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Prediction of obsolescence degree as a function of time: a mathematical formulation

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Abstract

Predicting the obsolescence risk of components is an important challenge in system life-cycle management to improve its durability. The obsolescence degree measures the obsolescence occurrence risk. Thus, it expresses the probability that an entity will become obsolete within a given time horizon. Some mathematical techniques have already been proposed to deal with this problem. Recent studies have also shown that machine learning methods can be an effective way to improve prediction capability. However, these two classes of techniques assess the obsolescence degree by a scalar at observation time. This does not permit the projection of its possible evolution over time. This paper proposes a new approach based on [probability distribution to model the obsolescence degree as a function of time](#). Based on sales data, the obsolescence degree is modeled as a function of time, and the remaining time-to-obsolescence is inferred. The proposed approach is tested in the prediction of smartphones' obsolescence. This study's results are then analyzed while proposing future work to be carried out to increase the approach's applicability.

Keywords:

Obsolescence, System Life-cycle Management, Distribution function, Prediction.

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Nomenclature

t_0	Start date of manufacturing
t_f	End date of supplier support
t_{Ob}	Observation time
t_L	Obsolescence threshold real date
\hat{t}_L	Obsolescence threshold predicted date
OD	Obsolescence degree
TTO	Time-To-Obsolescence
$\mathbf{R} = \{p_r\}$	Subset of reference products
$\mathbf{C} = \{p_c\}$	Subset of current products
V	Visible data for the time interval $[t_0, t_{Ob}]$
H	Hidden data for the time interval $[t_{Ob}, t_f]$
$g(t, a, b, \dots)$	Obsolescence probability density
$G(t, a, b, \dots)$	Cumulative distribution function
α	Admitted prediction error

1. Introduction

Over time, everything ages, which makes obsolescence inevitable. However, if this happens during the system's useful life, it becomes a critical issue both financially and in terms of availability. According to Park [1], a product is durable when it is considered reliable, robust, and long-wearing. Since the early 1990s, the rate of component obsolescence has increased rapidly, which lead to systems durability issues.

Obsolescence is a multi-dimensional concept that can be defined in different ways. Sandborn [2] defines it as "the loss or imminent loss of original manufacturers of items or suppliers of items or raw materials". Obsolescence is

the "transition of a required item still in use from available to unavailable from the manufacturer.", as defined by [3]. Pecht and Das [4] suggest that obsolescence occurs at the technological level: "a part is obsolete when the technology that defines the part is no longer implemented". Obsolescence also occurs when a system, product, or service is no longer desired or supported, even if it is still in good working order, e.g., due to new technologies [5, 6, 7]. The industrial sectors such as automotive, military, aeronautics, etc., are the most exposed to obsolescence problems by building long field life systems. Patently, the availability of components or suitability of used technologies cannot be guaranteed during their useful life [8] leading to the necessity of setting up parts obsolescence management. Many researchers have already worked on obsolescence management. These studies have shown that obsolescence prediction is a prerequisite to better obsolescence issues mitigation. Predicting the occurrence of obsolescence is the key factor for proactive and strategic management [9, 10]. Obsolescence occurrence or risk can be estimated using an indicator called obsolescence degree. This indicator reflects the probability or chance that an entity will become obsolete.

As obsolescence is inevitable and its impact is a growing problem. Thus, obsolescence prediction techniques must be improved to ensure proactive management of obsolescence. To our knowledge, existing obsolescence prediction techniques are used to predict the obsolescence probability at an observation date. However, obsolescence can instead be seen as a process that results in an obsolete product. It is considered as an action that takes time to move from the state of availability to the state of unavailability. Consequently, it is of interest to propose models of evolution that predict not only the date of the beginning of the obsolescence process but, above all, its evolution (more or less rapid) over time. The goal of this paper is to model the obsolescence process mathematically. [The model is determined by analyzing the data using a statistical test. This test is used to select the best distribution that fits the sales data. The proposed approach is illustrated on smartphone obsolescence, and more specifically for the iPhone and Microsoft models.](#)

The remainder of this paper is structured as follows. Section 2 presents a literature review on obsolescence. The research methodology is presented in section 3. Section 4 illustrates the proposed mathematical modeling. In order to come up with a mathematical model of an obsolescence process, we then propose to follow an approach described in section 5. Section 6 describes the results of applying this approach on smartphones case to evaluate its effectiveness. Finally, conclusions are drawn, and future works are presented in section 7.

2. Related works

This section presents a literature review concerning the presented research work. The first part is devoted to defining the different concepts linked to obsolescence. The second part introduces the different techniques used in obsolescence prediction. At the end of these analyses, the scientific issues are enumerated.

2.1. The obsolescence concept

Obsolescence is defined as "the state of being which occurs when an object, service or practice is no longer wanted even though it may still be in good working order" [11]. This definition introduces one of the obsolescence causes, which is linked to consumer's wishes. In other words, obsolescence related to fashion effects and consumer psychology [12]. However, obsolescence can also be due to many other causes. Figure.1 shows the main obsolescence causes:

- the technological evolution or innovation [13, 14],
- the loss of original suppliers from the market for a variety of reasons,
- the lack of support and/or spare parts from suppliers [15],
- the directives, rules and other laws imposed by governments such as the Restriction of the Use of certain Hazardous Substances (RoHS) Directive [16].
- the fashion effects and consumer psychology [12].

According to [17, 18, 19, 20], obsolescence can be categorized as follows:

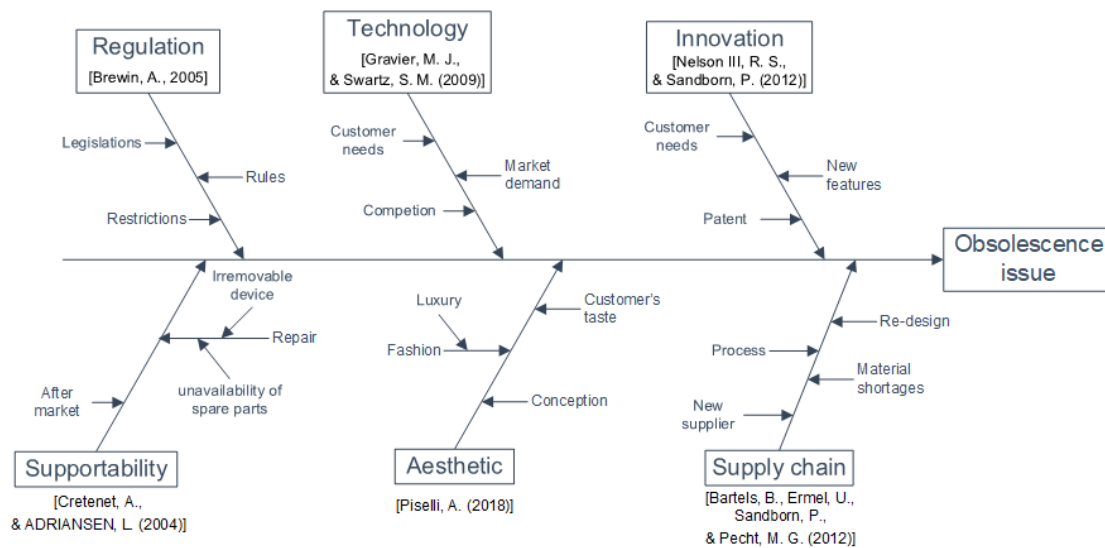


Figure 1: Obsolence causes mapping.

1. **Technological obsolescence** occurs when a new technology can replace an older one (higher camera resolution, for instance).
2. **Functional obsolescence** concerns the reduction of the usefulness, reliability, or performance of a system due to a change in its specific requirements. For example, the functionality "being able to save data on a CD" in laptops is more and more outdated with today's possibilities; it can be considered an obsolete feature. 55
3. **Logistical obsolescence** means that the system is no longer procurable due to diminishing manufacturing sources and material shortages.
4. **Ecological obsolescence** related to the discarding of a product for environmental reasons (e.g., high consumption of energy and satellite products, such as water and chemicals such as detergents) [19]. 60
5. **Economic obsolescence** concerns the disposal of a product because of its high cost of use, maintenance, and/or repair [21].

