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Forecasting Obsolescence Risk and Product Life Cycle With Machine Learning

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***Abstract*— Rapid changes in technology have led to an increasingly fast pace of product introductions. For long-life systems (e.g., planes, ships, and nuclear power plants), rapid changes help sustain useful life, but at the same time, present significant challenges associated with obsolescence management. Over the years, many approaches for forecasting obsolescence risk and product life cycle have been developed. However, gathering inputs required for forecasting is often subjective and laborious, causing inconsistencies in predictions. To address these issues, the objective of this research is to develop a machine learning-based methodology capable of forecasting obsolescence risk and product life cycle accurately while minimizing maintenance and upkeep of the forecasting system. Specifically, this new methodology enables prediction of both the obsolescence risk level and the date when a part becomes obsolete. A case study of the cell phone market is presented to demonstrate the effectiveness and efficiency of the new approach. Results have shown that machine learning algorithms (i.e., random forest, artificial neural networks, and support vector machines) can classify parts as active or obsolete with over 98% accuracy and predict obsolescence dates within a few months.**

***Index Terms*— Diminishing manufacturing sources and material shortages, electronic parts, life cycle stages, machine learning, obsolescence, sustainment.**

I. Introduction

OBSOLESCENCE occurs in almost all industry sectors, generally due to the availability of alternatives that are more cost-effective, those that can achieve better performance and quality, or some combination of the two. Currently, 3% of the world's electronic products become obsolete monthly due to technical, functional, legal, and style obsolescence [1], [2]. For example, technical obsolescence occurs in the music industry. Music was first recorded to vinyl, and then made portable by eight-track tapes and then cassette tapes. Since the 1980s, compact disks have superseded cassettes. Recently, the music industry is observing technology shift from MP3 to music streaming services. Each societal shift causes immense amounts of obsolete inventory from audio players to physical music vessels.

Over the past few years, the flow of electronic components and software into traditionally non-electronic products has increased the problem of component and software obsolescence in more industries. As obsolescence grows, the need for proactive management increases because reactive strategies are often more expensive than proactive strategies. Reactive strategies require additional resources (i.e., time and materials) to solve and can contribute to further delays that impact customer satisfaction. Proactive strategies allow firms to have more time to plan and react with an effective and low-cost approach [3]–[6]. The cornerstone of a viable proactive obsolescence management strategy is an obsolescence forecasting methodology.

In this paper, two machine learning-based methodologies that address obsolescence risk and life cycle forecasting are presented. Specifically, one method addresses obsolescence risk forecasting; the other method addresses life cycle forecasting. Obsolescence risk forecasting and life cycle forecasting are both umbrella terms under obsolescence forecasting. However, obsolescence risk forecasting refers to a process that predicts the probability that a given part will become obsolete. Life cycle forecasting refers to a process that predicts the length of time during which the product will be procurable. Both approaches can be adapted to forecast obsolescence in scenarios where obsolescence is present. The two techniques integrate machine learning to adapt over time to make forecasts more accurate as more obsolete instances are observed by the model. Specifically, the objective of this paper is to answer the following questions.

1) How can large-scale product obsolescence forecasting be addressed using machine learning?
2) Does machine learning-based obsolescence forecasting offer improvement over current obsolescence forecasting methods?

The contribution of this paper is to introduce a novel data-driven approach for large-scale obsolescence forecasting using machine learning. To demonstrate the approach, a real-world application example is presented using three machine-learning algorithms. These machine-learning algorithms are applied to a large data set of over 7000 unique cell phone models with known in-production or out-of-production statuses.

The remainder of this paper is organized as follows. In Section II, a brief overview of existing obsolescence methods

Manuscript received January 18, 2016; revised June 20, 2016; accepted June 27, 2016. This work was supported by the National Science Foundation through the Division of Industrial Innovation and Partnerships under Grant 1238335. Recommended for publication by Associate Editor P. Sandborn upon evaluation of reviewers' comments.

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Digital Object Identifier 10.1109/TCPMT.2016.2589206

adopted by industry is presented. This includes: 1) current life cycle forecasting methods; 2) current obsolescence risk forecasting methods; 3) difficulties experienced in industry; and 4) current commercial obsolescence forecasting methods. In Section III, the methodologies of life cycle forecasting using machine learning (LCML) and obsolescence risk forecasting using machine learning (ORML) are presented. Section IV provides a case study of LCML and ORML that is used to predict obsolescence in the cell phone market. Section V discusses the limitations of the LCML and ORML frameworks. Section VI provides conclusions that include a discussion of research contribution and future work.

II. Obsolescence

Obsolescence can have an immensely negative effect on many industries, the ramifications of which have generated a large body of research around obsolescence-related decision making and more generally, around studying products through the product's life cycle. To address the economic aspect of obsolescence, cost minimization models are presented for both the product design side and the supply chain management side of obsolescence management [7]–[9]. Extensive work has also been conducted on the organization of obsolescence information [10]–[12]. The organization of information allows one to make more accurate decisions during the design phase of a product's life cycle.

Obsolescence management and decision-making methods have three groups: 1) short-term reactive; 2) long-term reactive; and 3) proactive. The most common short-term reactive obsolescence resolution strategies include lifetime buy, last-time buy, aftermarket sources, and identification of alternative or substitute parts, emulated parts, and salvaged parts [3], [13]. However, these strategies are only temporary and can fail if the organization runs out of ways to procure the required parts. More sustainable long-term alternatives are design refresh and redesign. But these alternatives usually require large design projects and can carry costly budgets. In a 2006 report, the U.S. Department of Defense (DoD) estimated the cost of obsolescence and obsolescence mitigation for the government to be U.S. \$10 billion annually for the U.S. government [14]. The estimates in the private sector could be higher because smaller firms cannot afford the systems DoD uses to track and forecast obsolescence.

Obsolescence forecasting can be categorized according to two groups, obsolescence risk forecasting and life cycle forecasting. Obsolescence risk forecasting generates a probability that a part or other element may fall victim to obsolescence [15]–[18]. Life cycle forecasting estimates the time from creation to obsolescence of the part or element [2], [19], [20]. Using the creation date and life cycle forecast, analysts can predict a date range when a part or element will become obsolete [2], [13], [19], [20].

