond to the best-fitted ones and only consider independent explanatory variables, whose *VIF* is close to 1, indicating the absence of collinearity between them.

In general, the obtained models present well-adjusted r-squared (equal to or higher than 0.50), p-values approximately close to zero (overall *F*-test) and p-values higher than 0.05 in the Durbin-Watson tests. Comparing the adjusted r-squared of the multiple regression models with the r-squared of the simple regression models, it can be noted that the results are better in multiple models.

The value of the β_0 coefficient in these multiple regression models has no physical significance since, in some independent variables (e.g., volume in water storage tanks and power in wastewater pumping stations), the zero value cannot be introduced. Thus, there is no possibility that the value of the ADI_{av} or ADI_{max} can be equal to β_0. However, the multiple regression models should be used with caution, especially if values of independent variables are outside the domains of the variables used in the analysis (see, Table 2 and Table 3).

4.3. Validation of Deterioration Models

Model validation aims to compare the observed values (ADI_{av} and ADI_{max} obtained through inspections) and the predicted values (ADI_{av} and ADI_{max} obtained through simple and multiple regression models). The two most common measures to assess and compare the observed and predicted values are the root mean squared error (RMSE) and the relative absolute error (RAE). Model validation was carried out using a different data set than the one used to develop deterioration models. Four water storage tanks without major maintenance interventions (Data set 2) were inspected to identify and classify the anomalies in terms of severity, intensity and extension and to calculate the deterioration indices. Inspection results of Data set 2 allow the validation of the proposed methodology and of the obtained deterioration models for water storage tanks. The obtained deterioration models of wastewater pumping stations were not validated due to the lack of new inspectable assets.

The RMSE is the square root of the variance of the residuals, and it is scale-dependent, that is, has the same units as the dependent variable. This measure assesses how well the model predicts the dependent variable. Thus, lower values of RMSE indicate a better fit. RMSE shows a variation between 4.6 and 13.6, being low values in relation to the deterioration scale (i.e., between 0 and 100). The RAE varies between 13% and 39%, being the highest value associated with the maximum deterioration of civil work components. Comparing the RMSE and RAE of different models, the simple models present lower values than multiple models. In general, simple and multiple models of ADI_{av} present lower values of RMSE and RAE than simple and multiple models of ADI_{max}. This means that simple models have a better predictive power of asset deterioration than the multiple regression models and that the ADI_{av} models should preferably be used in comparison with the ADI_{max} models.

4.4. Service Life Prediction

The developed simple (Table 4) and multiple (Table 5) linear regression models, considering 22 water storage tanks and 17 wastewater pumping stations (Data set 1) and shown in Section 4.2, were used to predict the service lives of civil work components and equipment of water storage tanks and wastewater pumping stations.

The service lives can be predicted by using the simple linear regression models associated with ADI_{av} (since this index attends to the overall deterioration of the asset) and by considering the maximum recommended ($ADI_{av} = 40$) and the maximum admissible ($ADI_{av} = 60$) deterioration levels. The graphical interception between the deterioration levels (40 and 60) and the simple deterioration models allows to predict the service lives as depicted in Figure 2. For instance, for the civil work components of storage tanks (Figure 2a, represented by the blue line), ADI_{av} values of 40 and 60 correspond to the age of 41 and 66 respectively; considering that an asset with these ADI_{av} values has reached the end of its service life, these age values correspond to the predicted service lives of that asset (if current O&M practices are maintained). Note that ADI_{av} models in Figure 2 were projected outside the domains of the variable age used in the analysis (see, Tables 2 and 3) to predict the service life; in these situations, results should be used with caution since no information is available regarding asset deterioration.