Technological obsolescence does not necessarily impose functional obsolescence. In [22], the authors consider that the difference between these two forms of obsolescence is that the technological one is related to the technology owner (supplier-side). In contrast, the cause of functional obsolescence is related either to users or customers (client-side). 65

Weerasuriya and Wijayanayake [23] distinguish three categories of obsolescence: software obsolescence, hardware obsolescence, and liveware (people) obsolescence. Moreover, we can add two other obsolescence classes, which are Hardware-MaSME obsolescence and Knowledge-Information-Data (KID) obsolescence. These classes are defined as follows: 70

1. **Hardware obsolescence.** It generally depends on the end of the supply and availability of a product [2]. Sandborn [17] assumes that the hardware obsolescence occurs when the hardware cannot execute the software upgrades.
2. **Software obsolescence.** It occurs when the software becomes obsolete for several reasons independently of the hardware according to Abili et al. [24]. Obsolete software is no longer updated and will be increasingly exposed to security breaches, thus threatening the company. 75

3. **Liveware obsolescence.** Obsolescence of people occurs in the form of skills and knowledge of hardware and software becoming obsolete. The extent of people’s obsolescence can be seen by the amount of training and certification available for people to learn new hardware and software [25]. According to Allen and De Grip [26],
80 ”Skill obsolescence will lead to increased job insecurity over the life course, making it difficult to maintain an adequate level of labor market participation of older workers”.
4. **Hardware-MaSME obsolescence.** SD-22 Guidebook, [27], identifies Hardware-MaSME (Materials and Structural, Mechanical, and Electrical) obsolescence due to strict regulations on hazardous materials, the unavailability
85 of tools, or the retirement of suppliers.
5. **Knowledge-Information-Data (KID) obsolescence.** A piece of knowledge, information, or data is considered obsolete when it has lost its use-value. In other words, it does not contain its initial value as defined at the time of its creation (an outdated theory or information that is not usable or unused).

In this paper, we adopt the idea of Boissie [28] who argues that obsolescence occurs when an event directly impacts
90 the use, usefulness, functioning, and/or alters or renders unusable a product.

2.2. Obsolescence management

Sandborn [29] defines three main categories of obsolescence management methods: (i) Reactive management, which is applied to resolve obsolescence quickly and immediately when it occurs unexpectedly. (ii) Proactive obsolescence, which is used to predict the obsolescence of the critical components that are at risk of becoming obsolete. It
95 is intended to predict obsolete parts before their actual obsolescence. (iii) Strategic management is implemented from the system development to reduce its obsolescence risk and optimize its life-cycle by using several data: obsolescence data, logistics data, technology forecasting, and demand forecasting.

The main task of proactive management is the ability to forecast the product obsolescence risk. In this sense,
100 several techniques have already been developed.

2.3. Obsolescence prediction techniques

A prerequisite for any proactive obsolescence management approach is predicting when an element of the system-of-interest would become obsolete. This prediction can only be probabilistic, depending on many parameters, both endogenous and exogenous, to that system. Predicting obsolescence could allow rational decision-making and therefore
105 reducing as much as possible negative impacts. In this context, numerous studies have been developed to create models to forecast the obsolescence risk. As shown in Table.1, the suggested techniques can be divided into mathematical and machine-learning methods.

2.3.1. Mathematical methods

Several statistical techniques have been used to predict systems obsolescence. The first method developed in [8]
110 was based on the Gaussian model to estimate the life cycle phases of a product. Based on sales curves, the ”window of obsolescence” was defined as $[\mu + 2,5\sigma, \mu + 3,5\sigma]$, where μ and σ are the mean and standard deviation of the Gaussian function, respectively. This method is useful on part types having an evolutionary parametric driver. For instance, for flash memory chips, the evolutionary parametric driver is the memory size. This method is based on the assumption of the sales curve’s normality, which is not always true. To overcome these limitations, Sandborn
115 et al. [30] proposed a technique based on linear regression to predict obsolescence for electronic parts without clear evolutionary parametric drivers. Later, Sandborn [31], proposed a novel approach based on modeling the procurement life. In this article, obsolescence is defined as the loss of procuring a part from its original manufacturer. Therefore, the obsolescence date is determined as the difference between the forecasted procurement life and the introduction date using regression analysis. Other statistical methods have also been used for obsolescence prediction, such as
120 linear and logistical regression, time series, Markov chain, and flow graph, see Table.1.

According to [30], statistical techniques are restricted to predicting only small future changes. In this vein, Jenab et al. [32] present a model that includes a flow graph concept to calculate the mean time-to-obsolescence. Nystrom

and Leclerc [33] argue for a great need to improve predictions where significant changes are encountered.

Over the past decade, many researchers from various disciplines have become interested in the application of machine learning to improve problem-solving in many fields [34, 35, 36]. Thus, in recent years, researchers have applied machine learning techniques to predict obsolescence [20].

2.3.2. Machine learning based methods

The machine learning techniques used by researchers for obsolescence forecasting are displayed in Table.1. Jennings et al. [41] used Machine Learning techniques to define two methods: one called Obsolescence Risk Machine Learning (ORML) to predict the state (obsolete or available) of parts and the other called Life Cycle Machine Learning (LCML) to predict the date of obsolescence. The smartphone case study showed that the Random Forest algorithm seems to be the most effective method in terms of accuracy, interpretability, and maintainability/flexibility. However, the LCML framework results suffer from poor precision (error between 1 and 5 years), which makes it useless for short life-cycle systems.

Grichi et al. [42] used the Random Forest technique to predict the obsolescence status (Available/ Discontinued) of the part using the same database. The dataset used to illustrate this approach contains information about the launch date, some technical features, and the smartphone's status. Later, the Random Forest technique has been combined with a meta-heuristic genetic algorithm [39], and with a meta-heuristic particle swarm optimization, [43] to optimize the forecasting of obsolescence risk.

2.4. Scientific issues and problem statement

A careful study of the work cited in the previous section shows that they seek above all to determine the obsolescence risk at a given moment of observation or study. These methods aim at detecting the probability of obsolescence of subsystems or components. However, they do not provide insight into the evolution of obsolescence afterward (see Figure.2).

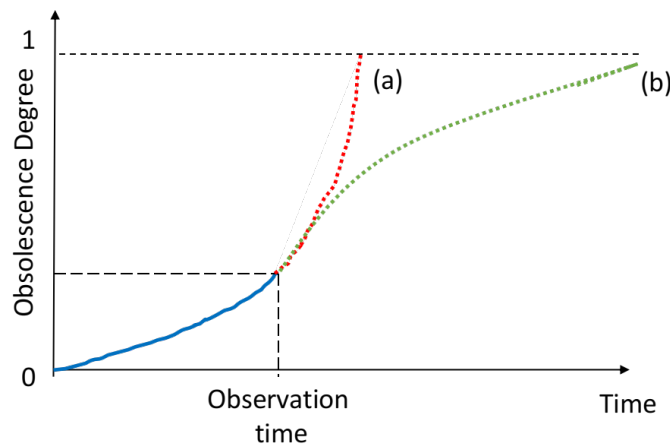


Figure 2: The obsolescence evolution over the time.

Suppose the only predictive information available on the obsolescence of a component is its point value, estimated at the time of observation. In that case, decisions to mitigate the consequences of obsolescence may not be appropriate. As shown in the figure, two different evolution of the obsolescence degree (exponentially fast (curve a) or slow (curve b)) require two different mitigation approaches. This means that even imperfect a priori knowledge of obsolescence risk evolution over time will be a valuable aid to make mitigation decisions. This paper aims to model the obsolescence degree as a function of time to inform decision-makers about the obsolescence degree and its evolution over time.

To our knowledge, apart from the technique proposed by [18], none of the prediction techniques found in the literature address the evolution of obsolescence over time. As it has been mentioned in Section.2.3.1, this technique is based on the number of sold products, modeled as a Gaussian distribution. The obsolescence window is defined using

Table 1: The forecasting obsolescence techniques.

CATEGORY	METHOD	APPLICATION	AUTHORS	Obsolescence	Remarks
Mathematical	Gaussian distribution	Integrated circuits	Solomon et al. (2000) [8]	End of production	The obsolescence zone is determined according to its distance from the mean, measured in standard deviations, on the Gaussian sales curve [$\mu + 2.5\sigma, \mu + 3.5\sigma$]
	Linear regression	Electronic parts	Sandborn, P(2017)[31]	Non-procurable from the original manufacturer	The obsolescence date is calculated as the difference between the procurement life and the introduction date.
	Logistical Regression	Electronic systems	Gravier, M. J., & Swartz, S. M. (2009) [13]	Technological obsolescence	Based on the logistic regression, obsolescence was assessed both as a binary (in or out of production) and a ternary (0, 1, or more manufacturers) variable.
	Logistical Regression	Field Programmable Gate Arrays	Gao, Liu, & Wang (2011) [37]	Technological obsolescence	The obsolescence date is calculated based on the production date, productive technology and some characteristics of the FPGA using logistical regression.
	Markov model	Numerical Example	Jaarsveld & Dekker, (2011) [38]	Logistical obsolescence (obsolescence of service parts)	Using the Markov model with two states (healthy demand vs. dead demand) Jaarsveld and al. present method to forecast obsolescence risk of spare parts from demand data.
	Flow graph	Hardware/ software (HW/SW) signalling systems	Jenab, K. et al. (2014)[32].	Technological obsolescence	A dynamic model based on graph theory concept to predict the obsolescence dates for HW/SW subsystems.
	Markov process and Compound Poisson Process	Generated Data	Yosra et al. (2019) [39]	Technological obsolescence	The model uses multiples states with a positive demand rate as well as negative demand.
	Time series modeling	Electronic part (Flash Memory)	Jungmok Ma et al. (2017) [40]	End of production	The time series based obsolescence forecasting method for electronic parts is presented. It used to forecast the sales data.
Machine Learning	Random Forest, Support Vector Machine, Neuronal Network	Smartphone	Jennings, C. et al. (2016) [41]	Technological obsolescence	This approach classifies products into two states available or obsolete.
	Random Forest	Smartphone	Grichi et al. (2017) [42]	Technological obsolescence	RF is used to select the main features to optimize the products classification (available or obsolete).

the standard deviation and the average of sales, for example, as shown in Figure 3.