Obsolescence forecasting is important in both the design phase of the product and the manufacturing life cycle of the product. It is estimated that 60%–70% of cost during a product's life cycle is caused by decisions made in the design phase [21]. Understanding the risk level for each component in proposed bills of materials developed in the design phase can help designers determine designs that have lower risk of component obsolescence and therefore reduce the lifetime cost impact. In addition, obsolescence forecasting can be used throughout a product's life cycle to analyze predicted component obsolescence dates and find the optimal time to administer a product redesign that will remove the maximum number of obsolete or high obsolescence risk parts.

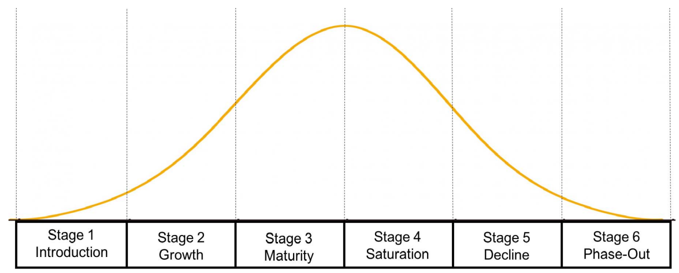

Fig. 1. Product life cycle model.

A. Life Cycle Forecasting

The key benefit of life cycle forecasting is that it allows analysts to predict a range of dates when the part will become obsolete [2]. These dates enable project managers to set time frames for the completion of obsolescence mitigation projects; aid designers in determining when redesigns are needed; and enable managers to more effectively manage inventory. All of these effects of life cycle forecasting reduce the impacts of obsolescence [2].

Currently, most life cycle forecasting methods are developed based on the product life cycle model. As shown in Fig. 1, the model includes six stages: introduction, growth, maturity, saturation, decline, and phase out. When sales fall enough to be considered in phase out, many firms will discontinue the product, rendering it unsupported and obsolete.

Solomon *et al.* [20] introduced the first obsolescence forecasting method that identified characteristics to estimate the life stage of a product. Characteristics such as sales, price, usage, part modification, number of competitors, and manufacturer profits, when combined, could estimate the stage and whether or not the product is close to phase out. However, the lack of a forecast indicating obsolescence in the immediate future is not useful for predictions of when, or if, a part might become obsolete in the long term [20]. One current method for life cycle forecasting utilizes data mining of sales data of parts or other elements and then fits a Gaussian trend curve to predict future sales over time [2], [19]. Using the predicted sales trend curve of a part, peak sales are estimated by the mean (denoted as μ in Fig. 2). Stages are then estimated based upon standard deviations (denoted as σ in Fig. 2) from the mean. Obsolescence forecasting predicts the zone of obsolescence. This zone is given between $+2.5\sigma$ and $+3.5\sigma$ and gives the lower and upper bound time intervals for when a part or element will become obsolete [19].

A potential shortcoming of this approach, however, is the assumption of normality of the sales cycle [19]. Another

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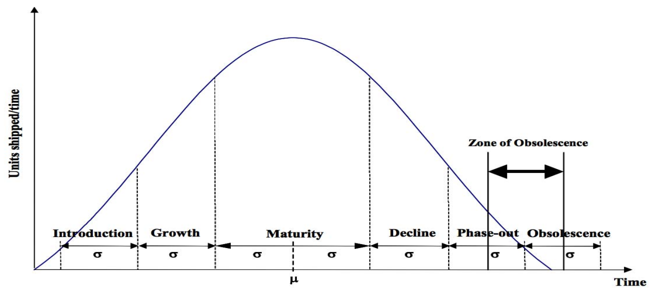

Fig. 2. Life cycle forecast using Gaussian trend curve.

method involves organizing part information sales, price, usage, part modification, number of competitors, and manufacturer profits into an ontology to better estimate the current product life cycle stage of the part and then fit a trend line using current sales to predict future sales [21]–[23]. The zone of obsolescence is estimated using the predicted future sales, but does not assume normality since the factors utilized in the Gaussian trend curve [25] are used to estimate the stage, not the curve shape.

Currently, most life cycle forecasting methods in the literature are built upon the concept of product life cycle model. This method involves data mining parts information databases for introduction dates and procurement lifetimes to create a function with the input being the introduction date and the output being the estimated life cycle [13]. The advantage of this method is the lack of reliance on sales data, the ability to create confidence limits on predictions, and the simplicity of a model with one input and one output [13]. However, this does not take into account the specifications of each individual part. As a result, the model could be skewed. For example, two manufacturers with two different design styles both make similar products. The first manufacturer creates a well-designed product and predicts that the specifications will hold in the market for five years. The second manufacturer does not conduct market research and introduces a new product every year to keep specifications up to market standards. Over the next five years, the first company will have one long life data point and the second company will have five short life data points; this will skew the model into predicting that the approximate life cycle is shorter than it actually is because the model does not take into account specifications.

B. Obsolescence Risk Forecasting

Another common method used for predicting obsolescence is obsolescence risk forecasting. Obsolescence risk forecasting involves creating a scale to indicate the levels of the chance of a part or element becoming obsolete. The most common of these scales is to use probability of obsolescence [15]–[18]. These scales, like product life cycle stage prediction, use a combination of key characteristics to identify where the part falls on a scale.

Currently, two simple models exist for obsolescence risk forecasting; both use high, medium, and low ratings for key obsolescence factors that can identify the risk level of a part becoming obsolete [15], [16], [18]. Rojo *et al.* [18] conducted a survey of current obsolescence analysts and created an obsolescence risk forecasting best practice that looks at numbers of manufacturers, years to end of life, stock available versus consumption rate, and operational impact criticality as key indicators for potential parts with high obsolescence risk. Josias and Terpenny [16] also created a risk index to measure obsolescence risk. The key metrics identified in this technique are manufacturers' market share, number of manufacturers, life cycle stage, and company's risk level [16]. The weights for each metric can be altered based on changes from industry to industry. However, this output metric is not a percentage, but rather a scale from zero to three (zero being no risk of obsolescence and three being high risk).