Table 6 depicts the predicted service lives of civil work components and equipment of water storage tanks and wastewater pumping stations using the simple linear regression models and their comparison with reference

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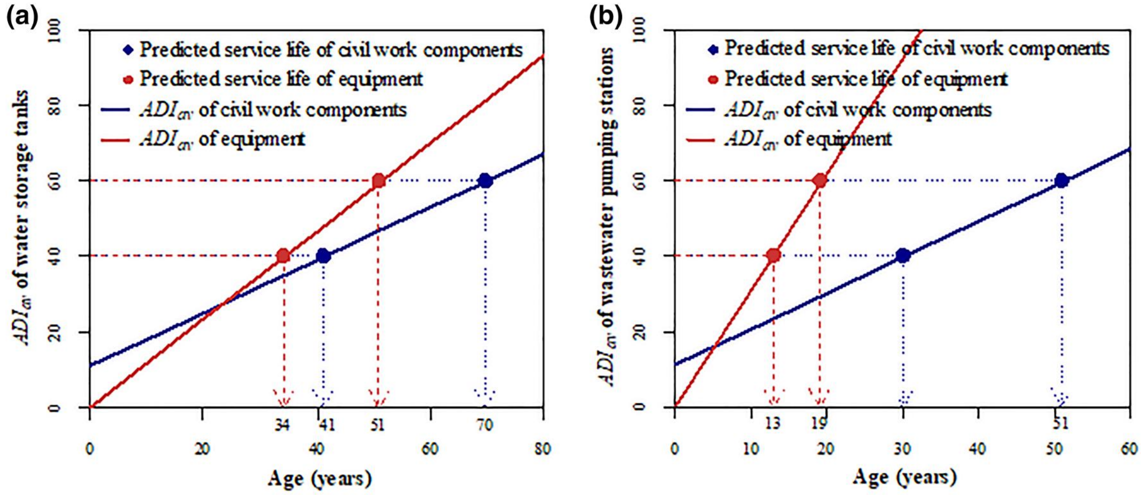

Figure 2. Service life prediction using simple linear regression models of ADI_{av} of civil work components and equipment of: (a) water storage tanks; and (b) wastewater pumping stations.

service lives in Portugal. In civil work components of water storage tanks, the predicted service lives are 41 years considering the maximum recommended deterioration level ($ADI_{av} = 40$) and 66 years considering the maximum admissible deterioration level ($ADI_{av} = 60$). The reference service life in Portugal of these components is 60 years, which is a value between the two predicted service lives.

In terms of equipment of water storage tanks, the predicted service lives are 34 years considering the maximum recommended deterioration level ($ADI_{av} = 40$) and 51 years considering the maximum admissible deterioration level ($ADI_{av} = 60$). As not all studied storage tanks include an associated pumping station (only 15 of the 22 inspected water storage tanks include a pumping station), the service life of the equipment is greatly influenced by the pipes, which have a longer service life than the pump groups.

Regarding the wastewater pumping stations, the reference service lives of civil work components (40 years) and equipment (15–20 years) are between the predicted service lives of 31 and 51 years for civil work components considering a deterioration level of 40 and 60, respectively; and of 13 and 19 years for equipment considering a deterioration level of 40 and 60, respectively. The lower values of predicted service lives for the equipment of wastewater pumping stations compared to the values for water storage tanks can be explained by the influence of wastewater pump groups that, in some inspected assets, represent the most important component. These results allowed to validate the reference service lives, which can be used when no information exists regarding asset deterioration.

Table 6
Summary of Service Lives Predicted by Simple Linear Regression and MLR Models and Its Comparison With Reference Service Lives in Portugal

Asset		Dependent variable (-)	Maximum deterioration level (-)	Predicted service life by SLR models (years)	Predicted average service life by MLR models (years)	Standard deviation (years)	Reference service life (years)
Water storage tanks	Civil work components	ADI_{av}	40	41	41	5.6	60
			60	70	74		
	Equipment	ADI_{av}	40	34	35	3.0	20[a]–50[b]
			60	51	55		
Wastewater pumping stations	Civil work components	ADI_{av}	40	30	30	1.9	40
			60	51	58		
	Equipment	ADI_{av}	40	13	13	0.4	10–15
			60	19	19		

[a]Reference service life of water pump groups. [b]Reference service life of pipes (general material).

