# Predicting and Evaluating Software Model Growth in the Automotive Industry

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Abstract—The size of a software artifact influences the software quality and impacts the development process. In industry, when software size exceeds certain thresholds, memory errors accumulate and development tools might not be able to cope anymore, resulting in a lengthy program start up times, failing builds, or memory problems at unpredictable times. Thus, foreseeing critical growth in software modules meets a high demand in industrial practice. Predicting the time when the size grows to the level where maintenance is needed prevents unexpected efforts and helps to spot problematic artifacts before they become critical.

Although the amount of prediction approaches in literature is vast, it is unclear how well they fit with prerequisites and expectations from practice. In this paper, we perform an industrial case study at an automotive manufacturer to explore applicability and usability of prediction approaches in practice. In a first step, we collect the most relevant prediction approaches from literature, including both, approaches using statistics and machine learning. Furthermore, we elicit expectations towards predictions from practitioners using a survey and stakeholder workshops. At the same time, we measure software size of 48 software artifacts by mining four years of revision history, resulting in 4,547 data points. In the last step, we assess the applicability of state-of-the-art prediction approaches using the collected data by systematically analyzing how well they fulfill the practitioners' expectations.

Our main contribution is a comparison of commonly used prediction approaches in a real world industrial setting while considering stakeholder expectations. We show that the approaches provide significantly different results regarding prediction accuracy and that the statistical approaches fit our data best.

#### I. INTRODUCTION

Software development in the automotive industry is facing steadily growing size and complexity among its artifacts. For example, at Volvo Cars in Sweden, the amount of software in cars has increased exponentially in the last twenty years: In 2006, vehicles contained 10.9MB of code, in 2011 around 117.5MB, and in 2014 already 917MB [1]. Other car companies have seen similar developments and according to Wyman [2], the entire automotive sector is facing increasing technological complexity. Concerning the amount of software and tests being introduced with autonomous vehicles, this upwards trend is not going to slow down anytime soon.

In practice, software exceeding size limits set by hardware or software requirements causes long loading, build, and deployment times. Hence, while software grows in size and complexity, situations arise where refactoring and software maintenance becomes necessary. When these situations occur unexpectedly and immediate maintenance become inevitable related delays slow down or stop whole development cycles and result in increased development costs. Reliable predictions of software status and quality can prevent such issues by foreseeing problematic growth in software. This can improve release planning processes and provide stakeholders with additional information on the evolution of their software. The need for such predictions at a collaborating automotive manufacturer led us to investigate this topic, particularly predicting the size of model-based software, hereafter software models.

Predicting software model size can be done by assessing growth information of past software development. By mining past software revisions and measuring the size of the software model time series data is created, which shows the models' quality development throughout the whole software life cycle. Many approaches for predicting time series data exist. Already in 1970, for example, Box and Jenkins [3] presented approaches to analyze and predict time series that are used by stock market or meteorology. More recently, machine learning approaches found their way to predict time series data as well [4]. In some application domains they have been found to outperform classical approaches regarding prediction accuracy [5].

However, it is still unclear how well such approaches perform in a real world, industrial setting where additional factors affecting their practicability need to be considered like the time to train the predictors or their maintainability. Empirical evidence is needed to show which approaches are applicable to data that is gathered from realistic scenarios in practice.

#### A. Research Goal and Research Questions

The goal of this study is to investigate to what extent existing approaches are applicable to predict model growth in practice. The following three research questions contribute to the goal of our study:

- RQ1 What are the most important prediction approaches for time series data that are mentioned in the literature?
- RQ2 Which expectations do practitioners have on the prediction of software size in practice?
- RQ3 How do the prediction approaches from RQ1 perform regarding the criteria elicited in RQ2?

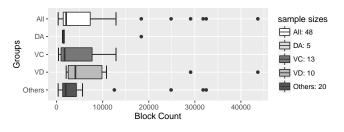


Fig. 1: Model size

Fig. 2: Overview over amount and size (number of blocks) of the models used in this study.

#### B. Contributions

First, we present five different prediction approaches elicited from literature and previous studies. They are artificial neural networks (ANN), support vector regression (SVR), long shortterm memory (LST), autoregressive integrated moving averages (ARIMA), and Holt's linear trend method (HOLT). Second, we list the expectations of ten stakeholders collected in questionnaires and workshops. According to the stakeholders in the automotive domain, predictions of software growth should be accurate for about one month period. Finally, this paper contributes by comparing the performance of the five prediction approaches in an industrial context in the domain of automotive software engineering. Our comparison includes traditional statistical approaches (HOLT and ARIMA) next to modern machine learning approaches (ANN, SVR, and LSTM) to provide empirical evidence about their performance regarding prediction accuracy. We find that the results received from applying the approaches in practice differ significantly from each other. We show that the statistical approaches outperform machine learning in our context.

# C. Paper Structure

The rest of the paper is structured as follows: We provide background knowledge in Section II and cover related work in Section III. In Section IV we outline our systematic approach to address the research questions. Following the methodology, we present, analyze, and discuss our results in Section V. Section VI concludes the research and presents future work.