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Two problems are then to be pointed out concerning the basis of the prediction models. First, sales information is rarely openly available. It is, therefore, necessary to use other data sources for prediction. Secondly, sales curves are very rarely Gaussian in that after the start of the component's decline, the sales curve follows an asymmetric trend, tending asymptotically more or less "slowly" towards 0. This is, for example, the case for modules supplied by Original Equipment Manufacturers (OEM) in the automotive industry. Indeed, even if the series life for a module is between 3 and 5 years, the duration of the contractual sales as spare parts is between 10 and 15 years after the end of commercialization [28]. In this case, the distribution of sales is far different from a Gaussian distribution. A Gaussian model is then a too simplistic model that does not reflect component sales long after the obsolescence process, in spare parts, as shown in Figure 3. Therefore, such a prediction of obsolescence is not sufficient to determine a real obsolescence risk. The obsolescence degree must be modeled by more realistic models and especially as a function of time. The goal here is to propose a prediction method that defines the obsolescence degree as a "good enough" function of time. This method is qualified as a dynamic prediction method.

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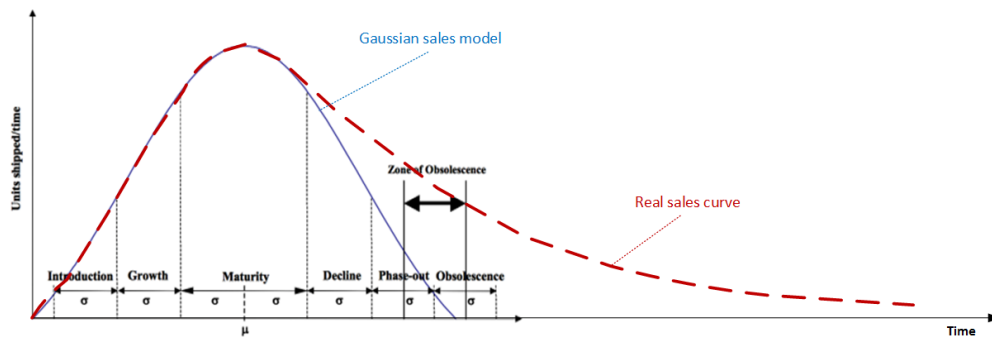


Figure 3: The Gaussian sales model according to Bartels et al. [18] and the real sales curve

3. The research methodology

To establish a model for predicting the obsolescence degree, we conducted an extensive literature review to identify the main concepts to consider in a prediction model.

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3.1. The research hypotheses

The illustrative case is about the iPhones obsolescence prediction. As we have not been able to find detailed sales data over time (on specialized websites or the Apple website), the idea was to identify data that can best reflect the evolution of sales. The choice went to Google Trends.

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In this line, two assumptions are made.

- **Assumption 1.** *Google Trends data reflects well enough the total sales of various models of iPhones.*

Total sales data were collected from the Statista platform during the 2008-2018 period¹. They represent the number of iPhones products sold worldwide. The Google Trends data can be collected freely from Google trends, see Figure.4. Our correlation analyses showed a very strong correlation between Google Trends data and total sales data; the correlation coefficient between these two sets of data is about $R^2 = 95.93\%$. This means that relying on Google Trends can reflect quite well the sales dynamics over time.

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This study aims to discover a well enough prediction model for every individual iPhone model. However, since we do not have access to such confidential data, we made another assumption verified.

¹<https://www.statista.com/statistics/263401/global-apple-iphone-sales-since-3rd-quarter-2007/>

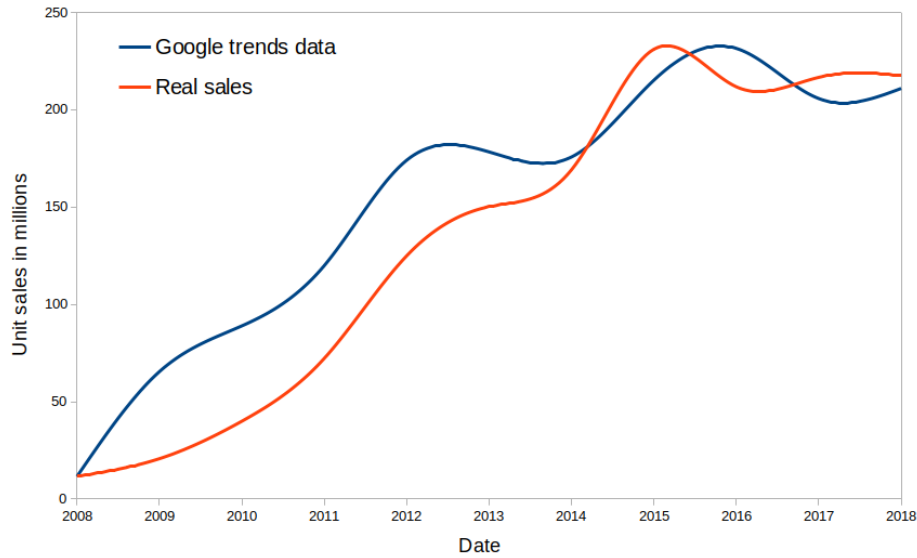


Figure 4: The total sales data evolution vs Google trends data evolution.

- **Assumption 2.** Sales of individual models of iPhones (e.g., 3GS, 4, 5S) follow the same pattern as the total sales of iPhones.

We were able to verify this assumption on a subset of smartphones for which the dates of occurrence of obsolescence were known. According to Apple (see <https://support.apple.com/fr-fr/HT201624>), a product is obsolete seven years after the end of its commercialization .

We have therefore compared the results of the prediction model applied to iPhone models and this 7-year horizon. The results are presented in Section 6. It appeared that the proposed Weibull model provides predictions with an estimation error of at most one year over a 10-year horizon (compare this with the precision of the techniques published in Jennings et al. [41]; between 1 and 5 years, cf. section.??). This represents an error of at most 10%. This precision, in the absence of any other individual sales information, seems quite reasonable.

3.2. The best candidate distribution law

To model the evolution over time of the obsolescence degree, it was decided to identify a distribution law that best approximates the data provided by Google Trends. 3 distribution laws were analyzed: normal, gamma, and Weibull. The study consists of using a Kolmogorov-Smirnov test² algorithm in Python to compare distributions and determine the most appropriate distribution law [44]. The distribution with the highest P-value is the most relevant one. This study allowed Weibull's law to be chosen as the most flexible and practical one that fits well with the outputs of Google Trends with p-value= 0.046 for iPhone 4S, as shown in figure 5.

The table 2 shows the P-values of the different distributions for the examples used in this test. As can be seen, for two of the smartphones, the Weibull distribution has the highest P-value defining it as the most adequate distribution. However, the test also shows that for iPhone 5, the Normal distribution has the best P-value. This observation indicates that the choice of the Weibull distribution in some cases can generate a prediction error. In the work presented in this paper, this phenomenon has not been studied; it is the subject of studies that will be carried out in our future work.

