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Spacecraft for Deep Space Exploration: Combining Time and Budget to Model the Trend in Lifespan

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Abstract. This paper develops a novel approach to modeling and predicting advancement in spacecraft technology for deep space exploration. As spacecraft lifetimes increase, ever more elaborate missions and even quasi-permanent bases become more and more possible. We use the NASA (National Aeronautical and Space Agency) yearly budget along with the time variable to model their relationship with spacecraft lifespans and compare the level of fit of our model with an exponential (generalized Moore's law) model. The results indicate that our model provides a better curve fit, suggesting the usefulness of NASA's budget in predicting the progression of space exploration technology. Additionally, the evidence that the NASA budget has a statistically significant impact on spacecraft lifespans suggests that the government could increase future funding of NASA to foster quicker technological improvement in space exploration technology.

Keywords: Predictive modeling, Moore's law, Space exploration, Technology foresight

1 Introduction

Many technologies have been shown to conform to the general form of Moore's law, which is the empirical observation that technologies often improve as exponential functions of time, **enabling predictions about their future,** although at different rates of change for different technologies [9]. Another observed regularity, Wright's law (also called the power law or experience curve), also provides approximations for the pace of technological improvement that are usually similar and of comparable quality [6, 17, 20, 23]. While these laws have served as models of technology progress in various technological domains, only a few studies have demonstrated that space exploration technology follows similar patterns [12]. The fact that the human population of space has historically exhibited a general upward growth trend [8, 28] also suggests that space exploration technology may follow an exponential growth pattern. Yet, some have argued that progress in human space exploration has come to a stop [3, 11]. Despite (or perhaps because of) these arguments, it remains debatable what proxies to use for measuring the performance of space exploration technology over time since progress in space exploration is a qualitative concept and thus not directly and quantitatively measurable.

A recent use of spacecraft lifetimes as a proxy for advancement in space exploration technology [6] found an exponential trend, as has been found for many other technological domains. Howell et al. [13] later compared the rate of spacecraft technology progress in the United States to that of the Soviet Union during the space race period and concluded that the former had a higher rate of improvement than the latter. Both of these studies chose to use a single proxy variable rather than a weighted combination of variables, thus helping to lower the risk of overfitting. Ultimately an overfitted curve may provide a perfect fit to the data but have limited predictive power and thus limited value [14]. Our study incorporates an additional causatively relevant variable into an otherwise exponential trend formula to pursue a more detailed model of advancement in deep space exploration vessels. Specifically, we utilize NASA's budget along with the time variable to model their relationship with spacecraft lifespans. Our goal is to identify a model that provides a good fit, useful forecasts, is intuitive and is readily applied.

First, we survey the previous work in applying Moore's law to study technological advancement, followed by a review of literature investigating the potential explanatory variables that affect technological progress. Then, we introduce our methodology of modeling advancement in space exploration technology. Next, the data fitting results and the extrapolation predictions for the progression of space exploration technology are presented, followed by a conclusion.

2 Literature Review

In 1965, Gordon Moore, a co-founder of Intel and Fairchild Semiconductor, published an article observing that the number of components per integrated circuit had doubled approximately every year from 1959 until 1965 [22]. He predicted that this growth would continue at around the same pace for at least the next ten years. He then in 1975 revised the growth rate to a doubling time of every two years [21]. The exponential progress in the number of components on a state-of-the-art integrated circuit eventually became known as Moore's law. Over the years, a generalized version of Moore's law has taken on a meaning as an exponential growth trend in a technology [23, 27, 30].

The generalized Moore's law has been observed in many other technologies besides integrated circuit chips since Moore's article. For instance, Nielsen [25] looked into internet bandwidth growth rates and projected that "a high-end user's connection speed grows by 50% per year," which suggests that internet bandwidth doubles almost every 21 months. Kryder proposed that disk drive areal density was increasing 1,000-fold every 10.5 years [33], which is approximately equivalent to a doubling of storage capacity every 13 months. Additionally, Carlson found evidence that the doubling rate of cost per performance of DNA sequencing and synthesis technologies has followed an even faster trajectory [29]. Sometimes referred to as the Carlson Curve, this exponential growth has come to be known as the biotechnological equivalent of Moore's law. More recently, Bailey et al. [1] and Nagy et al. [23] examined the cost and production data of 62 different technologies and found exponential relationships between performance and time in all of them.

Other studies have also contributed to strengthening the exponential curve as a model of technological advancement. For example, Koh and Magee [15, 16] studied the technological development of the information and energy technology domains with a broad functional category approach. They assessed the three functional categories of storage, transportation, and transformation for both domains and developed associated non-device functional performance metrics to analyze their technological improvement trends [5]. They found exponential progress in technology over time for all cases. Similarly, Magee et al. [20] looked at 28 different technology domains and employed 71 metrics to study how their performances evolve with time. The results show that these 28 technologies also seem to exhibit exponential progress, analogous to the original Moore's law for electronic chips.