Another approach introduced by van Jaarsveld uses demand data to estimate the risk of obsolescence. The method manually groups similar parts and watches the demand over time [17]. A formula is given to measure how a drop in demand increases the risk of obsolescence [17]. However, this method cannot predict very far into the future because it does not attempt to forecast out demand, which causes the obsolescence risk to be reactive.

C. Obsolescence Forecasting Scalability

For a method to be scalable, the framework must have the ability to adjust the capacity of predictions with minimal cost in minimal time over a large capacity range [22]. To achieve scalability in industry, obsolescence forecasting methods must meet the following requirements.

1) Do Not Require Frequent (Quarterly or More Often) Collection of Data for All Parts: The reason for this requirement is that many methods involve tracking sales data of products to estimate where the product is in the sales cycle [2], [19], [20]. A relatively small bill of material with 1000 parts would require a worker to find quarterly sales for 1000 parts and input them every quarter (or even more frequently). Companies have built Web scrapers to aggregate these data automatically, like specifications and product change notifications, but many manufacturers do not publish individual component sales publicly on the Web. Large commercial parts databases have contracts with manufacturers and distributors to gain access to sales data, but many companies not solely dedicated to aggregating component information have difficulty obtaining this information. The lack of ability of most companies to gather sales data makes forecasting methods requiring sales of individual parts extremely difficult to scale.

2) Remove All Human Bias About Markets: Asking humans to input opinion on every part leads to methods that are impractical for industry. In addition, finding and interviewing subject matter experts for long periods of time can be costly. Also, there may exist biases inherent in subject matter experts when estimating obsolescence risk within their field of expertise. These biases are largely due to experts being so ingrained in the traditions of their field that new products or skills can seem inferior when in fact they may supersede the expert's traditional preferences.

3) Account for Multifeature Products in the Obsolescence Forecasting Methodology: Methods have been developed to predict obsolescence of single-feature products [2], [19], for example, flash drives. The flash drive may vary slightly in size and color but only has one key feature, memory. When a flash drive does not have sufficient memory to compete in the flash drive market, companies phase out that memory size in preference for ones with larger memory. Creating models for single-feature products like memory is straightforward because the part has only one variable that only causes one type of obsolescence, technical. However, multifeature products, for example, a car, can have many causes for becoming obsolete, and this makes it much more challenging to model. Some examples might include: 1) style obsolescence that comes from changes such as eliminating cigarette lighters, ashtrays, and the removal of wood paneling from the sides of cars; 2) the functional obsolescence of cassettes, and now even CD players for MP3 ports or Bluetooth; and 3) the technical obsolescence of drum brakes giving way to safer and longer running disk brakes. With these multiple obsolescence factors, many of the current forecasting models fall apart. Any obsolescence forecasting method that does not meet the three requirements described above will most likely develop problems when trying to scale to meet the needs of industry.

Table I provides an overview of obsolescence forecasting methods that have been published in the last 15 years. Each method is characterized according to the type of obsolescence forecasting and whether it meets each of the scalability factors. Ideally, methods that do not require sales data or human input but should be capable of forecasting obsolescence for multifeature products. These characteristics are also indicated in Table I for each method. As shown, Sandborn *et al.*'s [13] is the only current method that does not require sales data or human inputs but does consider multifeature products. It creates a prediction model to predict lifespans of current products based on the past lifespans of similar parts, taking into account life cycle differences between manufacturers. However, this approach does not take into account the feature specifications of the part when predicting obsolescence dates. For example, one would expect that if two similar products are introduced into a market at the same time, and one is far more technically superior, the technically superior product would have a longer life cycle since it would be technically competitive in the market for a longer period. Without taking this technical progression into account, one of the key causes of technical obsolescence could be overlooked, leading to a potential decrease in accuracy of the model.

D. Commercial Obsolescence Forecasting Services

Because obsolescence forecasting can realize enormous cost savings for organizations, there are several companies that have emerged in recent years offering obsolescence forecasting and management as a service. Currently, some of the leading obsolescence forecasting and management companies include SiliconExpert, IHS, Total Parts Plus, AVCOM, and QTEC Solutions [23]–[27]. These companies focus on electronic components because of the high rate of obsolescence and have databases with information on millions of electronic parts such as part ID, specifications, and certification standards. The commercial forecasting services can be sorted into life cycle and obsolescence risk. Currently, SiliconExpert, Total Parts Plus, AVCOM, and QTEC Solutions offer life cycle forecasts, and IHS offers an obsolescence risk forecasting solution. However, none of these services offer both obsolescence risk and life cycle forecasting.

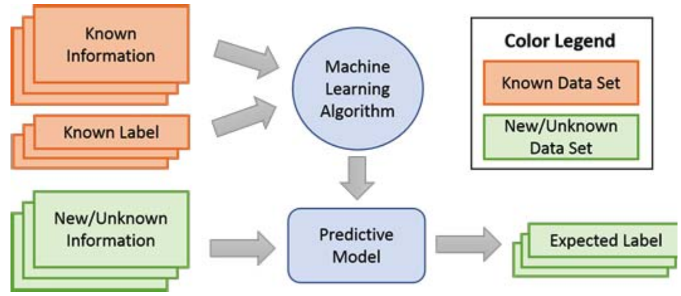

Fig. 3. Supervised learning process.

III. Methodology

In this section, two separate obsolescence forecasting methodologies and frameworks are introduced. Both approaches apply machine learning to improve accuracy and maintainability over other existing methods. The two approaches are differentiated by the two major outputs of the model. The first outputs the risk level that a product or component will become obsolete. This is termed ORML. The second method outputs an estimation of the date the product or component will become obsolete and is termed LCML.