3.3. Validation of the prediction model

In order to validate the prediction model and the approach, we have chosen to use the products for which time-to-obsolescence were available (production end date + a support duration offered by the supplier)³. The time-to-

²Kolmogorov-Smirnov test is a hypothesis test used to determine if a sample follows a given law known by its continuous distribution function

³For Apple products, the support duration is seven years, <https://support.apple.com/fr-fr/HT201624>

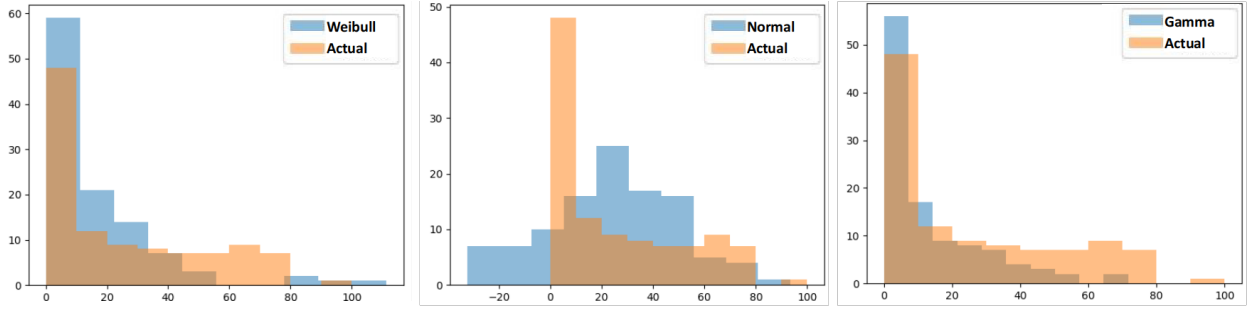


Figure 5: Comparison of different distributions for iPhone 4S.

Table 2: Presentation of the different P-values for each test example

	iPhone 4s	IPhone 5	iPhone 3G
Distribution	P-value		
Weibull	4.64E-02	2.93E-14	1.29E-02
Gamma	7.24E-07	2.93E-14	3.09E-03
Normal	4.43E-04	1.11E-06	4.86E-07

obsolescence is the length of time between the observation moment and when the smartphone is considered obsolete. 210
The studied products were subdivided into two classes:

- the *reference* base, noted \mathbf{R} , is used to determine prediction models for the products p_r for which the time-to-obsolescence is known and the obsolescence degree can be inferred. Products in the base \mathbf{R} are those for which the time-to-obsolescence prediction is close to reality, i.e., below an accepted risk factor, called α .
- the *current* base, noted \mathbf{C} , is composed of the products p_c for which a part of the data is voluntarily hidden. 215

The product-of-interest (let say iPhone 7 for which the obsolescence risk should be evaluated) is observed over the time interval $[t_0, t_f]$, where t_0 and t_f are the start date of manufacturing and the end date of supplier support. This time interval is more precisely subdivided into two. Figure 6 this principle:

- $[t_0, t_{Ob}]$. It covers those data between t_0 and the observation time moment t_{Ob} .
- $[t_{Ob}, t_f]$. This interval covers the time for which the evolution of the obsolescence degree should be identified. 220

Data of this p_c are accordingly divided into two sets:

- the set of visible data V (belonging to the interval $[t_0, t_{Ob}]$),
- the hidden data H (belonging to the interval $[t_{Ob}, t_f]$).

In the interval $[t_0, t_{Ob}]$, we choose the product p_r whose sales are the most similar of the visible data of p_c ; i.e. V . One fills the hidden data of the p_c by the data of the p_r relating to $[t_{Ob}, t_f]$. In other words, it is assumed that since the query/sales trends of the p_c and p_r products are close during the $[t_0, t_{Ob}]$ period, they should also remain similar over the $[t_{Ob}, t_f]$ interval. The time-to-obsolescence and the obsolescence degree are then calculated for this reconstructed data of the p_c product. This assumption is in turn qualified by determining the prediction error committed insofar as the data of p_c are known over the interval $[t_0, t_f]$ and it is possible to calculate this error. 225

By varying the observation time, t_{Ob} , it becomes possible to construct the obsolescence degree's evolution and thus calculate the time-to-obsolescence. 230

Section.5 gives the complete details about this proposed approach.

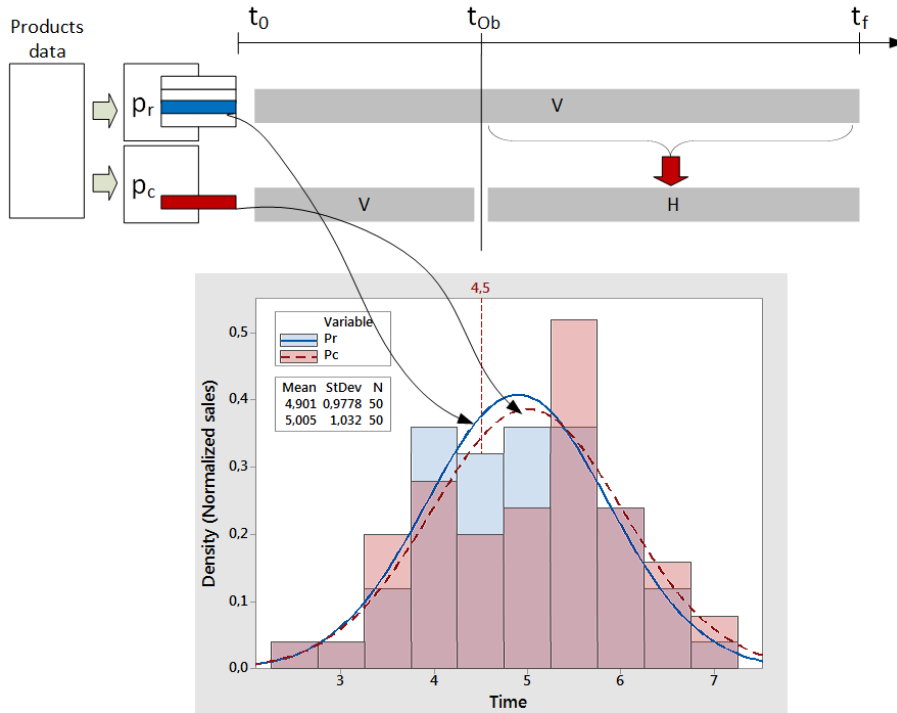


Figure 6: Principle of model validation exemplified for two products: a reference product p_r and an product-of-interest p_c

3.4. Example

235 Consider that the system studied is a smartphone introduced on the market at t_0 and withdrawn from the market at t_f . Our approach aims at a moment of observation t_{Ob} to study the evolution of the obsolescence degree OD of this system in time and to predict the remaining time-to-obsolescence TTO . To do this, the different iPhones are divided into two subgroups: (i) the reference base \mathbf{R} which includes smartphones with a known OD evolution, and (ii) the current base \mathbf{C} that includes the models (i.e. the products-of-interest) whose OD is not known, of which our studied system.

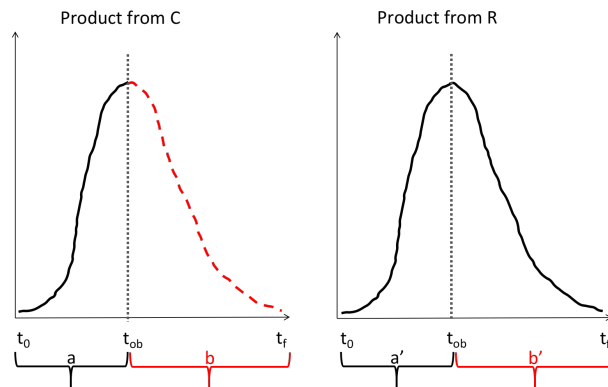


Figure 7: Determination of the obsolescence evolution of the \mathbf{C} base product.

240 As shown in Figure 7, the studied system's obsolescence evolution is determined from the data of the reference base \mathbf{R} by comparing data belonging to the interval a and data belonging to the interval a' . If they are similar, then the probability density is determined by completing the interval b by those data coming from the interval b' .

4. Mathematical formulation of obsolescence degree

Before proposing the prediction method in this section, we will propose a series of definitions clarifying the concepts used in the following developments, see Figure.8.

4.1. Main concepts

The obsolescence O of an product-of-interest e is considered to be a continuous random variable.