As discussed above, considerable research has demonstrated that the performances of a broad range of technologies increase exponentially over time. Nevertheless it is unclear why the exponential should be assumed to provide the most accurate possible predictions of technological performance. Moreover, the exponential alone cannot explain what influences technological improvements. As MacDonald and Schrattenholzer [18] stated: "*technology design that is left on the shelf does not become better the longer it sits unused.*" This suggests the need for knowing the factors that shape technology performance in order to build even better models for predicting technological performance.

Prior research has explored various explanatory variables that affect technological progress. Some studies have measured technology improvement rates based on insights obtained from patents [4, 5, 20, 26, 32], while others suggested using production, R&D spending, sales revenue, etc. [1, 9, 20]. Despite these efforts, the existing literature is often inconclusive about the preferable type of metrics. Magee et al. [20] propose techno-econometric metrics focused on value to the user (e.g. performance/cost figures) in preference to market-based metrics (e.g. number sold) and engineering metrics (e.g. digital chip pitch):

> *"The 'ideal' metric for assessing technical performance is one that would assess the economic value of an artifact independently of purely economic variables such as scarcity and strength of demand. An ideal metric would combine (in the 'correct' weight) all performance factors that have a role in a purchase/use decision. Thus, these 'techno-economic' metrics would measure the performance of an artifact as viewed by a user and not design variables as viewed by an engineer (the technical metrics) and also not the number of users or depletion effects as present in metrics focused more on marketing or economic impact."*

Some scholars take a broader view, looking at the driving forces behind technological innovation, which comprise pull drivers, such as market demand and profitability potential, and push drivers, such as new technology and innovative manufacturing processes [7, 19]. They argued that these two drivers are indispensable for technology evolution and a lack of either would change the path of technological advancement.

A number of researchers have emphasized the importance of public policies and government funding for the evolution of certain technologies [2, 31]. For many such technologies, the private sector may have limited incentive or ability to support research because the time needed to obtain benefit from the research results is often measured in years, if not decades, and they cannot assume the risks inherent in such research, nor can they continue funding research in a particular field over a long period of time if the payback is unclear. In our view, the importance of continued government funding in space exploration technology cannot be emphasized enough as space exploration is a long-term endeavor and requires steady funding to stay on schedule. A decreased level of funding would certainly result in delays in the development of new technology. This motivates our consideration of NASA's budget in modeling advancement in space exploration technology. Additionally, NASA's budget acts as both push and pull drivers for the advancement of space exploration technology. Not only does NASA funded research facilitate the creation of new technology (a push driver), but NASA funded missions provide applications (a pull driver) that motivate creating the required new technologies.

By fitting a curve defined by a new metric to space mission data and NASA's budget data, the results of our study will contribute to the literature related to the advancement in space exploration technology over time. Indeed, understanding technological performance in space exploration over time will enable better foresight in formulating technology policy and planning for exploration missions to distant astronomical objects [10].

3 Methodology

The space mission data for the period 1959 to 2020 is updated from the work of Hall et al. [10][1]. NASA's annual budget data was extracted from Wikipedia [34]. We used the data from the column showing budget in 2014 Constant Dollars, which takes inflation into account and thus provides a more meaningful assessment than the data from the column containing Nominal Dollars. Our study fits the following log linear model to the data:

$$\log_2 L_t = \alpha + \beta_1 t + \beta_2 \log_2 S_t + \varepsilon \tag{1}$$

The dependent variable L_t represents the maximum lifetimes in years of all the spacecraft launched in year t. A lifetime is calculated by subtracting the launch date of a spacecraft from its failure date and is measured in years. Variable t, the year that a spacecraft launched, ranges from 1959 to 1999 to account for the years for which all spacecraft launched are no longer operating (except for Voyager 1 and 2 launched in 1977, whose projected lifetime figures are based on published estimates). S_t represents a moving average of some specified window size in years for NASA's annual budget calculated for year t and measured in US$ millions. The parameters α, β_1, and β_2 are fitted using the method of ordinary least squares. The error terms, ε, are generated from the discrepancies between the fitted curve and each data point. We assume that the error terms exhibit a mean of zero and constant variance.

We fitted the model to the moving average data for each window size from 1 to 20 using root-mean-square error (RMSE) to measure the goodness-of-fit. Then we compared the resulting RMSE values and chose the window size that produced the lowest RMSE. This process produced the model with the best RMSE over all window sizes and model parameter values.

4 Results

The plots of RMSE vs. window size allow us to find the best fit to the data, based on the parameters and window size with the lowest RMSE. Figure 1 shows the minimum RMSE for the various window sizes. The minimum RMSE starts at 2.23 and decreases to a low of 2.13 at a window size of 9 before gradually increasing to 2.16 at window size 20. For comparison, we next included the Voyager 1 and 2 spacecraft which were launched in 1977 and are still operating. Their lifetimes were estimated using NASA's estimate [24] that the Voyagers will continue operating until 2025,

[1] Data was compiled into a Google Sheet file that can be viewed and/or acquired by accessing the following web address: https://docs.google.com/spreadsheets/d/1fpYB3pMHcq77vQPMvpkA-sWFPzr2zlcWnEsDyawVfyI/edit#gid=846789546

giving both spacecraft estimated lifetimes of 48 years. Figure 2 shows the minimum RMSE over the various window sizes for the data with the Voyager missions included. It can be seen that the window size with the lowest possible RMSE changes to 13 with a minimum RMSE of 2.22.