### II. BACKGROUND

# A. Context

This case study is conducted at a testing department of a German premium automobile manufacturer. The company produces approximately two million vehicles per year. In the automotive domain, multiple software projects are combined to create the software of a vehicle. Resulting artifacts from these projects are usually electronic control units (ECUs) to be installed into a vehicle. Simulations of ECUs are used during testing to replace incomplete real ECUs. This enables the emulation of a real car environment for ECUs under test. The simulations usually run on several real-time computers. All simulation models needed to simulate a complete vehicle were made accessible to the researchers for analysis. The models are realized with Matlab/Simulink. Detailed information about the simulation models cannot be disclosed, but in order to understand the distribution of size and attributes among them, an overview is provided in Figure 1. The figure shows the different groups of simulation models driver assistance (DA), vehicle control (VC), vehicle dynamics (VD), and others. The graphs depict the current model sizes within the groups and the whole data set, calculated by counting all blocks in the models. The sizes of the majority of the models range between 331 and 18,376 blocks, with seven positive outliers. The strongest outlier with 107,857 blocks within the others-group is not shown in the figure for visibility reasons.

#### **B.** Measurements

Recently, Gil and Lalouche [6] showed that the measure of size can predict the validity of any of the 26 metrics they used for comparison. Also, they say that the higher the correlation with size, the higher the ability of the metric to estimate external features of the software artifact. Similarly, our previous studies showed that size metrics are predictors for maintainability and software complexity when measuring simulation models in the automotive industry [7]. They outperformed cohesion and coupling measurements in their ability to assess model complexity and maintainability, accordingly.

The increasing size and complexity of software projects can cause severe problems especially in systems that are limited by the underlying hardware, for example, in embedded systems. Furthermore, at the case company, lack of maintainability among the software models causes significant delays in the development process and in the time it takes to introduce new engineers to a project. In this study, we assess these features by measuring model size in form of lines of code (LOC) and block count (BC). Both measurements can be considered as static code analysis as they do not require the models to run for providing results. Hence, they work even if syntax errors exist in the model. This keeps data preprocessing to a minimum and avoids unnecessary transformations or interpolation of missing values, which could skew the data unintentionally.

To calculate the LOC metric in this study, the .mdl files of the Simulink models are assessed by counting each line in the XML-like representation of the respective model. They do not contain comments or similar non-code related entities. The BC metric counts blocks in a model using the function *sldiagnostics*, which is built-in in the Matlab/Simulink environment. The function considers all blocks in the model, even masked blocks on the lowest layers. In a previous study, we show that both metrics correlate weakly to moderately, depending on the model under investigation. The correlation is not surprising as they both count model size attributes. As they are not completely similar, we expect that using two different size metrics in this study will provide an additional means for ensuring the validity of the results.

# C. Time Series Prediction and Evaluation

Prediction can be categorized into classification and regression. In classification, the goal is to assign and learn classes to a set of input values and predict these classes for each new input value. Regression, on the other hand, aims for learning the values of some input data and predicting a new value for new or unknown input data. An example for classification is predicting nominal categories like (requirement, feature, bug) for a set of natural language-based issue tracker data. A set of issues would be learned by the algorithm and a new issue would be predicted to be in one of the three categories. Predicting regressions usually regards an interval or ratio scale like the development of sales over time. Learning sales data of the past enables a prediction of the sales in the future. All approaches presented in this paper are applied to time series data. Time series are sequences of observations collected over time, usually in equidistant time intervals. In this study, we aim for predicting future values of time series, based on previous values of the same time series. Therefore, we use regression-based approaches.

Respectively, the approaches for evaluating the performance of predictions differ in classification and regression problems. Measures like F1-measure, Precision, Recall, etc. work well in classification. Contrary to classification problems, the performance of regressions problems is assessed by how close they approximate a real value. Hence, the data is usually split into one learning and one test set. Predictions are then made based on the learning set and compared with the test set. An error measurement is applied to evaluate the accuracy of the predictions.

## III. RELATED WORK

In this study, we combine research from the fields of statistical and machine learning predictions, mining software repositories, and software measurement.

Many existing studies assess different prediction approaches. Malhotra [5] studied 64 publications regarding the application of machine learning techniques for software fault prediction. Malhotra found that 19 out of 64 studies involved a comparison element between statistical and machine learning methods. The results demonstrate that the machine learning approaches mostly outperform statistical linear approaches. The author identified three frequently used machine learning approaches for software fault prediction: 1) decision trees, 2) neural networks, and 3) support vector machines. Fu [4] performed a literature review on prediction approaches as well. The author provides a comprehensive overview of existing techniques and classifies them according to their application. There is still a lack of concrete, in-depth evaluations of the applicability of the approaches in real-world cases. Lastly, Martínez-Álvarez et al. [8] also review recent work on time series prediction. They split results in linear statistical and non-linear machine learning approaches. We follow their notation in this study. They list multiple prediction approaches and error measurements currently used in literature. Their study, however, is specifically designed for electricityrelated time series. Accordingly, prediction approaches are