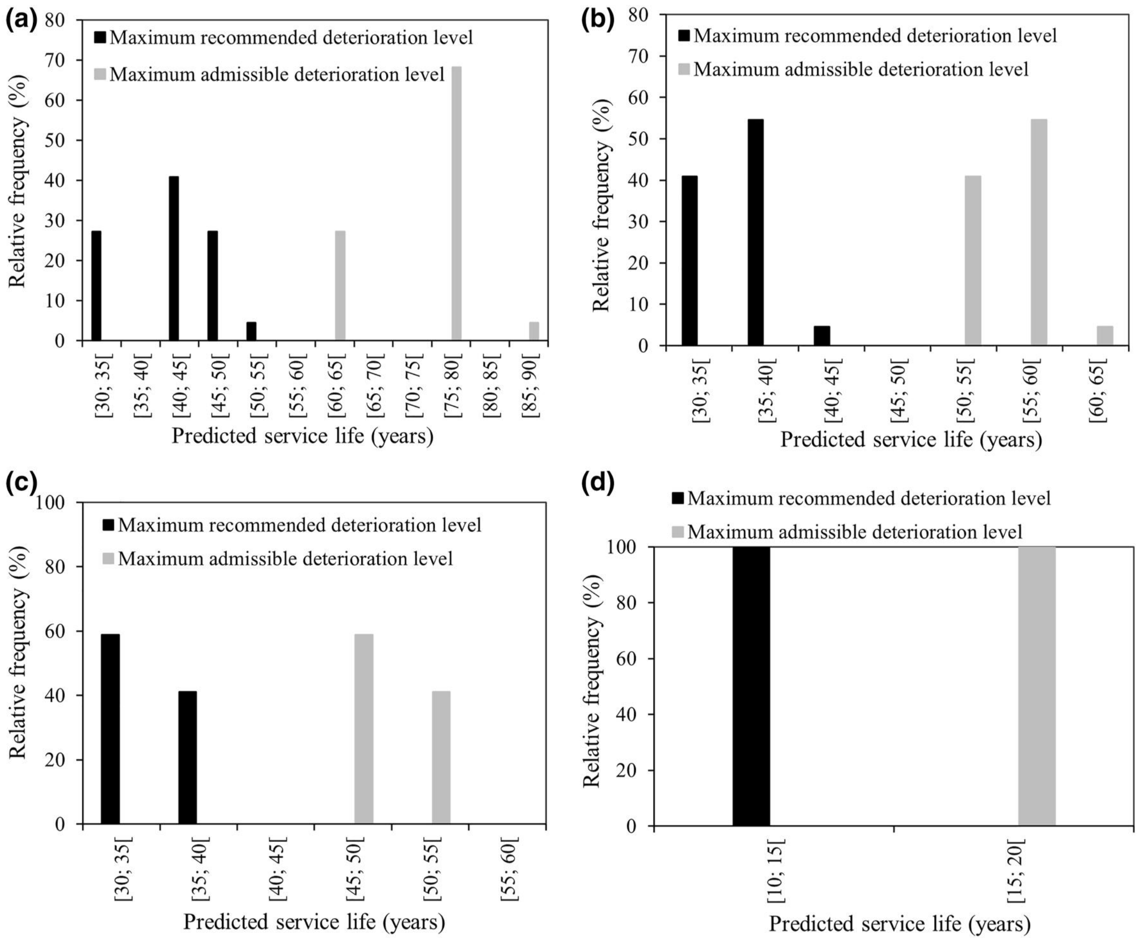

Figure 3. Relative frequency of predicted service lives using MLR models of ADI_{av} for each deterioration level: (a) civil work components of water storage tanks; (b) equipment of water storage tanks; (c) civil work components of wastewater pumping stations; and (d) equipment of wastewater pumping stations.

Obtained service lives through simple linear regression models are predicted considering only the asset age and not including the influence of other variables. Besides, one of the most frequent criticisms of the use of deterministic models in the prediction of service lives concerns the achievement of a deterministic value, not considering the random process of asset deterioration. To fill these gaps, multiple linear regression models are also used to predict service lives, in which several independent variables allow the prediction of service lives for assets with different characteristics and sets of in-use conditions. In order to include the random process of asset deterioration, it is considered that the regression models of the service lives have an error term with normal distribution, allowing the calculation of standard deviations.

The inspected assets of Data set 1 are used to predict the service lives considering the multiple regression models and knowing physical, operational and environmental characteristics. As a result, the relative frequency of predicted service lives of civil work components and equipment of water storage tanks and wastewater pumping stations in different age categories are plotted for the two deterioration levels (Figure 3).