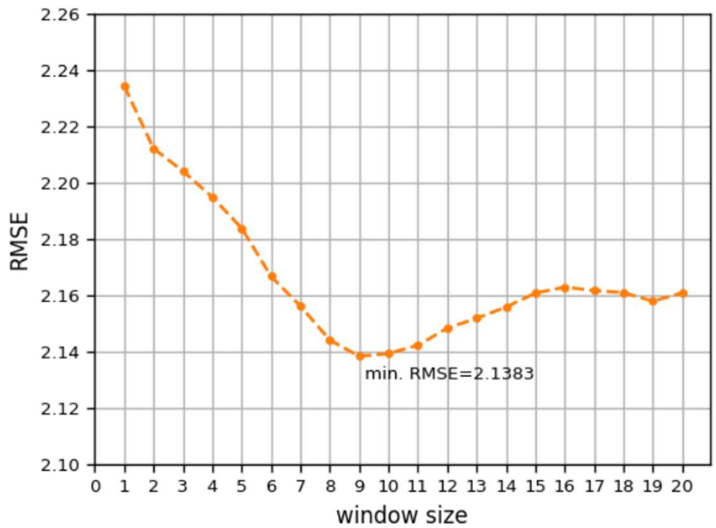

Fig. 1. Minimum RMSE vs. window size (excluding the Voyagers)

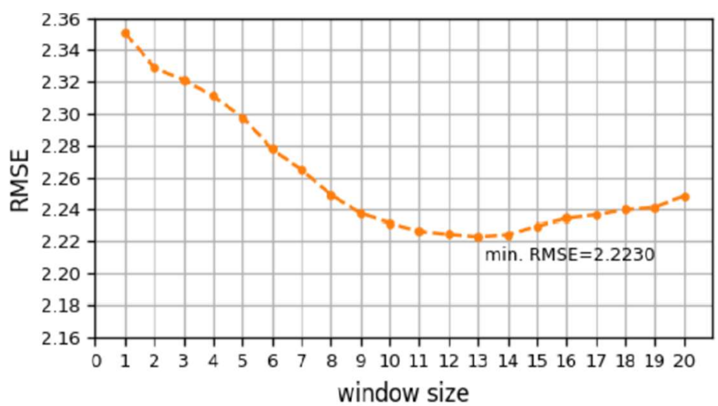

Fig. 2. Minimum RMSE vs. window size (including the Voyagers)

Figures 1 and 2 show that applying moving averages with window size 13 and 9 on NASA's annual budget (variable S_t) best fit the data with and without the Voyagers included respectively. Our next step is, therefore, to regress Eq. (1) to optimize its parameter values for each of the two cases, (1) excluding the two Voyager spacecraft and using a moving window of width 9, and (2) including the Voyagers with estimate lifetimes and a moving window of width 13.

Tables 1 and 2 show the parameter values of the fitted curve. Excluding the Voyagers from the analysis, when holding the other predictor variables fixed, a 1% increase in NASA's annual budget would raise the expected mean lifespans by approximately β_2=0.9365%, while including the Voyagers, a 1% increase would lead to approximately β_2=1.0593% increase. This is implied by Eq. (1) for values of β_2 near 1. The F-statistic indicates that in each model the explanatory variables are jointly significant in determining the lifespan in Eq. (1). The *p*-values are significant, and so permit excluding the null hypothesis that β_1 and β_2 are positive due to chance, thus indicating that time and budget really are associated with increasing lifespan. Thus we conclude that US government funding has a significant impact on the evolution of spacecraft lifespan.

Table 1. Results of curve fitting (excluding the Voyagers)

Coefficient	Value	*t*-stat.	*p*-value
β_1	0.0892	2.343	0.027
β_2	0.9365	2.307	0.029

Probability (F-statistic): 0.000583; Adj R-squared: 0.381.

Table 2. Results of curve fitting (including the Voyagers)

Coefficient	Value	*t*-stat.	*p*-value
β_1	0.0823	2.050	0.050
β_2	1.0593	2.401	0.023

Probability (F-statistic): 0.000662; Adj R-squared: 0.365.

Figures 3 and 4 present the logs of the lifespan values ($log_2\, L_t$) and the fitted curves. As can be seen from both figures, our models achieve greater accuracy in fitting the data than exponential curves, as a result of a lower value of the RMSE. To compare the predictions of the standard Moore's law (exponential) and budget-augmented models, we also used each of the models to extrapolate the fitted curves from year 2000 up to 2020. Actual spacecraft lifespan data is also shown for years since 2000, depicting a downward trend, a serious artifact attributable to recency bias wherein a significant proportion of spacecraft launched in recent years are still operating, so only the shortest-lived ones have failed thus downward-biasing the maximum lifetime figures for such years. This problem becomes progressively worse for more recent years since, for example, the maximum lifetime of spacecraft launched 2 years ago that have failed can be no more than 2 years. To complement the log scaled plots in Figures 3 and 4, we also generated linearly scaled plots in Figures 5 and 6.