Machine learning has gained popularity in many application fields because it can process large data sets with many variables. The applications of machine learning range from creating better recommendation systems on Netflix to facial recognition in pictures to cancer prediction and prognosis [29]–[31]. Specifically, in the field of design, machine learning has been used to gather information and develop conclusions from previously underutilized sources. For example, public online customer reviews of products are mined to better understand how customers feel about individual product features [32]. The results of these analyses can be used to improve products during redesign and in new product development by understanding customers' preferences in products. Another example of data mining and machine learning in design is the analysis of social media for feedback on products. Current work has shown that by using social media data, machine learning can predict sales of product and levels of market adoption [33]. Understanding the market adoption of features can indicate if the feature is a passing or a permanent trend.

Both ORML and LCML use a subset of machine learning called supervised learning. Supervised learning creates predictive models based on data with known labels. These predictive models are used to predict labels of new and unknown data. A common introduction problem in supervised learning is to create a model to predict whether an individual will go outside or stay inside based on the weather. Two data sets are presented and follow the process shown in Fig. 3. The first data set contains the temperature, humidity, and sunniness for each day and whether the subject stayed inside or went outside. This data set is the training data set because a predictive model with output, stay inside or go outside, will be trained using these data. The training data set is fed into a

TABLE I
LIST OF ALL METHODOLOGIES AND SCALABILITY FACTORS

Methods	Life-Cycle Forecasting	Obsolescence Risk Forecasting	Sales Data Required	Human Inputs	Multi-Feature Capable
ORML	-	✓	-	-	✓
LCML	✓	-	-	-	✓
Solomon et al. (2000)	✓	-	✓	✓	✓
Sandborn (2005)**	✓	-	✓	-	-
Josias (2009)	-	✓	-	✓	✓
van Jaarsveld et al. (2010)	-	✓	✓	✓*	✓
Sandborn (2011)**	✓	-	-	-	✓
Rojo et al. (2012)	-	✓	-	✓*	✓
Zheng (2012)	✓	-	✓	✓	✓

Notes:
*Human bias due to manually filtering the BOM
**Sandborn 2005 & 2011 are different methods but the same creator

machine-learning algorithm, which creates a predictive model that will most accurately classify the known label based on the known weather information. The new model can also be fed weather information where the label is unknown. The model will predict the label with the highest likelihood of occurring. The unknown data set is also called the test set because it will be used to test the accuracy of the predictive model. For the stay-inside-or-go-outside prediction model and all supervised learning models, the more the data with known labels submitted to the machine-learning algorithm, the more effective the predictive model. This means supervised machine learning is a strong fit for any problem where data continually flow in and can make the predictions more accurate. With prediction of product obsolescence, the stream of newly created and discontinued products allows the predictive models created using ORML and LCML to gain accuracy over time.

Supervised machine learning was chosen over unsupervised machine learning because the latter does not have a known data set. Unsupervised machine learning does not have a label to predict, but rather uses algorithms to fix clusters and patterns in the data. Similar methods could be advantageous to identifying groups of comparable products for product redesign or for cost reduction in the design phase. However, due to unsupervised machine learning finding groupings that are not explicitly obsolete versus active, supervised learning was chosen over unsupervised learning for this obsolescence forecasting framework.

In addition, machine learning models are not deterministic models. Many algorithms use randomization to split variables and evaluate the outcome. A byproduct of this trait is that the predictive models will vary slightly each time the algorithm is implemented. Even with these slight variations, machine learning models are highly effective and used in many predictive applications.

A. Obsolescence Risk Forecasting Using Machine Learning

The forecasting methods introduced and demonstrated in this paper are based on the concept that parts become

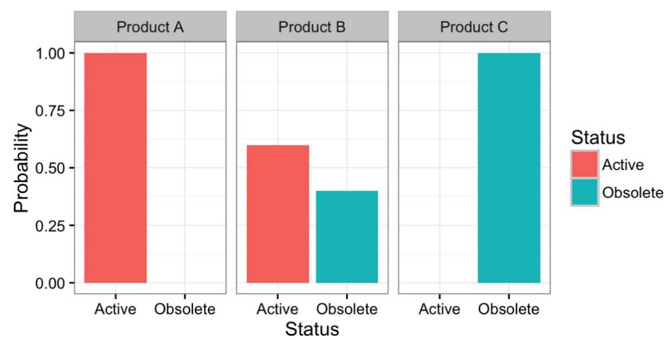

Fig. 4. Outputs of ORML.

obsolete because other products in the market have a superior combination of features, software, and/or other added value. The ORML framework, like the weather example, is shown information and attempts to classify the part with the correct label. However, instead of weather information, the technical specifications of current active and obsolete parts are fed into algorithms to create the predictive models. In Fig. 3, after the predictive model is created, the technical specifications of parts with unknown obsolescence statuses are structured in the same way as that for the known parts and input to the predictive model. The model outputs the probability that the part is classified with the label active or obsolete. The probability that the part is obsolete can be used to show the obsolescence risk level.

Fig. 4 shows the output from the ORML method. Product A shows a product with a 100% chance of the part being active. Product B demonstrates a mixed prediction with between a 60% chance of being active and a 40% chance of being obsolete. Product C shows the prediction of a product with a 100% chance of being obsolete.

One application of this output is to predict the obsolescence risk level for every component in two competing designs or subassemblies and then create a composite obsolescence risk level for each design using a combination of the components' risks. The new composite risk level could be used as an attribute in the process for selecting a final design.

B. Life Cycle Forecasting Using Machine Learning

The LCML framework is built on the same principle that parts become obsolete because other products in the market have a superior combination of features, software, and/or other added value, the difference being what the frameworks are predicting. Where ORML predicts the label active or obsolete, LCML uses regression to predict a numeric value of when the product/component will stop being manufactured.

LCML's ability to estimate a date of obsolescence is a highly useful metric. LCML will give designers and supply chain professionals a more effective way of predicting the length of time to complete redesign or find a substitute supplier or component. Understanding when each component on a bill of materials will become obsolete will allow designers the ability not only to provide time constraints on projects, but also more effectively time redesign projects to maximize the number of high risk components removed from the assembly.