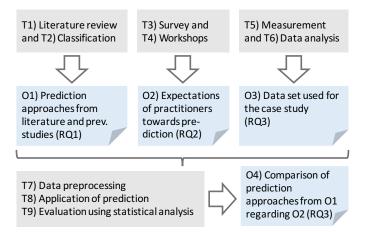


Fig. 3: The study design consists of four main tasks. Tasks are presented in gray squared boxes. They are attributed to our research questions. The outcomes are depicted in blue boxes with bent corners.

broadly addressed in literature. Therefore, in our study, we investigate the existing work in a literature review to find the approaches fitting our problem domain.

Size measurement is also well studied. Research investigating software size has shown that size can be used to assess productivity [9] and defects [10] in practice. Schroeder et al. [7] have shown that simple metrics like lines of code are well suited to assess software complexity and maintainability in a similar environment. Hence, in this study, we consider size metrics as a powerful and established metric.

Regarding the field of mining software repositories, many studies focus on predicting defects like Zimmermann [11]. Other studies have used software repositories to investigate refactoring practices (cf. [12]). However, to the best knowledge of the authors, no studies have been reported so far combining aspects of software repository mining and measurements with prediction approaches including machine learning approaches that are evaluated in a realistic industrial context.

## IV. METHODOLOGY

In this paper, we perform an industrial case study, in which we observe and investigate a specific case in a real world context [13] while avoiding interventions of researchers with the case [14]. We follow Runeson and Höst's guidelines on designing, planning, conducting, and reporting the case study [15]. Our study comprises quantitative and qualitative methods and consists of multiple tasks as outlined in Figure 3. In the tasks T1-T4, we answer RQ1 and RQ2 using a literature review, a survey, and workshops. Together with the measurements in task T5, they build the basis for the final evaluation of the applicability of prediction approaches in industry (RQ3). The tasks are outlined in greater detail in the following sections.

### A. Case and Subject Selection

The artifacts being assessed in this study are Simulink models simulating electronic control unit (ECU) functionality. All 70 models available at the department are considered for the data collection. Most models are still frequently updated with functionality or quality improvements; other models are only maintained to keep them usable in combination with the rest; a third group contains legacy models which are not used anymore, and the last group is formed by newly created models with little past data. Legacy models could skew the results as they might not represent the current development practices. Models that are too new do not provide sufficient data for our analysis. Hence, as previously shown in Figure 1, for this study only the first two groups are considered, and 22 models are removed from the data set. The remaining 48 models provide a representative view on the development conducted for integration testing at the case company. For the 48 models 4,547 revisions are assessed. This includes only revisions where one of the models? code was changed.

Six engineers participated in the industry workshops and ten in the survey. The first six engineers have 3.8 years experience on average (1-7 years) and the ten engineers 4.6 years (1-10 years). The engineers have the roles developer, tester, or team leader. All existing roles present at the department are considered for the survey. All engineers are working on the shared set of models while having different development foci including driver assistance, vehicle dynamics, and general vehicle control. All lead developers for the previously mentioned function groups are interviewed, as well as the respective team leader.

## B. Data Collection Procedure

Our study comprises several tasks involving data collection. They are outlined in detail below.

*T1) Literature Review and T2) Classification:* We conduct a literature review to investigate the most important prediction approaches. We examine existing literature that focuses on algorithms and approaches used in the context of predicting time series data, as well as their implementation in software development. Hence, the search string is constructed by combining synonyms of the three keywords *prediction, time series*, and *data mining*. We focus on research applying prediction approaches. Optimization or in-depth performance analysis of existing approaches is out of scope of the review. The literature studies of Fu [4], Malhotra [5], and Martínez-Álvarez et al. [8] are used as main source for approaches, as they provide existing investigations and comparison.

In the review, we identify the methods and details used for predicting time series. Based on this information, we identify the most common approaches applied to data similar to ours. Further details on methodology and results of the literature review are published separately.

*T3) Survey and T4) Workshops:* The goal of the survey and workshops in this study is to complement the quantitative analysis with practical information from practitioners and to provide a qualitative view on software size prediction. The survey in particular has the purpose to collect the practitioners' expectations on predictions. After introducing the topic the following questions were asked. The possible answers are depicted below the questions. The intervals for the answers are based on knowledge received during the literature work and gathered at the case company.

- 1) How long can a prediction take, at most? ( $< 1m, < 1h, < 12h, \le 24h, > 24h$ )
- 2) How accurate should a prediction be? (deviation from true values: 1%, 3%, 5%, 10%, \_\_%)
- 3) How far ahead should the prediction be accurate? (in days: 1, 2, 4, 7, 14, \_\_)
- 4) How much maintenance effort is acceptable to keep predictions running continuously?
- (freely specifiable in man-hours per day or week)5) What are additional important properties of a prediction?
- (free text)
  (Deal draw listing properties of a prediction)
- 6) Rank the prediction properties by their importance: (maintenance, run time, long-term accuracy, short-term accuracy, and additional properties mentioned before)

The questions aim to assess the importance of prediction properties, but also on possible quantification of these properties by asking for thresholds. Quantification is achieved by assigning values to the ranks assigned in the last question, ranging from one to the number of properties discovered. Those values are counted and compared to determine the importance of the properties.