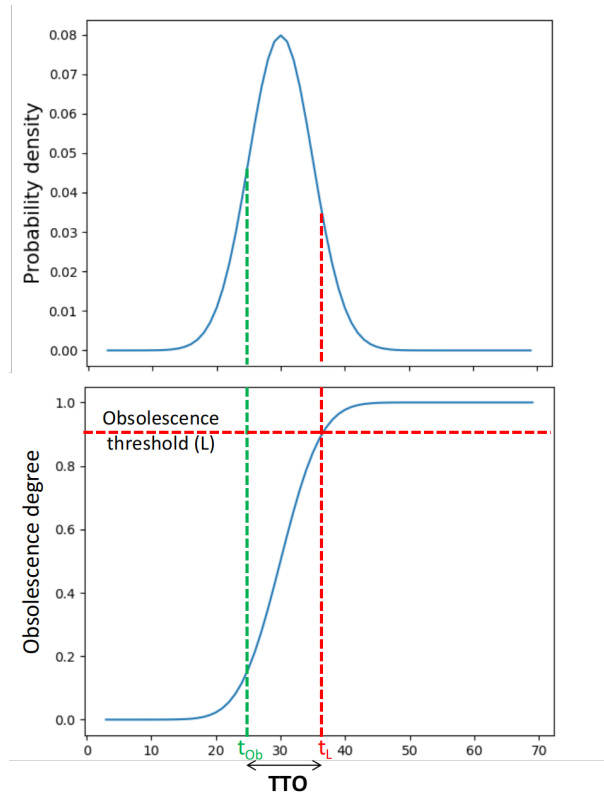


Figure 8: Obsolescence probability density (top) and Obsolescence cumulative distribution (bottom)

Definition 1. Obsolescence probability density. The obsolescence O of an product-of-interest e is defined by its probability density $g(t, a, b, \dots)$ where t represents time, and a, b, \dots are the parameters of the function g .

Definition 2. Obsolescence Degree, OD. For a given entity e , object to obsolescence, the obsolescence degree, noted $OD(e) \in [0, 1]$ (or the obsolescence cumulative distribution), is a real number that expresses the probability of exposure to obsolescence at an observation time t_{Ob} , computed as follows:

$$OD(e) = p(t \leq t_{Ob}) = \int_{-\infty}^{t_{Ob}} g(t, a, b, \dots) dt \quad (1)$$

The entity e is said to be obsolete if its $OD(e) \geq L$ where L is a predefined obsolescence threshold. L depends on the system-of-interest and can be defined by the field experts.

Definition 3. Time-To-Obsolescence, TTO. For a defined threshold of obsolescence L , the Time-To-Obsolescence is the time interval between the moment this threshold is reached t_L and the moment of observation t_{Ob} :

$$TTO = t_L - t_{Ob} \quad (2)$$

255 4.2. *Obsolescence probability density modeling*

As indicated in the previous section, the obsolescence probability density is defined by a general function $g(t, a, b, \dots)$. We also mentioned that the features of the entity-of-interest directly influence this function. Thus, the mathematical function best adapted to represent various forms, usually encountered by the data, is the one that allows to better approximate them.

260 To do this, a statistical test is used to determine the best distribution that fits the product sales data. This test compares different distribution laws, and the one that corresponds to most of the products in the reference database is used for the test products. As mentioned above, this work considers obsolescence as a function of time. Thus, the obsolescence degree is defined as the cumulative distribution function of the best distribution chosen by the statistical test. Thus, the parameters of the identified distribution are calculated using the algorithms of statistical software (such as Python, R, Minitab, Matlab, etc.).

5. **Obsolescence prediction approach**

The proposed approach provides the evolution of obsolescence degree (OD) of products based on sales data presented by Google Trends data (see Figure.9). These steps are described hereafter.

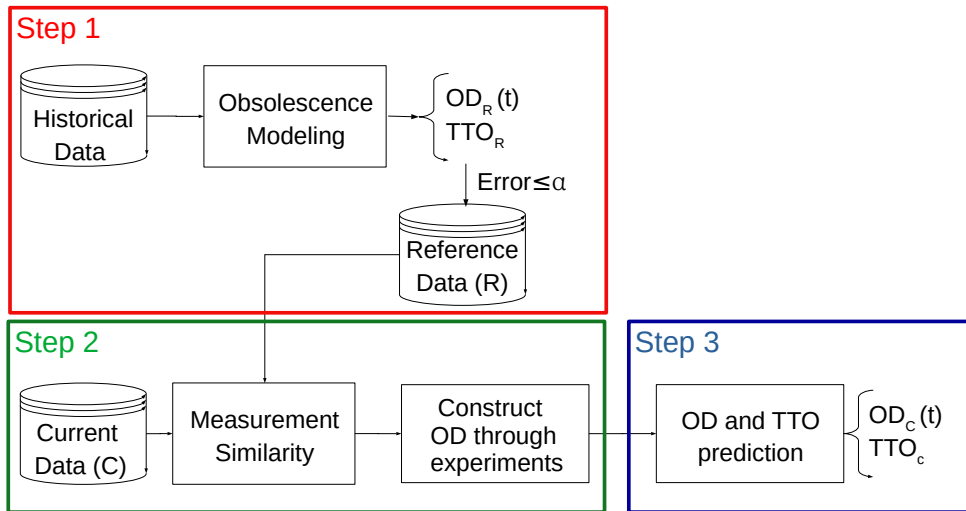


Figure 9: Proposed approach for OD and TTO prediction

5.1. *Step 1: Construction of the reference base R*

270 5.1.1. *Data Collection*

The first step is to collect the data to identify the product’s obsolescence. This data contains the sales qualities of each product or other information to estimate them. This information is extracted from Google Trends. Based on this data, the obsolescence probability density and the obsolescence degree of the product are determined.

5.1.2. *Obsolescence modeling*

275 As mentioned in section 4, the obsolescence degree can be modeled using a **distribution law**. In this step, the function of the obsolescence degree evolution of each product is determined by fitting the sales data to the **best distribution by applying a statistical test**. The proposed approach requires a similar obsolescence model for products of the same brand. For this purpose, among the different distributions selected, only the distribution that models the majority of the products to be used in the similarity test is considered.

280 Thus, the obsolescence degree is calculated as a **CDF of the most relevant distribution to fit the sales data**. The predicted obsolescence date is then calculated from the TTO value using Formula 2, where the ground experts provide the value of L .

5.1.3. Select the products to build the **R** base

The determination of the products of the **R** base depends on the prediction error. Indeed, this base must contain the products for which the prediction error remains lower than a limit of acceptability, called α . This means that after modeling the probability densities of the set of products as a Weibull distribution, we will select only those products e_i for which the difference between the predicted obsolescence date (\hat{t}_L) and the real value (t_L) remains less or equal to the threshold, α . More precisely:

$$R = \{e_i \mid \text{abs}(\hat{t}_L - t_L) \leq \alpha\}$$

where α is called admitted prediction error.

To fix the idea, in the case of Apple smartphones, the time interval (i.e., $[t_0, t_f]$) is about ten years, and the admitted prediction error is defined as 10%. Therefore, it is considered that a threshold of 12 months $\alpha = 12\text{months} = 10\%$ is an acceptable level of error; this value may be changed according to the study context.

The obsolescence density function of the products P_r is stored in the reference library **R** to be used afterward in the next step.

5.2. Step 2: Similarity measurement

5.2.1. Determination of the current base **C**

The global database containing the studied products is subdivided into two classes: the reference base **R** and the current base **C**. As mentioned above, the products in the **R** base are those for which the obsolescence date prediction is close to reality (the prediction error $\leq \alpha$). The other products are stored in the current base **C** to validate our approach.

5.2.2. Similarity measure

Remember that the database **C** contains those products for which the data are known for $[t_0, t_f]$; but they are subdivided into two subsets V and H to verify the suggested approach. This step aims to find the most similar product from the reference base R , whose data are the most similar of the subset V related to the current product of interest P_c . To do so, a similarity test is used. This test assumes that similar data exist in close proximity, i.e., similar data are close. The proposed similarity measure takes into account all data in the reference base **R** and compares in terms of distance the similarity with the known data of the product studied P_c .

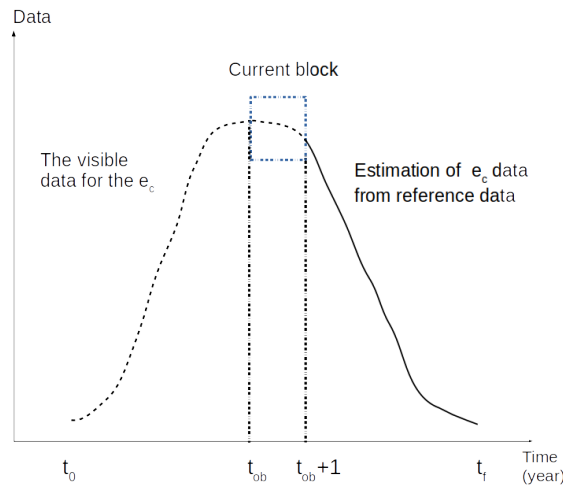


Figure 10: Illustration of the similarity measure process.

The sales data of all the reference product is stored in the library **R** as a vector (x_i, y_i) where x_i is the time and y_i is the number of queries (i.e., a relevant model of the sales quantity, see Assumption 1, in section 3.1). There are many similarity distance measurements in the literature, i.e., cosine similarity, Manhattan distance, Euclidean distance, etc.