The combinations of the ORML and LCML outputs in analyses have numerous applications in business decision making processes. Current commercial obsolescence forecasting methods and those in the literature only predict obsolescence risk or product life cycle. Since the ORML and LCML models both use product specifications as input and the same machine-learning algorithms to build the model, the only additional work needed to switch between predicting risk versus life cycle is changing the output in the training data. This is just one of the reasons a machine learning-based obsolescence forecasting method is superior. Currently, it is the only method that readily provides obsolescence risk and product life cycle, essential to improve accuracy.

IV. Case Study

The case study serves to demonstrate the accuracy and scalability of ORML and LCML as methods to forecast obsolescence. The cell phone market was chosen for the case study due to availability of data and the ease it provides in understanding the product and specifications. Although the case study is a consumer product, the ORML and LCML prediction frameworks can be utilized to predict component obsolescence found in larger complex systems.

The case data contain over 7000 unique models of cellular phones with known procurable or discontinued status, release year and quarter, and other technical specifications. The specifications include weight (g), screen size (in), screen resolution (pixels), talk time on one battery (min), primary and secondary camera size (MP), type of Web browser, and if the phone has the following: 3.5-mm headphone jack, Bluetooth, e-mail, push e-mail, radio, SMS, MMS, thread text messaging, GPS, vibration alerts, or a physical keyboard. The data set included 4030 procurable and 3021 discontinued phones. However, the data set only included 38 obsolescence dates. This means that the ORML portion of the case study had 7051 unique cell phone models while the LCML had 38. Although the data sets differ in size, each data set is suitable in size to demonstrate the ORML and LCML frameworks.

The data were collected from one of the most popular cell phone forums, GSM Arena, using a Web scraper. The original data set, and the code for the Web scraper, and machine learning models created in this case study can be downloaded from connorj.github.io/research. GSM Arena is an online forum that provides detailed and accurate information about mobile phones and associated features. For this reason, the data set can have missing values and even miss reported information. Even with these shortfalls with the data set, this more accurately represents data collected in industry and demonstrates the robustness of the ORML and LCML frameworks.

After formatting the data, the data set was split into two random groups. The first group represents 2/3 of the data set and is called the training data set. The training set is the data set used to create the prediction model. The second is the test set and represents the other 1/3. Although all the data sets are known in this case study, the test set will be put through the predictive model, and accuracy will be determined by comparing actuals obsolescence statuses and obsolescence date with the one predicted by the model. This practice is known as validation and is a best practice for model creation and evaluation because the data used to create a prediction model are never used to validate its accuracy [34]. Currently, the majority of the obsolescence forecasting models in the literature estimate model accuracy by using the same data used to create the model. The data set was split into a 1/3 test set and a 2/3 training set for an initial analysis for accuracy using confusion matrices. A more in-depth analysis was conducted where the ratio of training and test set sizes was changed and the accuracy was assessed (Tables V and VII) [35].

The next step in the case study was to run the training data set through a machine-learning algorithm to create a predictive model. Machine learning has many algorithms and infinitely more if counting all the slight variations that can be done to increase accuracy. Three machine-learning algorithms, artificial neural networks (ANNs), support vector machines (SVMs), and random forest (RF) will be applied to this case study [36]–[38]. Decision trees and SVMs were ranked first and third, respectively, on the list of top

TABLE II
NEURAL NETWORKS ORML CONFUSION MATRIX FOR CELL PHONES

	Prediction			
		Available	Discontinued	Total
Actual	Available	1295	67	1362 (95.08%)
	Discontinued	129	860	989 (86.96%)
	Total	1424 (90.94%)	927 (92.77%)	2351 (91.66%)

TABLE III
SVM ORML CONFUSION MATRIX FOR CELL PHONES

	Prediction			
		Available	Discontinued	Total
Actual	Available	1218	76	1294 (94.13%)
	Discontinued	92	827	919 (89.99%)
	Total	1310 (92.98%)	903 (91.58%)	2213 (92.41%)

TABLE IV
RF ORML CONFUSION MATRIX FOR CELL PHONES

		Prediction		
		Available	Discontinued	Total
Actual	Available	1243	72	1315 (94.52%)
	Discontinued	98	873	971 (89.91%)
	Total	1341 (92.69%)	945 (92.38%)	2286 (92.56%)

ten algorithms in data mining [39]. However, standard decision trees are often inaccurate and overfit data sets [41]. RF, an aggregation of many decision trees, averages the trees with the intention of lowering the variance of the prediction [41]. For this reason, RF was selected over standard decision trees. The algorithm listed second, K-means, is an unsupervised clustering method and would group similar products together rather than forecast an output. For this reason, K-means is not a possible alternative for an algorithm to be used for either ORML or LCML and therefore was not included in this case study. Although ANNs were not on this top 10 list, they were selected based on wide usage in deep learning, a subset of machine learning. Deep learning looks at the complex relationships between inputs in an effort to have a greater understanding of combined relationships with the output [41]. In the final step, once the algorithm constructs a predictive model, each part or element from the unknown data set is run through the model and receives a predicted label.

A. Results of Obsolescence Risk Forecasting

The accuracy of the ORML model is represented in a confusion matrix. The confusion matrix (Tables II–IV) shows how many cell phones were classified correctly versus those classified incorrectly. Numbers in the (available, available) and (discontinued, discontinued) cells are correctly classified and all other cells are misclassified.

The first algorithm used was ANN. The neural networks classification was done in R 3.0.2 using the package caret [40]. All the ANNs in this study were constructed with two hidden layers. The probability of each part being available or discontinued was output, and the highest probability label of available or discontinued was assigned. The actual statuses were compared to the predicted values, and a confusion matrix was developed (Table II). The model correctly predicted 91.66% of cell phones with the correct label in the test data set.

The next algorithm applied was SVM. The SVM utilized the SVM classification function from the package e1071 [41] in R 3.0.2 and a radial basis kernel was selected. The algorithm was implemented on the training data set that contained 66.6% of the total data. The prediction model then classified the remaining 33.3% of phones not used in the model creation. The actual statuses and the predicted statuses were compared, and the confusion matrix in Table III was created. The SVM model has a model accuracy of 92.4%.