Results show a clear difference in the predicted service lives considering the two deterioration levels, similar to the results of the service life prediction with the simple models. In the case of water storage tanks (Figure 3), 50% of the inspected storage tanks (11 tanks) present a predicted service life of civil work components between 40 and 44 years considering the maximum recommended deterioration level ($ADI_{av} = 40$) and of equipment between 70 and 74 years considering the maximum admissible deterioration level ($ADI_{av} = 60$).

The predicted service lives in water storage tanks are distributed in more age categories than in wastewater pumping stations, that is, between three and four age categories for the water storage tanks and only one or two for the wastewater pumping stations (Figure 3).

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The predicted service lives of civil work components and equipment of water storage tanks and wastewater pumping stations using MLR models are also presented in Table 6 for the two deterioration levels. The obtained values correspond to the average values of services lives obtained for all inspected assets. Results are quite similar to the values predicted with the simple models. However, the predicted service lives obtained by the multiple models allow to calculate the standard deviation.

4.5. Study of the Effect of Interventions on Asset Service Life

The development and validation of the deterioration models were carried out with assets without undergoing major rehabilitation interventions during their service life. Data set 3 is used herein to illustrate and discuss the effect of maintenance and rehabilitation interventions in improving the service life of vertical assets, corresponding to two storage tanks: one involving major rehabilitation intervention and the other involving maintenance intervention. The first storage tank (ST1) is used to illustrate the application of the obtained deterioration models before and after rehabilitation and to discuss the improvement of the service life attained with a major rehabilitation intervention; whereas the second water storage tank (ST2) is used to show the effect of maintenance interventions on service life prediction and to compare with the results of the ST1 with a major rehabilitation.

4.5.1. Effect of a Major Rehabilitation Intervention

The rehabilitation intervention in ST1 included repairing deteriorated concrete areas, reinforcing steel protection against corrosion, general painting of structures, rehabilitation and conservation of secondary components and washing and disinfection of the two units. This rehabilitation intervention had a total cost of 180,000 €, which represented 48% of the capital cost of civil work components necessary to build a new tank with the same capacity.

The obtained SLR models were used to predict the average ADI of this storage tank before the rehabilitation interventions. The predicted average ADI of this tank using SLR models (Figures 1a and Table 4) is 31, corresponding to good condition, and the predicted maximum ADI is 47, corresponding to reasonable condition. The age of the water storage tank was 28 years when the tank was rehabilitated (in 2015).

The inspection of civil work components was carried out immediately after the rehabilitation intervention. For the scope of this research work, the visual inspection system was applied using the photographic record of this inspection and no anomalies were identified. Thus, the calculated average and maximum ADI is equal to zero, corresponding to the inexistence of detectable anomalies. The rehabilitation intervention improved the condition of civil work components, obtaining a better ADI than that predicted by the SLR models for a new asset (ca. +11, cf. Table 4). However, the deterioration for asset ages below 11 years is unknown and SLR models correspond to an extrapolation of the obtained model. For that reason, an average ADI of 11 is considered for the civil work components of the rehabilitated storage tank (i.e., the same value as the average ADI for a new asset).

Figure 4 depicts the deterioration model of the average ADI of civil work components for this water storage tank before and after rehabilitation intervention and the predicted service lives in both models for the maximum recommended and admissible deterioration levels. Due to the rehabilitation intervention, whose total cost represented 48% of the construction cost, the predicted service life of the civil work components should be corrected. For instance, the predicted service life after the rehabilitation is 69 years (instead of 41 years) considering the maximum recommended deterioration level and 98 years (instead of 70 years) when considering the maximum admissible deterioration level, corresponding to an increase of 28 years.

4.5.2. Effect of a Maintenance Intervention

The ST2 was subjected to maintenance intervention. Note that this storage tank was inspected before the rehabilitation intervention, while the previous storage tank with major rehabilitation was inspected only immediately after the intervention. The maintenance intervention in the second water storage tank includes the repair, treatment and waterproofing of concrete surfaces to solve a water leakage caused by cracking, representing only 5% of its construction cost. Despite the low cost of this intervention, a significant improvement in the condition of civil work components of this storage tank is observed by the new average ADI value of 22 (represented by the number 2' in Figure 5), compared to the average ADI value, before the rehabilitation, of 47 (represented by the number 1' in Figure 5).