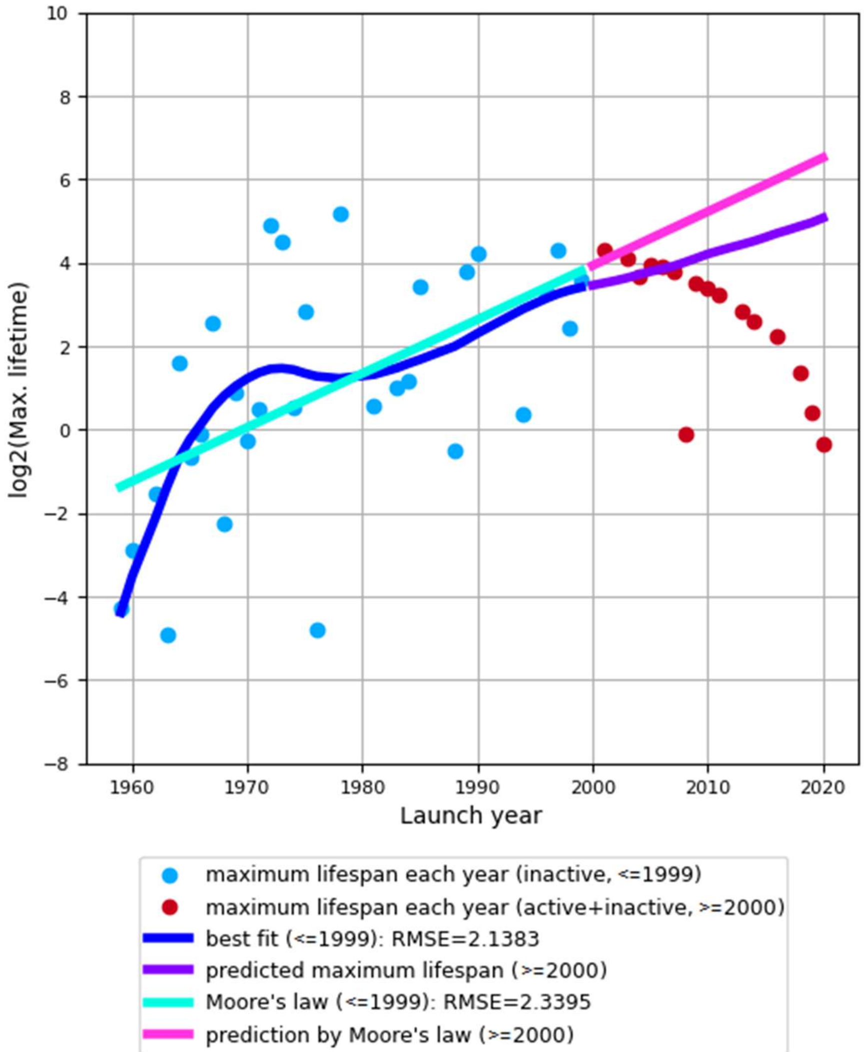

Fig. 3. Fitted curve vs. Moore's law (excluding the Voyagers from the analysis)