[45]. In this research, the Euclidean distance was chosen because of its simplicity and wide use in the scientific literature.

To calculate the distance between the two vectors i and j , we must first set the start dates: $t_0(i) = t_0(j)$. Then we adopt $t_f = \max(t_f(i), t_f(j))$. The interval $[t_0, t_f]$ is then subdivided into n observation points. It can be for example an annual observation point. The distance can then be calculated using the formula 3.

$$d(i, j) = \sqrt{\sum_{k=1}^n (y_{i,k} - y_{j,k})^2} \quad (3)$$

5.2.3. Construct the obsolescence probability density for $P_C \in \mathbf{C}$

The objective here is to validate the prediction technique. To do so, we will compare the data belonging to the V interval of the product-of-interest with the data of all the products of the reference base \mathbf{R} defined on the same interval. Thus, we are looking for the product of the R database whose evolution over the $[t_0, t_{ob}]$ interval is the most similar to the behavior of product-of-interest. Once this product P_r is identified, we will replace the data on the $[t_{ob}, t_f]$ interval of the product P_c by the data of P_r on the same interval. It is thus implied that the two products follow the same evolution. The obsolescence probability function of the product P_c is then made.

The proposed measurement metric is used to complete the obsolescence probability density of the product-of-interest whose life-cycle is partially known by extending the observation time window each year, as described in the Algorithm.1.

Algorithm .1 The proposed similarity measure.

Data:

- The different probability densities of the reference products.
- The part of the visible data V of the current product P_c .
- Obsolescence threshold value L .

Step 0: Report data from the reference base \mathbf{R} at t_0 .

Step 1:

Split the observation time interval into N blocks : t_{ob_i} for $i \in \{1, 2, \dots, n\}$

Step 2:

Repeat

Calculate the Euclidean distance between current and reference data at t_{ob_i} .

Until: Obsolescence is achieved, i.e. $t_{ob_i} = t_L$

Result: Probability density of current product is successfully built.

5.3. Step 3. Predict the obsolescence degree and the remaining Time-To-Obsolescence

At the end of the previous stage, we have, therefore, all the best estimates of the degrees of obsolescence, observation time after time, see Figure.10. In other words, the curve representing the obsolescence degree is available. Knowing the obsolescence threshold, L , the TTO can be read directly on the abscissa $t_L - t_{Ob}$.

6. Applications and results

Smartphones are the devices most subject to rapid renewal due to their obsolescence, whether technical, software, or aesthetic. Therefore, they are used as the illustrative case of the prediction approach.

6.1. iPhone smartphones obsolescence prediction

More specifically, various iPhone models were used to validate the proposed approach for two main reasons. First of all, Apple defines the obsolescence dates of smartphones⁴. The support for smartphones is coming to an end 7 years after the end of manufacturing. This provides an obsolescence date in accordance with the definition of the ISO 62402 standard (page 10,2019). In addition, we know the launch date of each iPhone, which corresponds to t_0 . Finally, the number of iPhone models offered at the same time remains relatively small compared to competitors such as Samsung or Xiaomi. This reduces the influence of one iPhone on others without patently eliminating it completely. Some iPhone are then used for the analysis, see Table.3.

Table 3: The subset of the reference iPhone models.

Model	Discontinued date	Obso_date (+7y)
iPhone 4	September 10, 2013	2020
iPhone 5	September 10, 2013	2020
iPhone 5C	September 9, 2015	2022
iPhone 5S	March 21, 2016	2023
iPhone 6 Plus	September 7, 2016	2023
iPhone SE (1st gen)	September 12, 2018	2025
iPhone X	September 12, 2018	2025

To build the library of different obsolescence density functions, we used the results from Google Trends which allows to follow the evolution of queries (in Google’s search engine) on a particular subject. The evolution (the y-axis is 100% normalized) can be requested by country or worldwide. As indicated, we have assumed that a smartphone can be considered obsolete when it can no longer attract users. This assumption has been validated through experiments carried out, see section.3.

In the case of this study, we therefore looked for the evolution (i.e. the trend) of queries on Google about different iPhone models. Figure.11 shows the interface of Google Trends and its results obtained for iPhone 4.

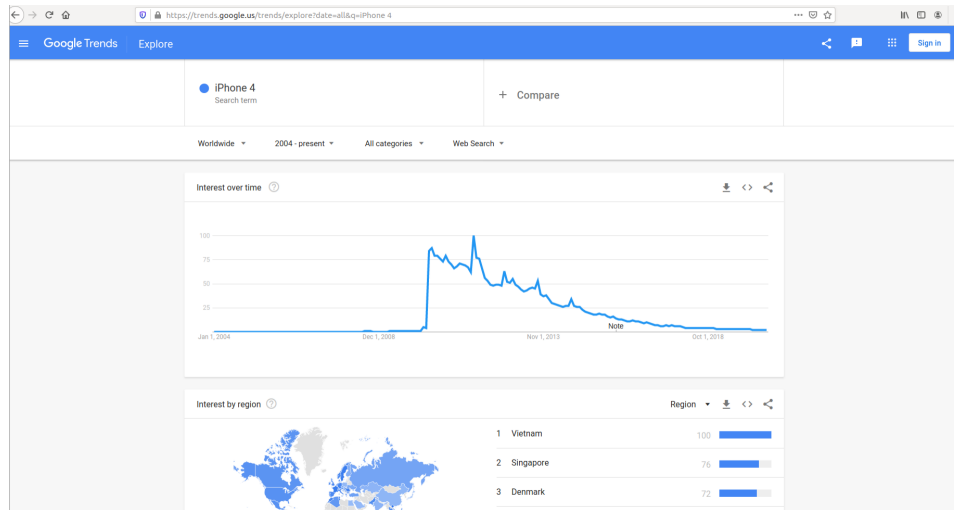


Figure 11: The interface of Google Trends for the example of iPhone 4.

We have extracted data from Google Trends for all iPhone models. Among those models, the prediction error was less than $\alpha = 10\%$ for $\mathbf{R}=\{4, 5, 5C, 5S, 6Plus, SE, X\}$. As a common basis \mathbf{C} we chose the models 3G,3GS,4S.

⁴<https://support.apple.com/fr-fr/HT201624>

6.1.1. Obsolescence study for the reference database \mathbf{R}

The needed parameter at this step is the obsolescence threshold L to use for the rest of the study. In Sandborn's work [8, 18], the obsolescence interval starts at 2.5σ after the mean value according to a Gaussian distribution. This corresponds to a threshold of 95% in this case.

355 As far as we are concerned, we have chosen a threshold of 90% from a pessimistic perspective leading to the determination of a solution earlier than the threshold of Sandborn's model. The choice of the threshold is therefore linked to the general policy of obsolescence management. If for a product, obsolescence does not create real problems (and therefore high resolution costs) an optimistic approach could have been used. In this case, the threshold of 95% (or more) seems quite reasonable. On the other hand, when product obsolescence can generate problems whose resolution requires a significant effort (financial and human), a 90% threshold leads managers to a proactive solution.

360 Looking at the Weibull distributions of the reference smartphones, it was possible to determine the obsolescence threshold at 90% as it can be seen in Figure.12.

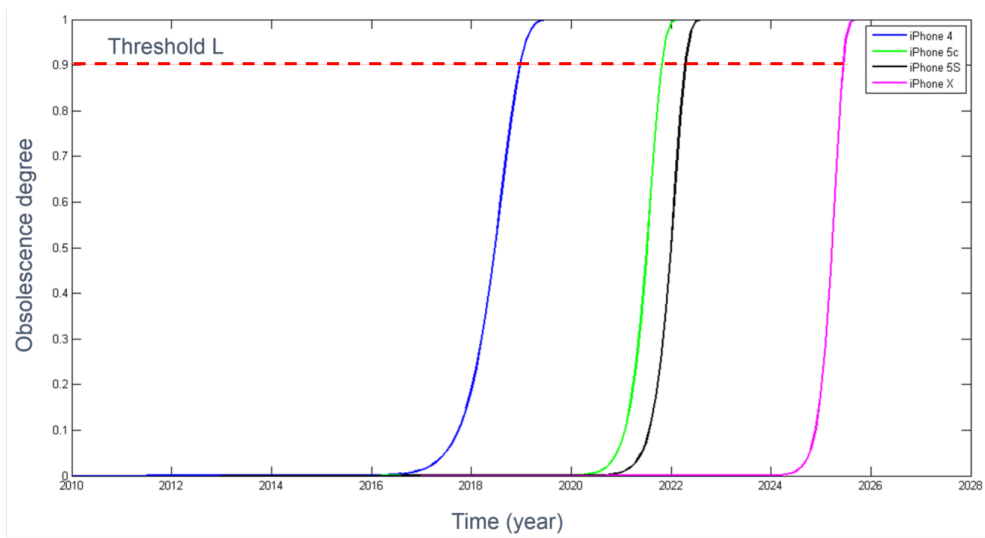


Figure 12: Determination of the obsolescence threshold from OD of $P_r \in \mathbf{R}$

The results presented in Figure.13 prove that the model used based on the Weibull distribution can detect the date of obsolescence with a root mean square error (RMSE) equal to $7.5\% \leq \alpha = 10\%$, which corresponds to about 9 months of uncertainty.