The industry workshops serve the two purposes of discussion and verification of the gathered results. Findings extracted from the anonymous survey are discussed and evaluated. The workshops are conducted without a prescribed structure to allow for discussions about the intermediate results and to find additional input like prediction properties of interest. This provides input for RQ2 as well as it validates the applicability of prediction approaches in practice.

T5) Measurements and T6) Data Analysis: Having the expectations from practitioners and the background on prediction approaches from literature, the data set for the predictions under investigation has to be created. The two size metrics described in Section II-B are applied to all 4,547 revisions of the 48 software models. This results in two measurement values, one for LOC and one for BC for each revision and therefore two lists for each model. The lists depict the development of the size metrics over time. On the resulting data set, manual data interpretation and time series analysis are performed to understand how the data behaves and to fit appropriate prediction approaches later. Investigations include analysis of trend, seasonality, and outlying/random data. The analysis of the time series shows that they are mostly determined by their trend. All models grow in size. We expected seasonal behavior including, for example, regular increases in size within release cycles but the data set does not express this types of seasonality. In Figure 4, the development of the LOC measure is depicted for one model. The y-axis contains the measurement values and the x-axis the number of commits.

*T7) Data Preprocessing:* To evaluate the prediction accuracy using ground truth data, the data set, consisting of measured models throughout revision history, is split up. The data is divided into three sets: a training set, a validation set, and a

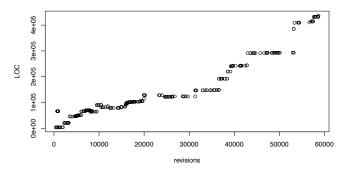


Fig. 4: The evolution of model size for one example model measured with the LOC metric.

TABLE I: Summary of the collected revision data for the 48 models.

	No. of	Min	Max	Avg.	Period
	revisions	rev.	rev.		
All Revisions	4,547	20	439	94	1/2013-6/2016
Learning set	3,766	16	351	78	1/2013-12/2015
Validation set	405	2	44	8	1/2016-3/2016
Test set	376	2	44	7	4/2016-6/2016

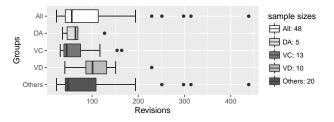


Fig. 5: Amounts of model revisions available in this case study, grouped by functionality.

test set. The training set is determined by our previous study, where we collected measurement data between 2013 until 2015. A second data collection was performed in 2016. This data is split equally into a test and a validation set. The resulting data set, which is used for all further analysis in this case study, is summarized in Table I. Altogether, we collected data from 4,547 revisions in the time between 2013 and mid-2016. In this set, we found at least 20 and at most 439 revisions per model. Additionally, Figure 5 shows the distribution of all revisions throughout the groups of functionality.

To perform a time series analysis according to Box and Jenkins [3] the time intervals between data points have to be equidistant. However, in the context of revisions and commits, this is not the case, as commits and consequently measurements are conducted whenever a developer decides to make changes to the project. There are multiple ways to address this problem. Eckner [16] presents an approach directly applicable to nonequidistant data and Rehfeld et al. present a re-sampling approach [17]. Both are not widely applied. Analyzing time series without constant intervals, also called unevenly spaced time series or irregularly sampled time series, still requires further research.

Specifically in our case, a more intuitive and straight forward approach is data interpolation. A fixed time interval is chosen, for example, daily intervals. Missing values are interpolated. This practice is applied widely but is not without critique. A data set can be misinterpreted if it cannot be ensured that in between two data points no significant change of values has occurred. This value would inevitably be missed by interpolation. In our case, it is safe to assume that data values actually do not change in between time samples, as we measure every time a change to the models was made in form of a commit. The software does not change in between commits and any missing measurement value can be interpolated from the previous data point. This results in time series, which changes step-wise with each commit while values stay similar in between commits.

We decided to interpolate the data to daily intervals. If multiple commits occurred to the same model on a single day we use the latest. According to above descriptions, if no commit was made the value for this day is copied from the previous day. Those daily intervals might introduce bias, as multiple observations during a single day are hidden, but it provides a realistic data set for practical observations.

Additional steps like differentiation and normalizing of the time series might be necessary. Differentiation removes the trend of a time series and enables separate investigations of trend and seasonality. Normalization of the data might be necessary, particularly for the use with neural networks as they are often adjusted to work with inputs ranging from 0 to 1.