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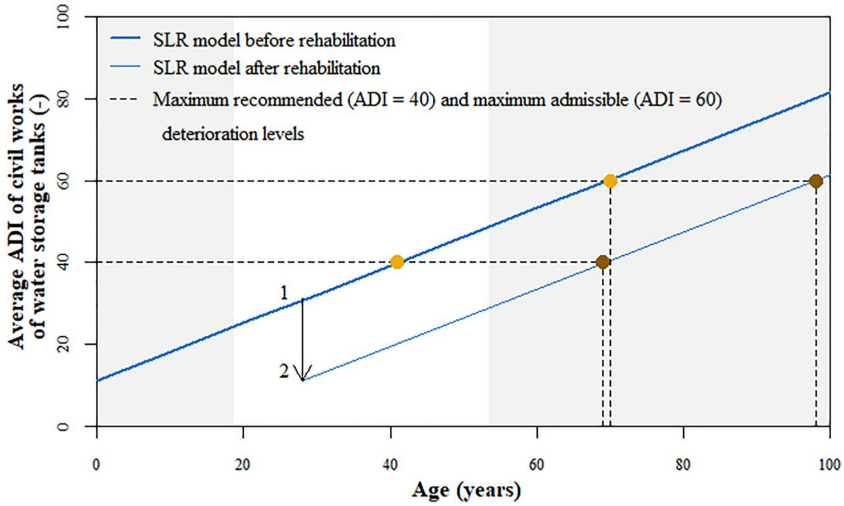

Figure 4. Illustration of service life prediction of civil work components of water storage tanks with major rehabilitation interventions using deterioration models of average ADI (ADI before and after rehabilitation interventions are represented by numbers 1 and 2, respectively).

The age of civil work components of this water storage tank was 29 years at the date of the rehabilitation intervention (in 2019), thus, the predicted average ADI by the SLRM is 30, lower than the observed value (i.e., 47), due to bad construction. The predicted service life of this storage tank after the minor rehabilitation intervention is 53 years considering the maximum recommended deterioration level and 80 considering the maximum admissible deterioration level, corresponding to an increase of 11 years.

A minor rehabilitation intervention, representing only 5% of its construction cost, allowed to increase the service life of civil work components by 11 years (corresponding to 18% of the reference service life for these components, i.e., 60 years), while a major rehabilitation intervention, representing 48% of the construction cost, allows to increase the service in 28 years (corresponding to 46% of the reference service life).

These results show that minor and periodic maintenance interventions can maintain the good asset condition and extend its service life quasi-indefinitely (even if the sum of the interventions reaches or exceeds the value of the construction of a new asset). This strategy is preferable to major sporadic rehabilitation interventions, not ensuring good condition during the asset service life.

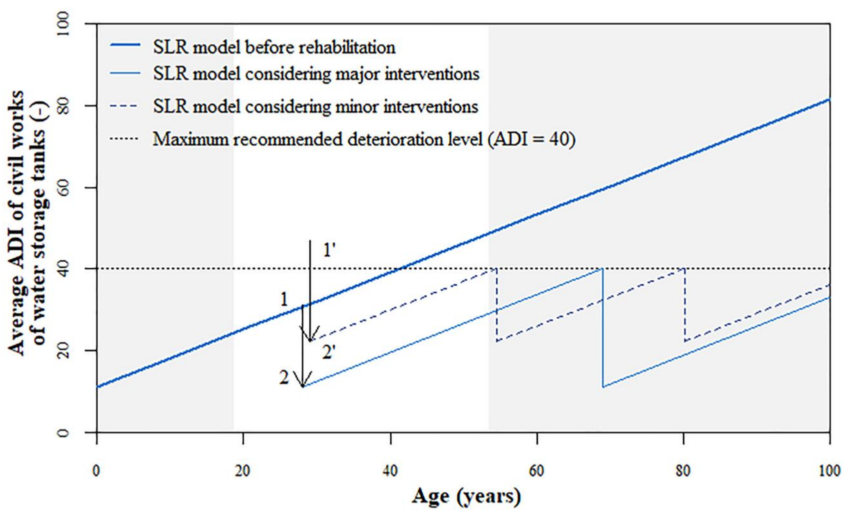

Figure 5. Illustration of SLRM adjustment considering minor and periodic interventions and major rehabilitation interventions.