The last algorithm applied was RF. The model was implemented in R 3.0.2 using the package randomForest [42]. The randomForest function was set to have 500 trees for all RFs in this case study. The model was trained with a 66.6% training set and was tested with 33.3%. The predicted test set and the actual statuses are compared in Table IV. The model received an accuracy of 92.56%. This was the highest of all three algorithms.

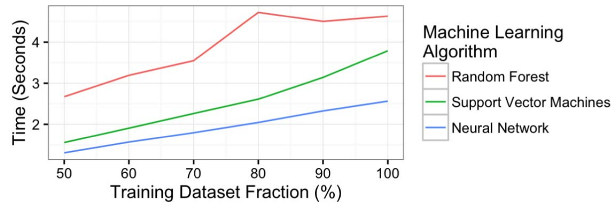

Fig. 5. Overall average evaluation speed by the training data set fraction for ORML.

For Tables II–IV, the training size was held constant at 66.6%. Table V illustrates how changing the percent of instances from the data set used to create the model affects accuracy. ANN and SVM preform at about the same accuracy for every training size, while RF always performs at a higher accuracy.

The algorithms were compared using the prediction model creation time for each of the 50%–100% training sets used in Table V. Ten predictive models were created for each training size, and the average time was plotted (Fig. 5). All the algorithms increased in time at a near constant rate. ANN is the fastest algorithm, followed by SVM, which is followed by RF.

Although the speed of creating these predictive models is relatively small (<1 min per model), it is important to remember that this case study is only creating prediction models for one product type. If ORML was scaled to create a prediction model for each component on a 10 000 component bill of materials, these relatively small differences in times would compound rapidly.

Four characteristics, identified in [43], were measured to rank the algorithms. The first two characteristics were performance-based: accuracy and evaluation speed. The rankings of the algorithms in Table VI for the first two attributes were determined by best model accuracy and by average time to complete the ten simulations of each of the six different training set sizes. The second two characteristics were usability-based: interpretability and maintainability/flexibility. Interpretability is defined as the ability for analysts to comprehend the model and analyze the output. Maintainability/flexibility represents the models' ability to adapt over time and how much work is required to keep the model running.

RF was ranked best (first) in interpretability due to the visual nature of decision trees and the ability of analysts to follow the flow of the tree to understand the steps in the classification model. SVM was ranked second because, while the concept of creating a plane to separate the available and discontinued groups is easy to understand, due to the high dimensionality of the data, there is no obvious visual representation of this model. Last, neural networks were ranked third out of the three because of the complexity of the trained network and the black-box nature of this classification method.

Maintaining machine-learning models requires regular inputs of data to maintain the accuracy of the model because

TABLE V
AVERAGE ACCURACY OF PREDICTIONS BY TRAINING SIZE FOR ORML

Training Size (%)	Random Forest			Neural Network			Support Vector Machine		
	Training (%)	Testing (%)	Overall (%)	Training (%)	Testing (%)	Overall (%)	Training (%)	Testing (%)	Overall (%)
50	98.8	92.2	95.5	91.8	91.2	91.5	90.9	91.7	91.3
60	98.5	92.5	96.1	91.4	91.7	91.5	91.0	92.2	91.4
70	98.5	92.9	96.8	91.5	91.9	91.6	91.3	92.3	91.6
80	98.2	93.3	97.2	91.7	91.1	91.6	91.6	91.7	91.6
90	98.2	94.3	97.8	91.7	91.2	91.6	91.7	91.2	91.6
100	-	-	98.3	-	-	91.1	-	-	91.6

TABLE VI
SUMMARY OF MODEL PREFERENCE RANKING FOR ORML

	RF	Nnet	SVM
Performance based characteristics			
Accuracy	1st	3rd	2nd
Evaluation Speed	3rd	1st	2nd
Non-performance based characteristics			
Interpretability	1st	3rd	2nd
Maintainability/flexibility	1st	2nd	3rd

both neural networks and SVMs require only numeric variables; all variables must be converted to numeric. Creating numeric indexes can be time-consuming and will slow down the data entry process. For this reason, RF was ranked number one. In Table VI, as the training set size decreased, the accuracy of the neural network test set dropped faster than that of the SVM test set. While fewer data points were required, the neural network was not flexible and could not perform as well as the SVM, making SVM ranked second and neural networks third.

Overall, RF was ranked first in all attributes except speed where it was ranked third. For this reason, RF is the most appropriate algorithm for ORML in the cell phone market. This result can be verified by the accuracy of the RF model where 100% of the data set was used to create and test the model. RF was able to correctly classify 98.3% of the cell phones.

B. Results of Life Cycle Forecasting

This section contains the results of the cell phone case study to forecast obsolescence by using the LCML framework. First, the results of 2/3 training set and 1/3 test set are shown and discussed. Similar to the ORML section, the model accuracy is examined as the training size changes, and the speed of each algorithm is assessed. Finally, each algorithm is ranked based on the following four characteristics: accuracy, evaluation speed, interpretability, and maintainability/flexibility.

The LCML framework predicts the date when the product/component will become obsolete. Since the output is a numeric rather than a binary classifier, the results cannot be easily presented in a confusion matrix. For this reason, the actual obsolescence dates versus the predicted obsolescence dates were plotted to visually represent the accuracy

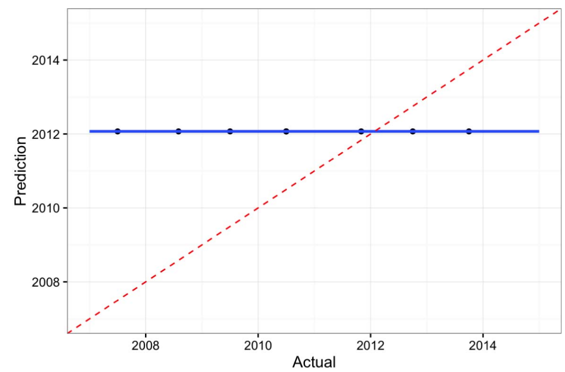

Fig. 6. Actual versus predicted end of life using neural networks and LCML.