*T8) Application of the Predictions:* The selection of prediction approaches is based on the outcome of the literature review. The criteria for the selection is how often an approach is mentioned in literature. The approaches have to be mentioned as being able to handle similarly structured data sets as in our case. For our study, both, statistical and machine learning approaches are considered.

In addition to the most used approaches, we add two approaches used previously on the same data set. In our earlier study, the autoregressive integrated moving average (ARIMA) approach was applied. As ARIMA is an established approach to predict time series, we consider it as an appropriate benchmark. Similarly, Holt's linear trend method complements the approaches from literature. Both approaches are explained in more detail together with the literature review results in Section V-A.

The application of the prediction approaches also has to consider their respective parameterization. Much time and effort is spent on optimizing parameters of predicting approaches to the data at hand. Research is conducted on how to fit prediction approaches best to a specific data set. Furthermore, for the majority of the approaches there are parameter estimation algorithms. As it is not the aim of this study to investigate perfect parameterizations but instead to provide a practical overview of existing approaches and their applicability in practice, we decided to use existing parameter estimation

	Prediction A	oproach 1	Prediction A		
Measurement	LOC	BC	LOC	BC	
Model 1	RMSE_LOC_11	RMSE_BC_11	RMSE_LOC_21	RMSE_BC_21	
Model 2	RMSE_LOC_12	RMSE_BC_12	RMSE_LOC_22	RMSE_BC_22	
Model n	RMSE_LOC_1n	RMSE_BC_1n	RMSE_LOC_2n	RMSE_BC_2n	

Fig. 6: Evaluation of the calculated error measurements. For each approach, the measurement results for all models are compared regarding their prediction error.

algorithms. The libraries providing the approaches usually also provide optimization algorithms for parameter estimation.

The selected and configured approaches are then applied to the two lists containing the measurement data for the LOC and BC metrics created in task T5 for all 4,547 revisions of the 48 models. Therefore, we created the predictions for each metric and each model, respectively.

#### C. Analysis Procedure

In this section, we describe how the data from literature (T1, T2) and the data collected in the survey and workshops (T3, T4) is evaluated to answer RQ1 and RQ2, respectively. Furthermore, the analysis to determine the performance of the prediction approaches is outlined in step T9 to answer RQ3.

*T1), T2) Classification of Literature and T3), T4) Analysis of Survey/Workshop Results:* The approaches found in the literature are selected by comparing how often they are mentioned for the use on data with a similar structure. For the assessment of survey results we combine the answers in a table and visualize results to make informed decisions on their implications.

T9) Evaluation of Prediction Results: For evaluating regression-based prediction accuracy, we determine how close predicted values are to the ground truth data. There are multiple possible prediction error measurements mentioned in literature having different strengths, weaknesses, and biases. Additionally, many approaches are very closely related. Based on Adhikari and Agrawal [18] and Hyndman and Athanasopoulos [19], we select the root mean squared error (RMSE) as it is widely used and has advantages of making errors comparable across models. RMSE is calculated by  $\sqrt{\sum \frac{(Prediction-GroundTruth)^2}{n}}$ . In order to systematically compare the results, we follow

In order to systematically compare the results, we follow guidelines from Basili et al. [20] and Wohlin et al. [21]. We create a hypothesis, determine independent variables, and run statistical tests to find statistical significant observations. The comparison of the prediction results is visualized in Figure 6.

Using the data presented in this form, the analysis starts with determining the distribution of the data to decide if parametric or non-parametric tests should be used. The next step is comparing the prediction approaches by their prediction errors with the goal to determine if there is a statistically significant difference among the error measurements grouped by the different approaches. Hence, we define following hypothesis:

H0 The samples of error measurements for the different approaches originate from identical populations.

Ha The samples come from different populations.

A one way ANOVA (parametric) or a Kruskal Wallis test (nonparametric) test is used to reveal significant differences within the independent groups of prediction errors (RMSE). Using these tests, we can show if there is one approach performing significantly better or worse than the others regarding prediction errors. This is conducted for both metrics individually. Additionally, we also investigate maintenance effort and run time that the practitioners were asked about in the survey and the workshops.

## D. Validity Procedure

To ensure validity while conducting the study, we focus on employing multiple combinations of approaches and methods in order to avoid bias. We use five different prediction approaches with different underlying algorithms, two different size metrics, and 48 independent models with and without data interpolation. We are performing rigorous statistical analysis using established statistical tests.

#### V. RESULTS

In the results, we consecutively answer the research questions by presenting the outcomes of the associated tasks. We present prediction approaches elicited from literature and previous studies, followed by the practitioners' expectations collected in the survey and workshops. Lastly, we present and analyze the prediction results.

## A. Predictions approaches Identified in Literature and Previous Studies

In this section, we answer RQ1, on the most important prediction approaches currently used in literature on similar data. The results of the literature review reveal two major insights. Firstly, the distinction between linear and non-linear approaches, whereas linear approaches are often outperformed by non-linear ones, especially in cases when the data exhibits lots of random noise (cf. [5], [22]).