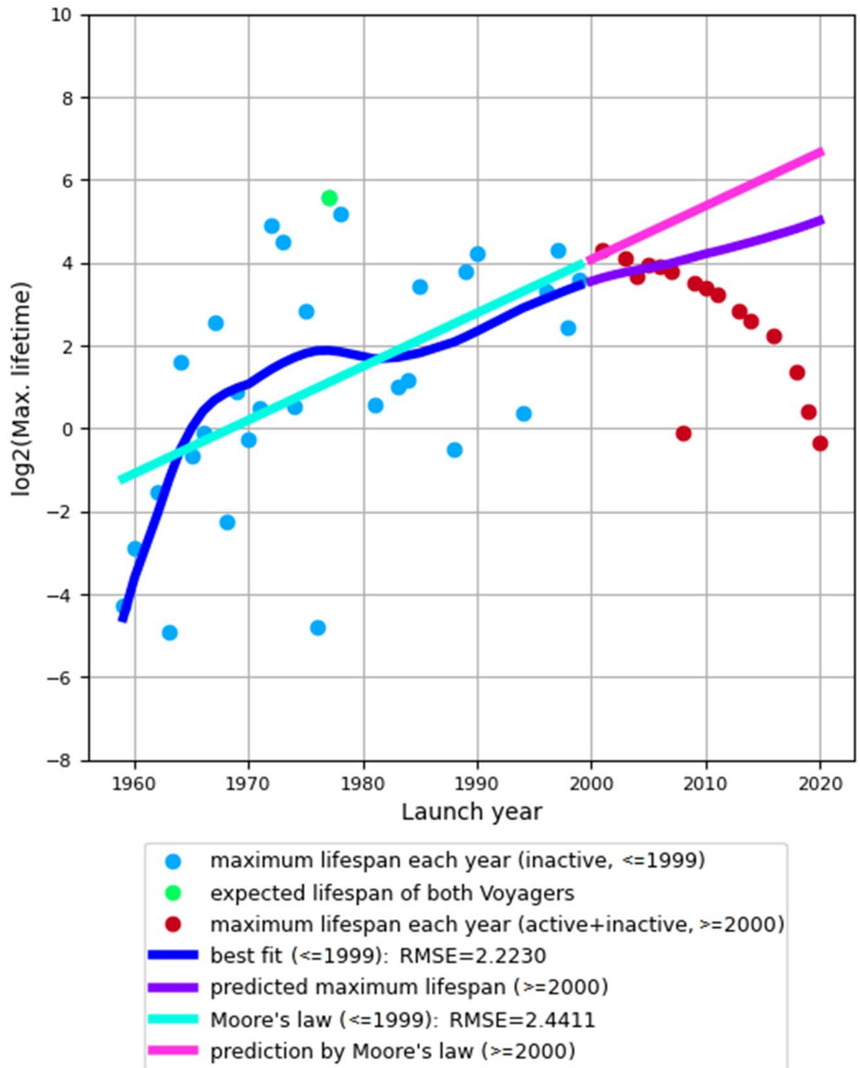

Fig. 4. Fitted curve vs. Moore's law (including the Voyagers in the analysis)

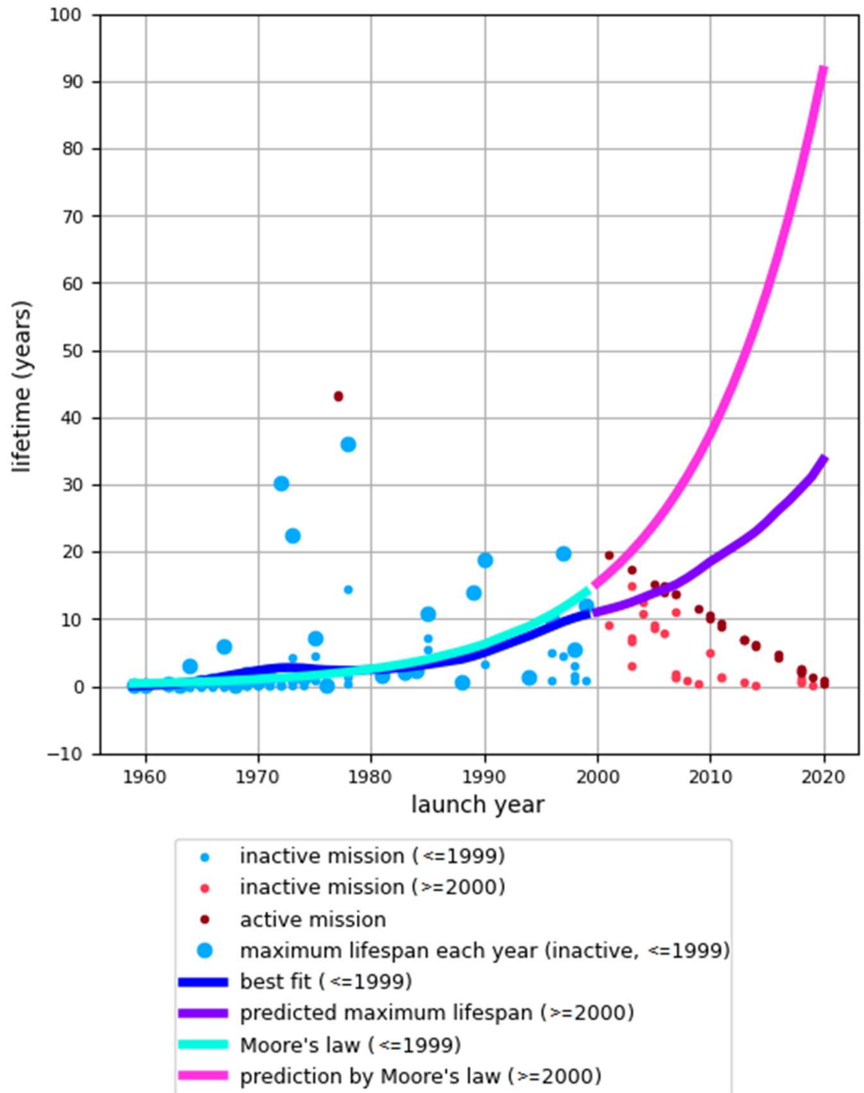

Fig. 5. Fitted curve vs. Moore's law (excluding the Voyagers) with linear scaling