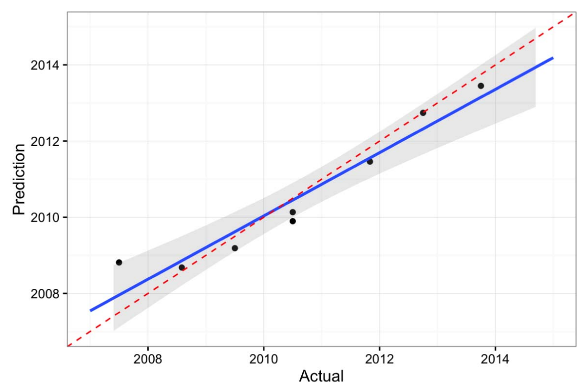

Fig. 7. Actual versus predicted end of life using SVM and LCML.

of each model. A dashed line at 45° was plotted to show a prefect one-to-one prediction rate. Unlike ORML, to assess the model accuracy, the percentage correct cannot be used to gauge model success. For the LCML framework, mean square error (MSE) will be used to determine accuracy as follows:

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(\hat{Y}_i - Y_i)^2$$

where n is the number of predictions made, $\hat{Y}$ is the predicted obsolescence date, and Y is the actual obsolescence date. The lower MSE indicates that the predicted and actual values are closer, i.e., the model has a higher accuracy.

One big challenge of the LCML section of the case study was the lack of obsolescence dates available through our Web scraping data source. Users of the cell phone Web forum

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TABLE VII
AVERAGE MSE OF PREDICTIONS BY TRAINING SIZE FOR LCML

Training Size (%)	Random Forest			Neural Network			Support Vector Machine		
	Training	Testing	Overall	Training	Testing	Overall	Training	Testing	Overall
50	0.47	2.00	1.27	4.71	5.73	5.10	0.36	0.88	0.56
60	0.41	1.81	1.01	4.75	5.67	5.10	0.33	1.41	0.74
70	0.40	1.22	0.68	4.70	5.89	5.15	0.34	1.02	0.60
80	0.39	0.74	0.48	4.80	5.65	5.12	0.39	0.92	0.59
90	0.33	1.09	0.44	4.87	5.75	5.21	0.32	1.34	0.71
100	-	-	0.36	-	-	5.21	-	-	0.60

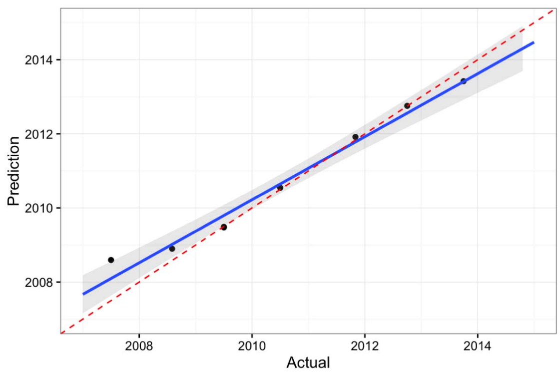

Fig. 8. Actual versus predicted end of life using RF and LCML.

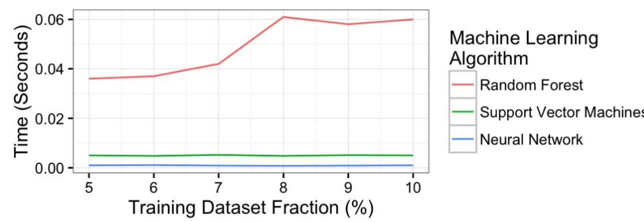

Fig. 9. Overall average evaluation speed by the training data set fraction for LCML.

TABLE VIII
SUMMARY OF MODEL PREFERENCE RANKING FOR LCML

	RF	Nnet	SVM
Performance based characteristics			
Accuracy	2nd	3rd	1st
Evaluation Speed	3rd	1st	2nd
Non-performance based characteristics			
Interpretability	1st	3rd	2nd
Maintainability/flexibility	1st	3rd	2nd

commonly updated cell phone specifications and whether the phone was procurable or discontinued, but rarely listed an explicit date of obsolescence. For this reason, substantially less data was available for the LCML case study.

The first algorithm tested with the LCML framework was ANN. The neural networks require a large amount of data to create accurate prediction models. Since the LCML data set was smaller, the neural network was unable to create a model. If no model is created, then the algorithm defaults to taking an average of the training set and always applying the average for all predictions. The results of this method are shown in Fig. 6. The prediction model received an MSE of 4.77. The square root of the MSE determines the average prediction error. For neural networks, the average prediction had an error of 2.18 years. An error that large would not be useful in the cell phone market when the average lifespan of the product is only 1–2 years.

The next algorithm applied was SVM. In contrast to neural networks, SVM utilized a smaller data set and created an accurate prediction model (Fig. 7). In Fig. 7, the solid line is the line of best fit of the actual versus predicted end of life. The best-fit line and the dashed prefect prediction line are fairly similar. The MSE of the model is 0.36 and is much more accurate than the MSE of 4.77 for neural networks.

The last algorithm testing the LCML framework was RF. RF, similar to SVM, constructed an accurate obsolescence date prediction model. The model had a 0.52 MSE. The slightly higher model error rate can be seen when comparing Figs. 7 and 8. SVM was capable of predicting closer to the dashed or prefect prediction line.

An analysis of how changing the training set size affects the prediction model's accuracy was conducted with results displayed in Table VII. The model was created with the training set and then tested on the training, testing, and overall data sets. Each was conducted ten times, and the MSE was averaged. For neural networks, the MSE remained constant throughout training size changes. This was largely due to the model only using the average obsolescence date to predict the obsolescence dates in other predictions. RF was a steady decrease in model error as the training sizes increased, while SVM had a more consistently low model error.