Notably, both linear and non-linear approaches have their strengths and weaknesses. The linear approaches exhibit good prediction performance when time series comprise stationary, non-trending data (cf. [23]). This is because linear approaches predict values based on the previous data in the time series. To circumvent this weakness, approaches exist to make input data for linear approaches stationary. Non-linear approaches such as support vector machines (SVM) and artificial neural networks (ANN) have their strengths in the robustness of the prediction if the data is limited or from a short-term period. However, their weakness is a lengthy training process as mentioned by Sapankevych and Sankar [24], Vanajakshi and Rilett [25], and Meyfroidt et al. [26].

Secondly, a majority of identified studies highlight the implementation of SVM and ANN implemented in a variety of domains. From literature and previous studies, we extracted the approaches as listed in Table II. They are briefly outlined in the following paragraphs.

Category	Approach	Tool	Library	Parameter estimation algorithm	Parameters
Statistical, Linear	HOLT	R	forecast	none	none
Statistical, Linear	ARIMA	R	forecast	built-in optimization	AR, I, MA
Machine Learning, Non-Linear	SVR	Python	scikit-learn	grid search	kernel, C, gamma
Machine Learning, Non-Linear	AVNNET	R	caret	caret	lag, hidden neurons
Machine Learning, Non-Linear	LSTM	Python	Keras	manual and built-in grid search	lag, # epochs, hidden neurons, optimizer

TABLE II: The approaches used in this study and their specifications.

TABLE III: The answers collected from the survey, verified in the workshops.

	Importance Rating			max time	max time	acceptable	how far to	acceptable maintenance
	accuracy	accuracy	mainte-	run-	to predict	error	predict	
	long	short	nance	time				
P1	4	2	3	1	>24h	10%	14 days	"automation, big initial effort acceptable"
P2	2	3	1	4	< 1h	10%	21 days	"less than a man-day per week"
P3	4	3	2	1	<12h	10%	7 days	"3h per week"
P4	4	3	1	2	>24h	10%	30 days	"automation, moderate initial effort acceptable"
P5	4	1	3	2	< 1h	5%	90 days	"1h per week"
P6	4	2	3	1	$\leq$ 24h	15%	28 days	"2h per week"
P7	3	2	4	1	$\leq$ 24h	5%	30 days	"automation, only little initial effort acceptable"
P8	1	4	3	2	<12h	3%	14 days	"25-30h per week"
P9	3	2	4	1	<1h	10%	28 days	"automation"
P10	1	4	3	2	$\leq$ 24h	5%	14 days	"2-4h per week"
AVG	3	2.6	2.7	1.7	/	8.3%	27.6 days	/

Holt's linear trend method (HOLT): This approach is serving as a reference for comparison. As shown in Section IV-B in task T6, the time series are characterized by their upwards trend. Smoothing approaches like Holt's are designed for forecasting trends (cf. [19]). It is provided with R using the "holt" function contained in the forecast package and does not require configuration. The only input required is the time series itself.

Autoregressive integrated moving average (ARIMA) model: ARIMA is an advanced regression approach and commonly used with time series data. The approach combines an autoregressive function (AR), differentiation (I), and a moving averages function (MA). These three functions are also the three main configuration parameters. ARIMA was used in a previous study with similar data to create models for outlier detection. The R package "forecast" provides an "auto-arima" function, which compares multiple ARIMA configurations and selects the configuration according to the model quality. The only input required is the time series itself.

*Feed-Forward Artificial Neural Network (ANN):* Feed-forward artificial neural networks are widely used for time series analysis. As neural networks are based on learning from past data, it has to be determined which input should be provided to the network and how. To receive comparable results, we teach the ANN with the same data as all other approaches: one time series is learned to create predictions for the same data. For training and prediction, we provide the network with a set of past data points, called lagged data points, instead of feeding one data point at a time. Hence, the network can learn to predict a point in the future from multiple past

revisions. We use the "AVNNET" implementation provided by the "caret" package in R as it provides automatic parameter estimation functions. The only configuration parameter was the size of the input.As ANNs base upon activation functions, typically ranging from 0 to 1, we adjust our data to this range using normalization.

Long Short Term Memory (LSTM): Long short term memories are recurrent neural networks, which have drawn attention in the field of forecasting time series in the recent years due to their performance (cf. [27], [28], and [29]). An LSTM enhances a plain feed-forward neural network by a memory layer to store information from a previous learning step and reuse it to influence a current learning step. The "Keras" package provides LSTM algorithms for Python. It also provides a grid search algorithm for parameter estimation. The grid search tries all provided combinations of configuration parameters and determines the network with the least error in a given test data. As for the ANN, LSTM is provided with lagged, normalized input. The following parameters are tried during the grid search: Number of hidden neurons, length of lagged input, number of epochs to train, and the optimizer to be used.

Both neural networks use random weights of the neurons in the beginning of learning. Hence, the results created are not deterministic every time the networks are trained. To address the non-determinism and receive similar results for each teaching of the networks, we average the results of multiple runs following an established method in the field (cf. [30]).