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6.1.2. Obsolescence study for the current database \mathbf{C}

In this part of the application, one should find OD and TTO for the 3 products of \mathbf{C} ; the obsolescence threshold being set just before.

Determination of OD for $P_c \in \mathbf{C}$.

370 In section.5.2, the principle of iterative construction of the obsolescence curve for the \mathbf{C} commodities was detailed. The iteration step was chosen equal to 1 year. Each iteration step for any product P_c is performed as follows:

- Define t_{Ob} .
- Determine the product P_r whose data during the interval V is closest to the data in interval V of P_c .
- Complete the data from the H interval of the P_c with the data from the H interval of the P_r ⁵.
- Determine the Weibull density function for the data thus obtained.

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⁵It is therefore considered that the evolution of the P_c during H should be the same as the evolution of the P_r over the same interval.

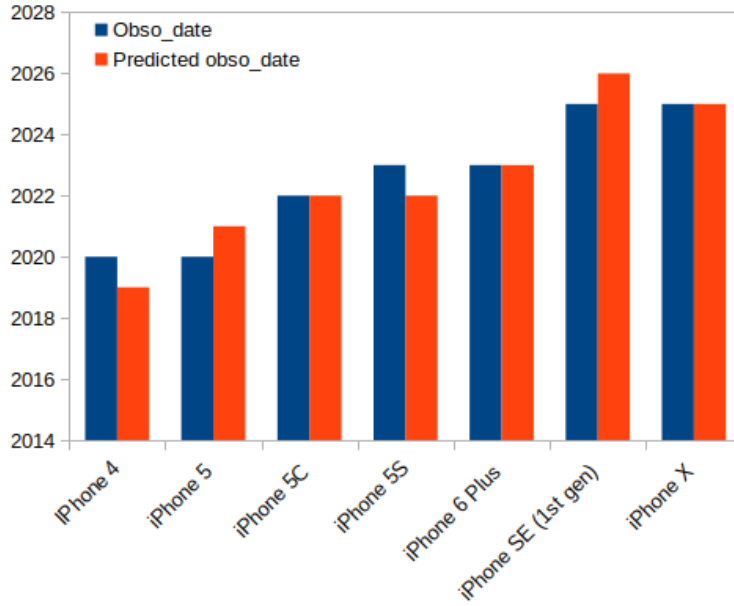


Figure 13: Time-To-Obsolescence predicted by Weibull distribution for $P_r \in \mathbf{R}$ compared to the known obsolescence date as defined by Apple

- Determine the OD of the P_c using equation 4:

$$OD = p(t \leq t_{ob}) = \int_{-\infty}^{t_{ob}} \frac{k}{\lambda} \left(\frac{t}{\lambda}\right)^{k-1} e^{-\left(\frac{t}{\lambda}\right)^k} dt \quad (4)$$

For the next iteration, update the observation date $t_{ob} := t_{ob} + 1y$.

Determination of TTO for $P_c \in \mathbf{C}$.

For each iteration performed in the previous step, the TTO must also be calculated. To do this, we simply need to make the difference between the t_L , the obsolescence time and the observation time t_{ob} , see equation 2. This iteration is repeated until reaching the real obsolescence date. The results of the prediction process are shown by Figure.14. 380

6.1.3. Results

Table.4 summarizes the performance of the suggested approach and compare it to the reality as defined by Apple.

In order to estimate the predictive capability of the proposed approach, the prediction results of TTO and OD are compared to the "real" results. 385

Comparison of predicted and real TTO. The real TTO data are obtained using the 7-year duration definition provided by Apple. The prediction error is quantified by an RMSE defined at each observation date. This error ranges from 0.04 (i.e. 0.4 months) to 0.37 (i.e. 4.4 months). Comparing these errors against the lifetimes (from start of manufacture to the obsolescence declared by Apple) of the three products 3G, 3GS and 4S, gives the error percentage of 0.37%, 2.2%, 3.6%. 390

Comparison of predicted and real OD. In the same manner, the predictive capability is quantified using the root mean square error for each iPhone. The results are 0.16%, 0.06% and 0.02% for 3G, 3GS and 4S respectively. 395

6.2. Microsoft smartphones obsolescence prediction

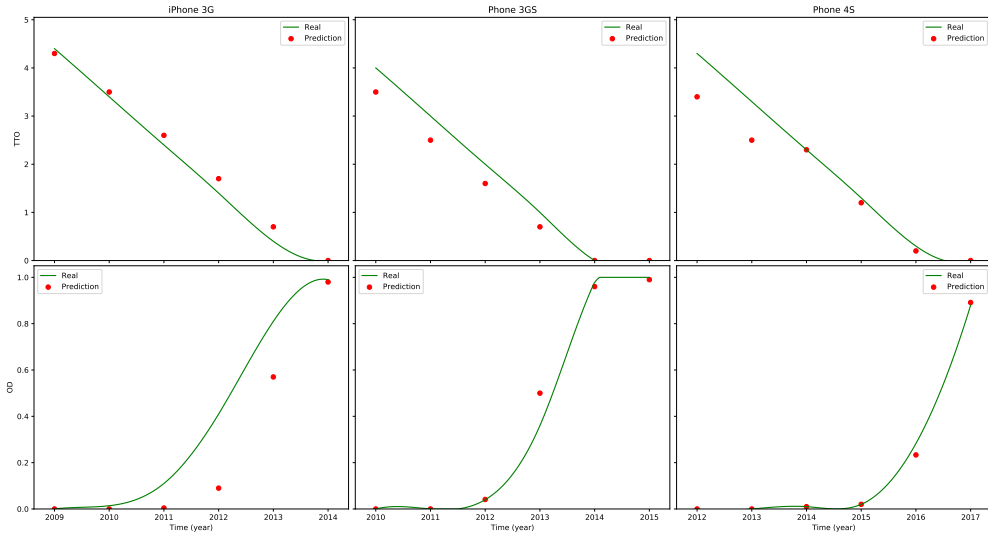


Figure 14: OD and TTO prediction for different iPhone devices.

Table 4: Results summary for Apple devices.

	Observation date	TTO_real	TTO_predicted	RMSE	OD_real	OD_predicted	RMSE
iPhone 3G	2009	4,4	4,3	0,04	0	0	0,16
	2010	3,4	3,5		0,014	0	
	2011	2,4	2,6		0,11	0,004	
	2012	1,4	1,7		0,41	0,09	
	2013	0,4	0,7		0,81	0,57	
	2014	0	0		0,99	0,98	
iPhone 3GS	2010	4	3,5	0,22	0	0	0,06
	2011	3	2,5		0	0	
	2012	2	1,6		0,04	0,041	
	2013	1	0,7		0,36	0,5	
	2014	0	0		0,98	0,96	
iPhone 4S	2012	4,3	3,4	0,37	0	0	0,02
	2013	3,3	2,5		0	0	
	2014	2,3	2,3		0,02	0,02	
	2015	1,3	1,2		0,23	0,19	
	2016	0,3	0,2		0,83	0,84	
	2017	0	0		0,95	0,96	

The same approach is applied to Microsoft smartphone models. Since the operating system of the Microsoft phones is changed to Android, many models became obsolete⁶. The life cycle of Microsoft smartphones is about five years. Based on this information, the various Microsoft models are used to study the proposed approach's performance. As mentioned above, the obsolescence date corresponds to the end of support (EOS) date announced by the manufacturer.

As shown in Table 5, nine devices are chosen to be in the base \mathbf{R} : $\mathbf{R} = [\text{Lumia 430, 535, 550, 640, 640 XL, 730, 830, 930, 1520}]$. Data from Google trends are collected to be used as the sales data for each product. Thus, to find the best distribution law to fit this data, the statistical test described in section 3.2 is applied. The comparison between Gamma, Normal and Weibull distributions for six different devices shows that the best distribution chosen is the Gamma distribution. According to Table 6, the data of four devices out of 6 are fitted as Gamma distribution. The different P-values are given.

Based on the Gamma fitting of data, the obsolescence threshold is determined. As shown in Figure 15, the

⁶<http://www.windowphonearea.com/will-microsoft-end-support-windows-phone/>

Table 5: Devices used in in the reference base.