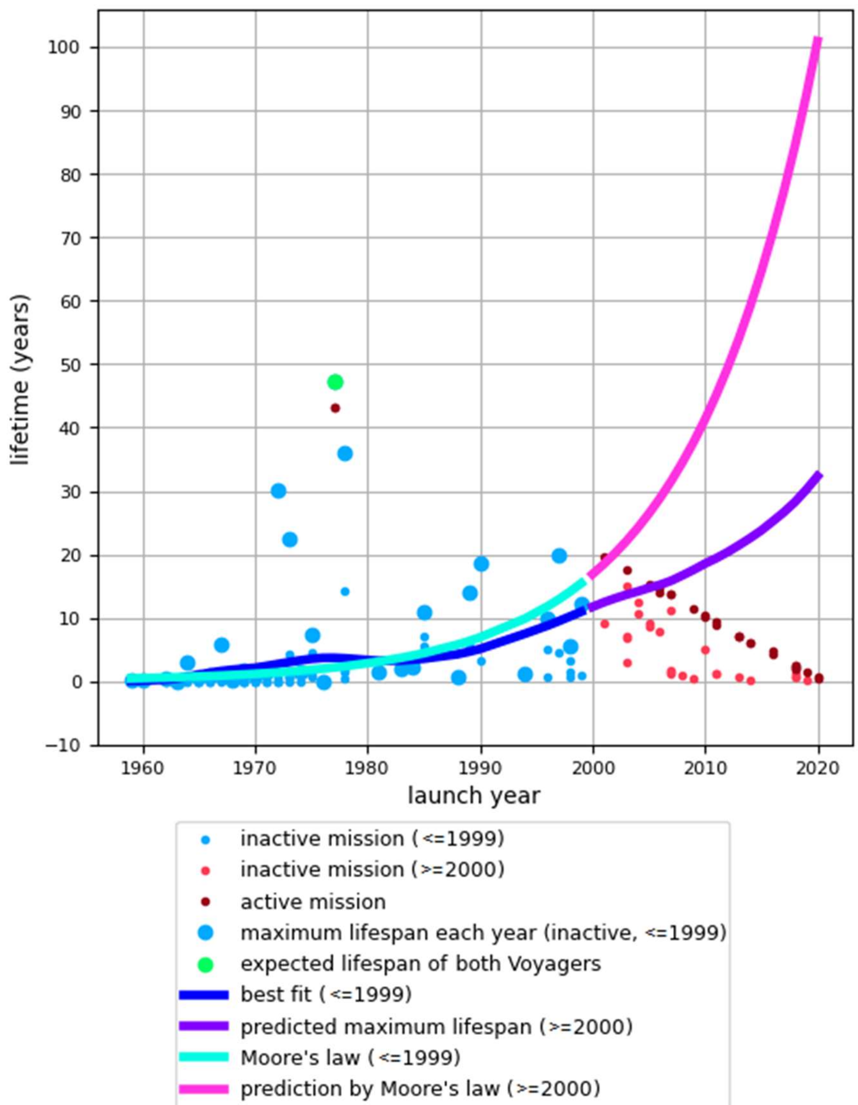

Fig. 6. Fitted curve vs. Moore's law (including the Voyagers), linearly scaled

To extrapolate predictions of future spacecraft lifespans from the fitted models, we next tested hypothetical NASA annual budgets for the years 2021-2030 using 5% and -5% annual growth rates. The extrapolations are illustrated in Figures 7 and 8. The plots demonstrate that NASA's future budget is predicted to have a significant impact on advancements in spacecraft lifespan. Figures 9 and 10 show these projections in linear space.

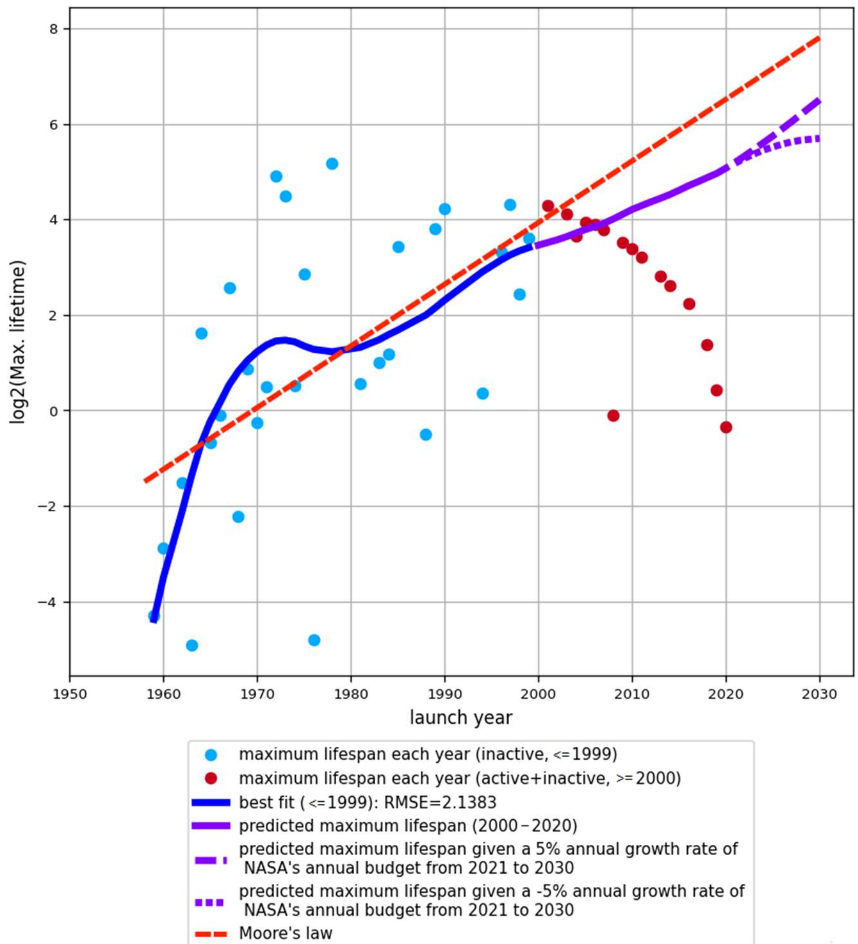

Fig. 7. Predicted lifespans of spacecraft during 2021-2030 (excluding the Voyagers from the analysis)