Figure 5 illustrates the adjustment of SLRM when maintenance interventions (sometimes referred to as minor rehabilitation interventions) and major rehabilitation interventions occur.

5. Conclusions

This study aims to propose a methodology for the development of deterioration models and service life prediction of vertical assets of urban water systems and to demonstrate the application of the proposed methodology using different data sets. A four-step procedure for service life prediction is proposed: (a) Asset inspection and deterioration indices calculation; (b) Identification of main factors that contribute to asset deterioration; (c) Deterioration models development and validation; and (d) Service life prediction.

A data set composed of 22 water storage tanks and 17 wastewater pumping stations (Data set 1) was inspected and used to demonstrate the application of the proposed methodology. Firstly, factors that contribute to the deterioration of water storage tanks and wastewater pumping stations and respective deterioration mechanisms are analyzed and classified into three categories: physical, operational and environmental. The same case study is also used to develop simple and multiple linear regression models of average and maximum deterioration of civil work components and equipment of the studied assets. Most of the obtained simple linear regression models for average deterioration present determination coefficients higher than 0.6, showing their good predictive power.

The model validation is carried out using a different data set composed of four water storage tanks (Data set 2) to study the difference between predicted and observed values of ADI considering two measures of goodness-of-fit: root mean square error and the absolute value of the relative error. The simple models have better predictive power of asset deterioration than the multiple models. Moreover, the ADI_{av} models should preferably be used in comparison with the ADI_{max} models due to less variability of data.

Service life prediction is carried out using the obtained average deterioration models and considering two different maximum asset deterioration levels: maximum recommended deterioration level ($ADI_{av} = 40$) and maximum admissible deterioration level ($ADI_{av} = 60$). Predicted service lives are compared with the reference values in Portugal. These results allowed to validate the reference service lives since these values are similar to the predicted service lives. Furthermore, predicted service lives through multiple linear regression models are calculated to include the influence of other variables besides the asset age (i.e., tank volume, construction material of tank, type of practices, total hydraulic power and the existence of a building in wastewater pumping stations). A normal distribution of predicted service lives is considered to calculate the average service life and the data variability through the standard.

A third data set is used to illustrate and to discuss the effect of rehabilitation interventions on the service life of vertical assets. Two water storage tanks with different levels of rehabilitation interventions are used, one storage tank involving a major punctual rehabilitation intervention and the other involving maintenance intervention. Results show that periodic and well-established interventions are a preferable maintenance and rehabilitation strategy over major sporadic rehabilitation interventions since frequent maintenance interventions can maintain the good asset condition and extend its service life quasi-indefinitely.

It is important to notice that average and maximum deterioration indices should be calculated, providing complementary information for asset management. The average deterioration value indicates an average degradation, which is important for asset valuation; however, this value itself is not sufficient to identify critical components of the assets requiring urgent interventions. Conversely, the maximum deterioration value allows identifying the assets with the highest failure risk, with components in worse condition, being a more appropriate index for the prioritization of interventions.

Future works should include the increase of the inspected assets to obtain more robust deterioration models using linear regression analysis representative of Portuguese utilities and the use of other supervised machine learning algorithms for service life prediction, such as decision trees and neural networks. Additionally, more case studies should be analyzed to assess the effect of different maintenance and rehabilitation interventions on the asset condition (i.e., deterioration indices) and on the asset service life.

Notwithstanding, this study is a step forward in the development of deterioration models and service life prediction of urban water assets reducing the level of subjectivity usually inherent to these approaches. Additionally, the proposed methodology can be applied to any constructed asset with different infrastructure characteristics and O&M practices to develop deterioration models and to predict asset service lives in different countries.

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Data Availability Statement

The three data sets include infrastructural, operational and condition data that were provided by water and sewage utilities anonymously and confidentially, thus data will be available on request.

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