Support Vector Regression (SVR): Support Vector Regression is based on the Support Vector Machine. We implement it using the "scikit-learn" package in Python. The configuration parameters are the error metric to be used for predictions, the kernel, the penalty parameter C, and the coefficient for the kernel *gamma*. The scikit-learn package provides a grid search algorithm to find the best set of configuration parameters.

#### B. Expectations of Practitioners towards Predictions

In this section we answer RQ2 on the stakeholders' expectations towards predictions. Findings from the survey are summarized in Table III. The table shows that predicting over long intervals is most important to the stakeholders. The respective answer received three points, on average. Still, maintenance and short term predictions are almost similarly relevant, with 2.7 and 2.6 points, respectively. Hence, the answers to the consecutive questions have to clarify the expectations. Interestingly, run time received only 1.7 points, on average, and is least important for the stakeholders. The related answers for how much time a prediction may take vary strongly. Some engineers expect a prediction tool which they can have at hand for their work during the day, the other group seems to expect predictions to run over night. The answers for accuracy are more clear: Engineers accept not more than 15% error within the predictions and 8.3% on average. Both, the results for the error rates and for how far to predict confirm the results of the importance rating. It seems that rather high error rates are acceptable as long as predictions stay within the boundary, even for long distances. Hence, we interpret that short-term predictions, for example, until the next day are not sufficient. Engineers expect accurate predictions for 27.6 days on average.

The acceptable maintenance times mentioned by the participants highlight the need for automation. Engineers expect the predictions to run in an automated way and accept associated initial effort. Engineers expect less than three hours of maintenance work on the predictions per week. The importance of maintenance time was expected, as man-hours are a valuable resource. The received results were discussed and validated in consecutive stakeholder workshops.

#### C. Prediction Results

In this section we present results from applying the elicited approaches to the measurements. We answer RQ3 by concluding about the applicability and accuracy of the approaches regarding the priorities elicited in the survey and workshops.

1) Prediction Accuracy: The results of the accuracy investigations are summarized in Figure 7. The figure shows how the errors computed by RMSE for all five approaches are distributed among the data. In general, most errors are low while some outlying spikes are visible. If there are spikes, the approaches mostly increase altogether like for model 5 and 28. Still, sometimes only the machine learning approaches are outlying, like in model 16 and 21.

We investigated the prediction accuracy using the engineers' expectations. According to Table III, on average, practitioners found a deviation of 8.3% from the ground truth acceptable. Hence, we count the number of models where predictions, on average, deviate more than 8.3% from the ground truth.

TABLE IV: Results of the accuracy investigations with practitioners' expectation of less than 8.3% error (48 models total).

	HOLT	ARIMA	SVR	ANN	LSTM
# of models above 8.3%	7	6	17	11	12

TABLE V: Accuracy comparison using the Kruskal-Wallis test.

		short term prediction		long term prediction		
		LOC BC		LOC	BC	
	HOLT	110.25	112.23	114.02	113.27	
Kruskal-	ARIMA	87.67	100.60	98.00	105.67	
Wallis	SVR	144.96	151.35	137.54	146.17	
Ranks	ANN	126.38	110.54	125.02	113.75	
	LSTM	133.25	127.77	127.92	123.65	
p-values		0.001	0.004	0.059	0.043	

Table IV shows the results of this analysis. This data shows the robustness of the approaches by counting the amount of models for which the required accuracy could not be achieved. We conclude that the approaches HOLT and ARIMA fail in the least cases. SVR predictions deviated most from the ground truth data. The two statistical approaches seem to outperform the three machine learning approaches, considering the stakeholders' expectations. Among the machine learning approaches, ANN performs best.

Additionally, we address the hypothesis on a difference between the approaches, by performing statistical tests on the error data, as previously shown in Figure 6 in Section IV-C. Thereby, we expect to generate a more reliable and significant evaluation. The 48 values of RMSE for all five approaches are not normally distributed. Hence, we use the Kruskal-Wallis analysis of variance for comparison. This test compares multiple non-parametric samples to determine if they come from the same population. The samples in our case are the accuracy results of the predictions, represented as RMSE. We test four different data sets: The results for short and long term prediction accuracy on both, the LOC and the BC data set, respectively. Whereas for the long term the whole set of predictions is used, we consider four revisions into the future as short term. Four predictions is the smallest amount of prediction length which is achieved by all approaches. Accordingly, for evaluation of short term predictions the full dataset of 48 models is used. For long term predictions eight data sets are excluded. Hence, we have four sets of accuracy results for all five approaches which can be investigated independently. The result of conducting Kruskal-Wallis tests on all four sets are shown in Table V. The test compares group medians, shown in the center of the table. From comparing the medians, differences within the error values are visible. Evidence on this observation is provided by the p-values in the lower part of the table. Regarding the short term predictions, we can reject the null hypothesis of equal populations. We have evidence that at least one approach is significantly different. For long term predictions we can reject the null hypothesis in case of the BC metric, both considering a significance level  $\alpha$  of 0.05.