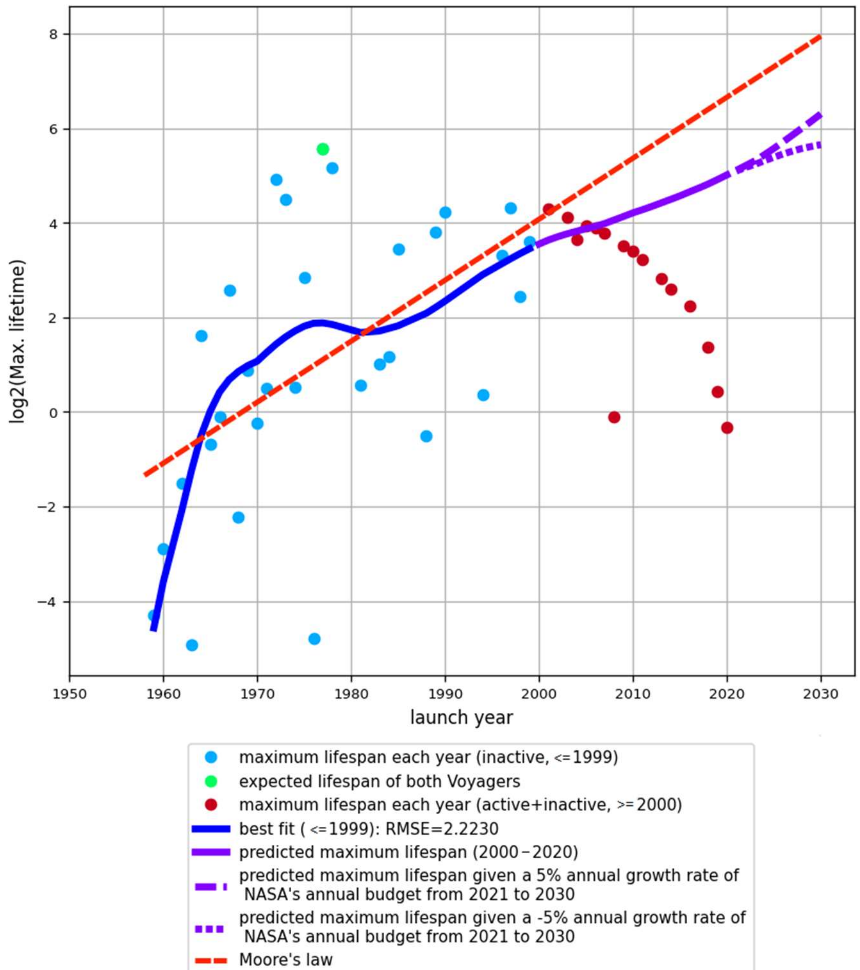

Fig. 8. Predicted lifespans of the spacecraft during 2021-2030 (including the Voyagers in the analysis)