The times to create each model were recorded and plotted in Fig. 9. Neural networks took nearly no time to average the dates in the training set. SVM was slightly slower than neural networks, but forecasted the obsolescence date with a far greater accuracy. RF was third and was almost eight times slower than SVM.

The last step in the algorithm analysis was to rank the algorithms by the four key characteristics outlined previously in this paper (Table VIII). Although RF was rated higher in both nonperformance-based characteristics, SVM performed much better on accuracy and speed. For these reasons, SVM is the most appropriate algorithm for forecasting obsolescence dates using LCML in the cell phone market.

V. LIMITATIONS

Like other obsolescence forecasting frameworks, LCML and ORML have limitations and problems that may compromise

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the validity of the estimations. This section addresses these problems and limitations and provides greater insight into the frameworks.

The first problem can arise from the start, during data collection. The data must be both fairly reliable and up to date. As demonstrated in the case study, the data do not need to be complete, but the more complete the data are, the more accurate the prediction is. Another important part of the data formatting process is variable selection and creation. The correct variables can easily capture the change in the market and can indicate when parts or elements are becoming obsolete. However, these variables might not always be a simple measure of memory, screen resolutions, or another metric. For example, a variable may need to be created to denote the highest, medium, and lowest memory levels of a phone. Apple, Inc., usually ends production of the highest and medium versions of a phone, but still produces the lowest memory version of the prior model phone to capture the market of people looking for a cheap iPhone. The size of memory in the lowest memory version of the iPhone has changed over time, and using only phone memory would not capture this trend in the predictive model.

With the diversity of industry where obsolescence is present and these frameworks can be used, there will be no uniform indicator between industries. A good metric to measure obsolescence for flash drives is probably memory. However, for cell phones, the features like thread text messaging and screen resolution are more useful than memory. Furthermore, good metrics can change over time. When cell phones were first invented, connectivity was one of the most important factors and little emphasis was on features. Now connectivity is given and features determine phone obsolescence.

Another problem with obsolescence forecasting frameworks is finding acceptable prediction accuracies from industry to industry. An industry like transistors, with exponential change such as that described by Moore's law, would likely be predicted more accurately than the cell phone market due to the complexity of the products and different marketing and pricing aspects.

The last problem is the one that plagues all machine learning and statistical models. If the data used to build the model do not represent the current real world, the model will not be effective. In obsolescence, there is an extremely high chance of this occurring due to rapid innovation or invention. When Apple released the first iPhone, it was the first in many categories and because of that, it accelerated the obsolescence of many of the phones in the current market. A machine learning or statistical obsolescence model at the time built with past obsolescence data would not predict the jump in technology this innovation would cause. This means that the obsolescence forecasting frameworks introduced in this paper and all current obsolescence models cannot predict large jumps in innovation, but are better suited to track steady improvements in an industry.

VI. Conclusion

The case study demonstrated the power of the ORML by correctly identifying active and obsolete cell phones with an accuracy as high as 98.3%. RF was selected as the best algorithm for the ORML framework in the cell phone market based on model accuracy, speed, interpretability, and maintainability/flexibility. The second half of the case study showed the accuracy of the LCML framework and showed that cell phones' obsolescence dates can be predicted within a few months of the actual obsolescence date. The best algorithm for LCML in the cell phone market was SVM based on the four key characteristics named above.

One of the contributions of this paper is introducing the two category types of obsolescence forecasting: obsolescence risk and life cycle. Each method was examined for its ability to scale using the three characteristics: requiring sales data for all products in each component's market, human inputs for each part, and capability to handle multifeature products/components. Machine learning was introduced as a technique employed to utilize knowledge in large data sets and help automate complex systems. This made machine learning a prime candidate for solving the problem of scaling obsolescence forecasting models to industries' needs. The first machine learning framework introduced was ORML, and this provided a risk index of each product being active or obsolete. The second machine learning framework was LCML, and this framework provided an estimate of the lifespan of the product. A case study using ORML and LCML was demonstrated using cell phones and showed a high level of accuracy of these frameworks. Then the limitations of applying these frameworks to current obsolescence forecasting systems were discussed to better understand the implications and potential causes for inaccuracy.

One additional way the ORML and LCML frameworks are unique, when compared to current methods in the literature and commercial software, is the straightforward switch between predicting obsolescence risk and life cycle. Since both models utilize the same inputs, the only change needed to switch between the two methods is to change the output in the training set during model creation. This simple characteristic of the ORML and LCML makes it one of the most adaptive obsolescence forecasting frameworks.

With obsolescence affecting almost all industries, reducing the cost of impact would save millions of dollars annually. The easiest way to reduce the impact is by involving obsolescence mitigation planning in earlier phases of design and supply chain management. This shift from a reactionary approach to a proactive approach would only be possible through more accurate obsolescence forecasting that can scale to industries' needs. This paper establishes machine learning as a capable technique to meet industries' large-scale needs while maintaining an extremely high accuracy for predicting obsolescence.

In the future, the methods and frameworks presented in this paper will be applied to additional case studies. These additional studies are likely to demonstrate further that machine learning is a highly effective solution to obsolescence forecasting. Additional investigations will be carried out to utilize obsolescence risk and life cycle predictions to aid practitioners in transitioning from reactive to proactive approaches. To scale the ORML and LCML frameworks, integration with large component information databases, like SiliconExpert, IHS, Total Parts Plus, AVCOM, and QTEC Solutions, will be needed to allow users to predict obsolescence risk and life cycles over millions of parts in seconds. Examples of cost analysis tools built on top of these prediction models will be explored where bills of materials could be submitted and the risk levels of each component could be calculated. These individual risk levels could be combined to show overall risk levels of different designs. The overall risk levels could be used in the early design stage and even in redesigns to help choose the best design to minimize the impact of obsolescence through the product's life cycle. Life cycle forecasting could also be used to help make lifetime buy or last buy orders more accurate by better understanding when the products will no longer be procurable.

Acknowledgment

Any opinions, findings, and conclusions or recommendations presented in this paper are those of the authors and do not necessarily reflect the views of the National Science Foundation.

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