Device	Introduction date	End-of-support
Lumia 430	03-2015	10-2018
Lumia 535	12-2014	10-2018
Lumia 550	11-2015	12-2019
Lumia 640	04-2015	06-2019
Lumia 640 XL	04-2015	06-2019
Lumia 730	06-2014	11-2018
Lumia 830	9-2014	10-2018
Lumia 930	07-2014	10-2018
Lumia 1520	11-2013	10-2018

Table 6: Statistical test to select the best distribution for Microsoft devices sales data.

Device / distribution	Gamma	Normal	Weibull
Lumia430	5.13E-18	3.05E-07	1.64E-06
Lumia535	2.44E-03	1.10E-06	5.93E-06
Lumia550	1.57E-03	6.32E-08	3.59E-04
Lumia730	3.40E-11	1.16E-07	3.40E-11
Lumia930	2.08E-02	9.00E-06	4.04E-07
Lumia640	2.08E-02	9.00E-06	4.04E-07

threshold in this application is equal to 99%. This threshold is then used in the prediction of DO and TTO.

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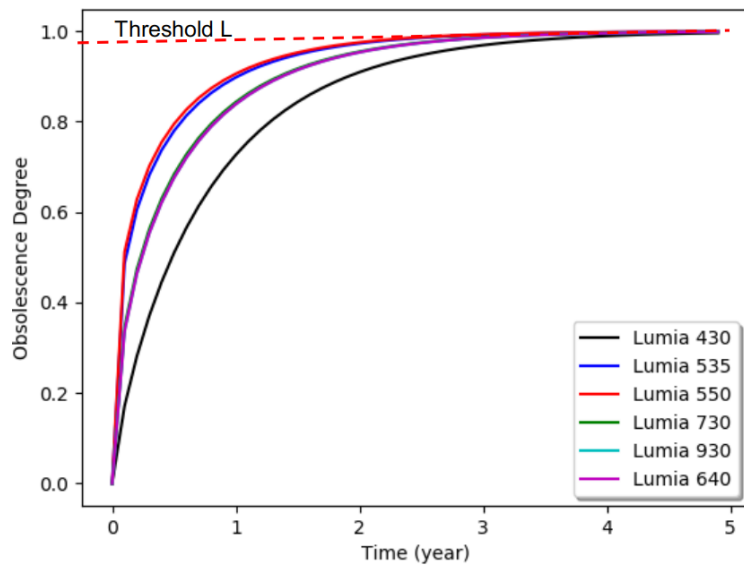


Figure 15: Determination of the obsolescence threshold.

This application considers that the obsolescence of Microsoft brand products follows the Gamma law. Based on this, three devices are used to validate our approach using the similarity test described in section 5.2.2. The results of the prediction process for these test devices are given by the Figure 16.

Table 7 displays the test results on the devices Lumia 650, Lumia 950, and Lumia 950 XL. For the OD prediction, the mean square errors are 2%, 4%, and 3%, respectively. Thus, OD can be predicted over six years of observation with a maximum error of 3 months. Table 7 shows the TTO prediction results with an error between 0.29 and 0.50.

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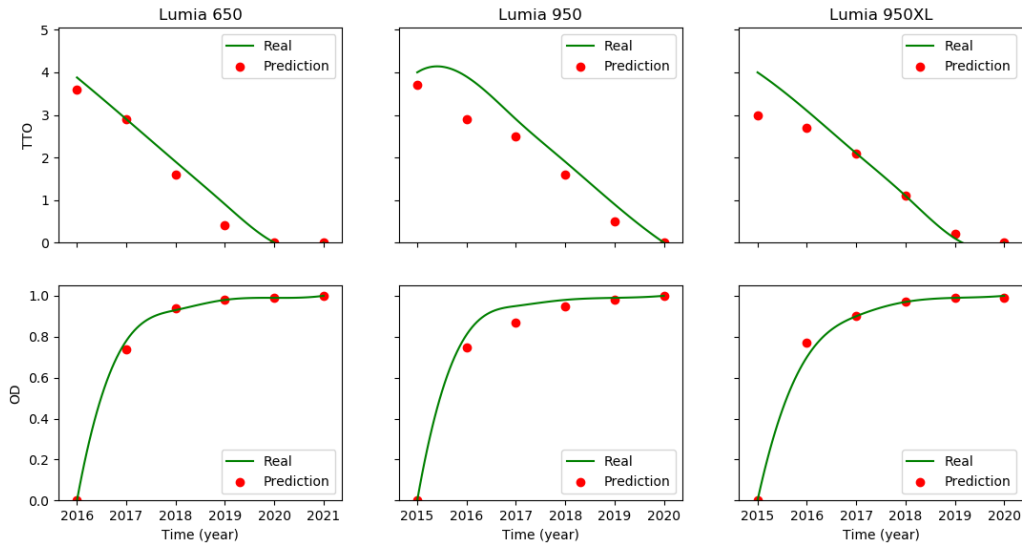


Figure 16: OD and TTO prediction for different Microsoft devices.

6.3. Discussion

The prediction errors of TTO and OD remain very small and acceptable. Among the reasons that can explain these errors, the use of Google Trends data instead of actual sales data seems to be a major contributor. However, in the absence of actual sales data, we do not currently have techniques to minimize this error.

Another limitation of this work is related to the use of the proposed similarity measure that considers the hidden H data of the P_c product of interest as similar to the P_r data over the interval $[t_{ob}, t_f]$. For example, if we take the visible data of P_c over 3 months and the observation horizon varies up to 10 years, there is a good chance that we will find many similar products over this interval. In other words, the smaller this interval is, the more likely we are not to choose a good product from the \mathbf{R} base. Since the obsolescence problem is less important at the beginning of the product launch, the prediction error (related to the wrong choice of P_r at the beginning) improves as the interval increases.

7. Conclusion and perspectives

This paper proposes a dynamic approach to assessing the obsolescence degree or obsolescence risk over time. This new approach is a data-based technique for estimating the evolution of system obsolescence based on data. Detecting and predicting system obsolescence is as challenging as any forecasting since it should inform decision-makers of potential risks. Methods and techniques (based on mathematical tools or machine learning techniques) have already been used to predict the date of obsolescence. However, these works are limited in detecting obsolescence since they do not consider the obsolescence degree evolution over time.

In this paper, we overcome these limitations by proposing a methodology for predicting obsolescence based on mathematical modeling. The validation of the proposed approach was done by studying smartphone obsolescence. The contribution, therefore, concerns the prediction of obsolescence as a function of time. The results are encouraging, even if many areas for improvement are open.

Table 7: Results summary for Microsoft devices.

Device	Observation date	TTO_real	TTO_predicted	RMSE	OD_real	OD_predicted	RMSE
Lumia 650	2016	3.88	3.60	0.29	0.00	0.00	0.02
	2017	2.90	2.90		0.78	0.74	
	2018	1.90	1.60		0.93	0.94	
	2019	0.90	0.40		0.98	0.98	
	2020	0.00	0.00		0.99	0.99	
Lumia 950	2015	4.00	3.70	0.50	0.00	0.00	0.04
	2016	3.90	2.90		0.81	0.75	
	2017	2.90	2.50		0.95	0.87	
	2018	1.90	1.60		0.98	0.95	
	2019	0.90	0.50		0.99	0.98	
	2020	0.00	0.00		1.00	1.00	
Lumia 950 XL	2015	4.00	3.00	0.44	0.00	0.00	0.03
	2016	3.10	2.70		0.70	0.77	
	2017	2.10	2.10		0.90	0.90	
	2018	1.10	1.10		0.97	0.97	
	2019	0.10	0.20		0.99	0.99	
	2020	0.00	0.00		1.00	0.99	

First of all, a data-based approach to assessing the obsolescence degree should be considered. Data-based approaches are best suited to solving such complex problems and have been successful in other areas. Thus, an effective obsolescence management strategy begins by contextualizing the system in its environment to identify the relevant characteristics that describe system obsolescence. Recall that the obsolescence causes are different. Thus, it is necessary to characterize the environment of the studied component (or system). Thus, a complete obsolescence management strategy must go beyond the study of the system's functional and non-functional requirements to study the system within its environment. This may include many other factors such as regulations, competitors, the user, the economic climate, manufacturers, etc.

To go further, the authors believe that it is necessary to jointly use mathematical models (the prediction of obsolescence based solely on models) and artificial intelligence techniques. This permits the best use of large amounts of collected information from heterogeneous sources from one side and the power of mathematical theories from the other. The current work of the authors focuses on the description and exploitation of these mixed approaches.

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