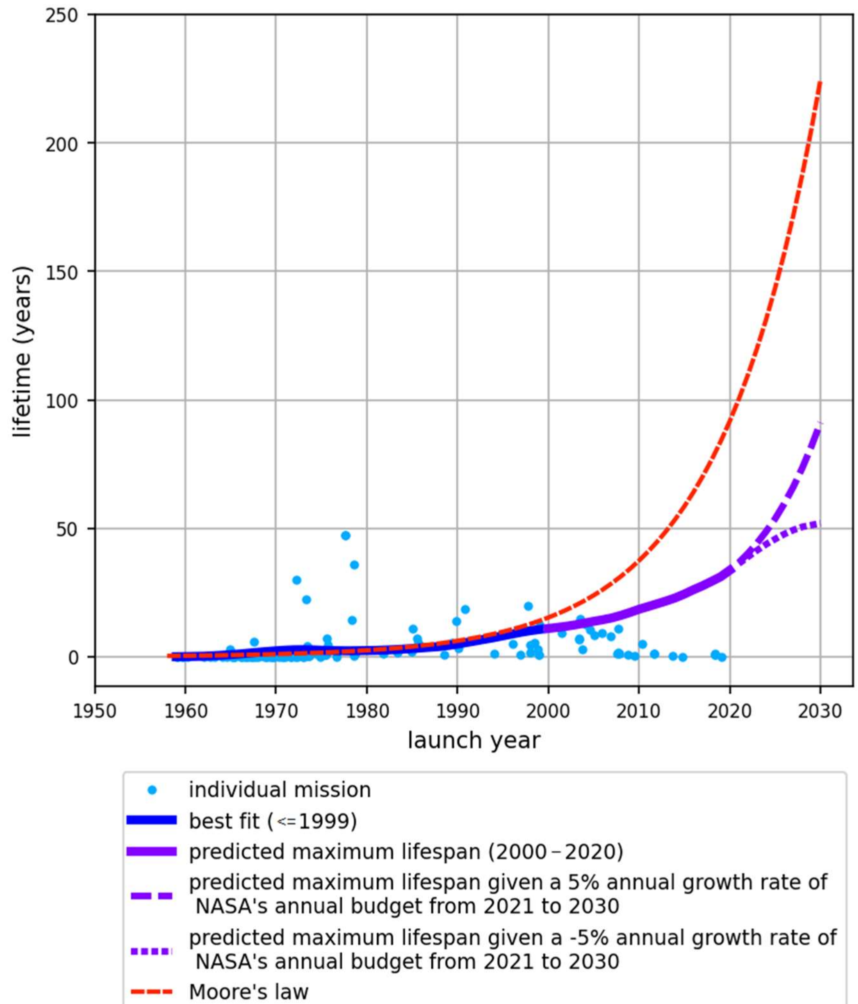

Fig. 9. Predicted lifespans of spacecraft from 2021-2030, linearly scaled (excluding the Voyagers from the analysis)

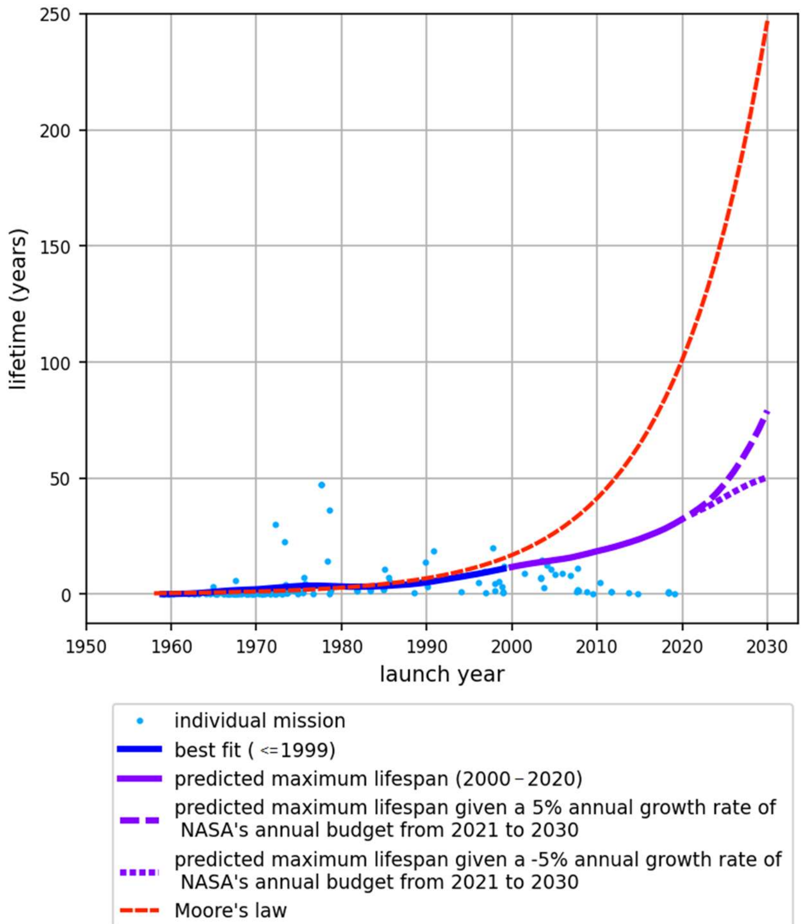

Fig. 10. Predicted lifespans of spacecraft during 2021-2030 with linear scaling (including the Voyagers)

5 Conclusions

We have established an improved model of advancement in space exploration technology by augmenting a basic exponential model with an additional factor, the NASA budget. We tested our model against data on the lifespans of deep space exploration spacecraft, finding lifespan to be a useful proxy for space exploration technology performance. We first showed that accounting for the NASA budget enables models with improved fit to the data. We then extrapolated the model to show how the future NASA budget is predicted to significantly impact the lifespans of future launches, thus highlighting the importance of continued government funding in advancing the technical performance of deep space exploration vessels.

Overall, the empirical results of this study identify our model as fitting data about the technical performance of deep space exploration technology better than the general exponential curve. Furthermore, we found statistically robust evidence that increases in NASA's budget can be expected to boost technical performance of future spacecraft. This result can be useful in crafting government policies regarding future funding of deep space exploration.

This work could be usefully extended in future research in multiple ways. One direction is to test the validity of the model on new data as more spacecraft lifespans becomes available in the coming years. It may also be valuable to devise more accurate models by introducing other relevant independent variables besides time and NASA's budget into the model. A natural example of that would be to incorporate space program budgetary data from other organizations that fund deep space missions. Modeling efforts in general often must balance model detail with model parsimony to best achieve validity, accuracy, understandability, and maintainability while avoiding overfitting. Further investigation of product lifespans as a measure of technical performance will cross-fertilize the fields of reliability analysis and technology foresight. That is expected to enable identifying, understanding, and applying new techniques for technology foresight.

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