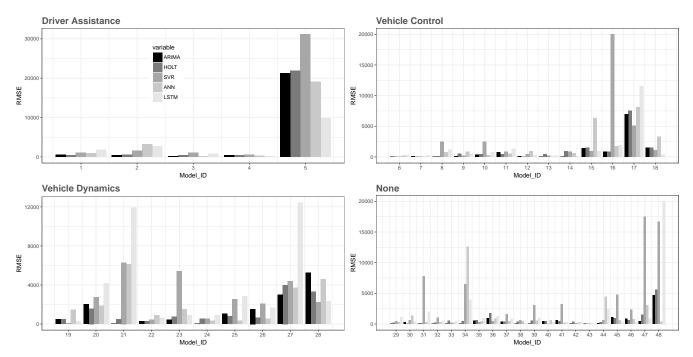


Fig. 7: Overview of the prediction errors (RMSE) by approach using the LOC metric, arranged in the four groups of functionality.

The ranks provided by the test indicate the effect size. ARIMA has the lowest medians within RMSE of all approaches, while SVR has the highest. By running separate tests in between the groups, we found that the predictions performed by SVR are significantly worse than the others. Between the other groups, no statistically significant difference could be detected. Lastly, the results suggest that the approaches converge towards long term predictions. All approaches decrease in accuracy when predicting long-terms.

2) Prediction Maintenance Effort: The implementations of the approaches in the different languages using different libraries strongly depend on expertise with the respective language. Maintenance effort based on code size or complexity cannot be used as metrics cannot be compared among different languages. Nevertheless, as we used parameter estimation algorithms, which automatically estimate the optimal set of parameters, the maintenance effort for future predictions is small for all approaches. As data changes, the algorithms will find matching sets of parameters. Hence, we evaluate all approaches to performing equally well.

3) Prediction Run Time: Run time depends on the implementation and the underlying computer system used. Still, run time differences can be compared. Machine learning approaches require a learning period while statistical approaches do not require this step. It depends on the accuracy required how long learning periods have to be and how often they are performed. If run time is an important aspect, statistical approaches are preferable. In practice predictions can run during night time. So run time is not an issue in the context of predicting time series of model growth in the automotive industry.

#### D. Threats to Validity

As this case study focuses on one specific case in industry, we assess generalizability to other domains as a threat to the validity of the results. We mitigated this threat by designing the study in a way to cover multiple different models, two metrics, and data formats to reduce the chance that results are just obtained by chance in the context. We also provide detailed descriptions of our data set as well as the approaches and tools used. We expect that replications with similar preconditions produce similar results, even in different domains.

When using machine learning and particularly deep learning approaches, there is always the possibility of further optimization. While the results obtained from these approaches might be improved further, we mitigated this threat to construct validity by using automatic parameter estimators to ensure a fair treatment of all approaches.

Furthermore, the approaches might perform differently using other programming languages or libraries. Even though the approaches should be implemented as specified by formulas in publications, it could happen that the same approach is implemented differently in different libraries/tools. Hence, there is a threat that results can differ when replicating the research with different libraries or tools. We mitigated this threat by implementing our approaches with widely used libraries and tools.

Due to the small sample size in the survey, it does only represent a fraction of the whole industry. We tried to mitigate this threat by considering practitioners in all different existing roles at the department. Additionally, the lead developers of all function groups were surveyed. Still, in other domains, the expectations towards predictions might differ.

## VI. CONCLUSION AND FUTURE WORK

In this study we compare five prediction approaches, HOLT, ARIMA, SVR, ANN, and LSTM, which were elicited from literature or used previously on the same data set. Our results show that all five are applicable to predict time series of software size measurements performed on simulation models in the automotive industry.

We identify differences regarding their performance, particularly with respect to prediction accuracy, which is assessed by calculating the differences between predictions and ground truth data. We find that SVR performs significantly worse than the other four approaches, in three out of four data sets. The data also indicates, that the linear, statistical approaches outperform the non-linear machine learning approaches regarding accuracy, using our data set. This might be due to the comparably small amount of training data available (between 6 and 351 data points, 73 on average) or the shape of the data that is mostly steadily increasing. For cases with similar data in related application areas we recommend linear approaches like HOLT or ARIMA, or feed-forward neural networks like ANN.

Additionally, we also contribute by reporting on practitioners expectations towards model growth predictions, collected in a survey with ten local developers, testers, and team leaders. We find that they expect predictions to be accurate on long term (about one month) and that short term predictions (about 4 days) of model growth is less important. We also conclude, that predictions are expected to run automated with low amount of maintenance. Run-times of predictions are not an issue for most practitioners.

Future investigations are intended to reveal clusters of time series favoring specific prediction approaches. We might be able to extract general attributes of data sets that favor specific approaches, like the size of the data set or the distance between data points. Accordingly, we would be able to suggest prediction approaches matching specific attributes of a dataset.

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