Modelling Future Launch Traffic and its Effect on the LEO Operational Environment

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Launches are a significant source of uncertainty for the evolution of the space environment, which creates a major challenge for predicting the state of the environment in future. Many space environment models that require an estimate of launch traffic will either use no launches as a baseline or repeat historical data. Recent shifts in launch traffic because of New Space have shown that this approach is unrealistic and does not account for potential further changes in launch traffic. Our proposed approach to modelling launches is a parametric model that can simulate various future launch scenarios. This model calculates the total number of objects launched per year using an exponential-logistic curve to capture the sharp increase in launch traffic. To determine the location and physical characteristics of launched objects, the model fits probability distributions to data from previous launches. These distributions can vary over time to simulate other changes in launch trends aside from the number of objects. The launch model can be used along with other debris environment modelling tools to simulate the evolution of the space environment and accordingly to calculate the risk of collision for new missions. Results are shown for the collision likelihood of some example missions in LEO based on a launch scenario generated by the model.

I. Introduction

The rapid growth of New Space has brought about an unprecedented surge in the number of objects being launched into Low Earth Orbit (LEO). This is a result of the increased availability of commercial launches, which has enabled many more entities to launch satellites and has seen the beginning of several large satellite constellations. The growth of the space sector has many benefits, including increased democratisation of access to space and a greater number of available space services. However, it has also resulted in far more traffic from active payloads in LEO [1]. This creates difficulties for mission operators, who have to process more conjunctions, and threatens the long-term sustainability of the space environment.

The issue of increased traffic in space has motivated more research into models of the space environment. Such models aim to capture future trends in the number and location of objects in space – including active payloads and debris. Most space agencies have published software for this purpose, which include the LEGEND simulator from NASA [2], DELTA from ESA [3], MEDEE from CNES [4], SOLEM from CNSA [5], and NEODEEM from JAXA [6]. One significant source of uncertainty in all of these models is launch traffic. The number of objects launched in future will depend on several factors that are difficult to predict, such as availability and cost of launches or demand for new missions.

Most existing approaches to modelling space traffic repeat historical launches into the future. This is the case in published analyses of MEDEE [4], NASA's ORDEM software [7] and SOLEM [5], which all use 8 years of launch data repeated over several decades. This approach of repeating historical launches fails to account for the sharp increase in traffic seen since 2019 that is largely due to Starlink launches. Other models might include theoretical constellations as separate from other launches, which when considered separately follow a more predictable trend. For example, in a study on debris mitigation measures, the authors include a theoretical mega-constellation of 1000 satellites [8]. This is still less than the current number of Starlink satellites in orbit, which highlights the difficulty of estimating the rate of future satellite launches.

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In this work, we propose a new parametric model of future launches that better captures recent trends compared to other approaches. This model leverages historical launch data to estimate characteristics of future launches and can adjust the launch rate based on qualitative assumptions on future trends. Another aspect of this model that is different to previous methods of predicting launches is the ability to vary the physical and orbital characteristics of launched objects over time. This is necessary to allow for changing demand in different orbital regions or the types of payloads launched, as has been observed in the past. One potential application of this launch model is for predicting the risk of collision for future missions based on the evolution of the environment. This is demonstrated with an example for theoretical new missions in LEO.

The remainder of this paper is organised as follows. Section II presents the methods that comprise the proposed launch model. Section III shows example scenarios created using the model to demonstrate its applicability. Finally, Section IV gives an example application of the launch model to predicting long-term risk.

II. Methods

The proposed launch model has the following steps:

1) Calculate the trend in total number of objects launched per year,
2) Determine the proportion of each object class (payloads, rocket bodies, mission related objects) based on historical data,
3) For each object class, sample orbital and physical parameters from a distribution fit to historical data,
4) (Optionally) define time-varying weights for each distribution to account for changes in orbital and physical characteristics over time.

Each of these steps takes into account historical launches and has parameters that can be adjusted depending on predicted future launch behaviour. The following sections give further details on each part of the model.

A. Total Launch Trend

The total number of objects launched in a given year are modelled with the following logistic-exponential curve:

$$N(t) = n_0 + \frac{A \cdot exp(d(t - t_0))}{b + exp(-c(t - t_0))}, \tag{1}$$

where N is the total number of objects launched in year t. The parameters in this expression (n_0, A, b, c, d, t_0) can be adjusted to create different forecasts. Figures 1 to 4 show the effect of each parameter on the trend. t_0 is the time of the inflection point in the curve and n_0 is the initial value of N at a time $t \ll t_0$ as shown in Fig. 1. Figure 2 shows the effect of varying A and b, which both control the magnitude of increase in N. Increasing A or decreasing b results in a larger number of objects launched in the future.

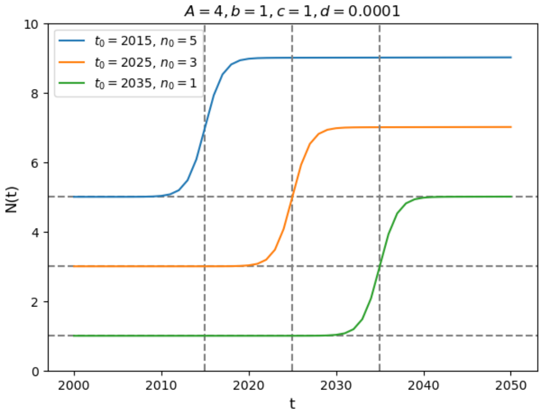

Fig. 1 Effect of t0, n0.

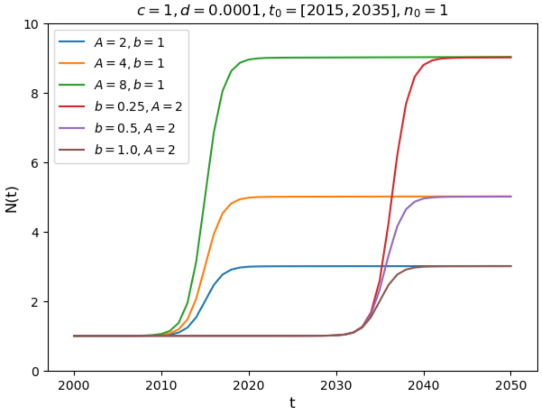

Fig. 2 Effect of A, b.

The parameter c controls the rate at which N increases as shown in Fig. 3. Higher values of c result in a steeper rate of increase in the number of objects launched. Figure 4 shows the effect of varying d, which controls the rate of increase in N where $t > t_0$. When $d = 0$, the number of objects launched reaches a plateau some time after t_0. Increasing d instead results in a further exponential increase in the number of objects launched after t_0.

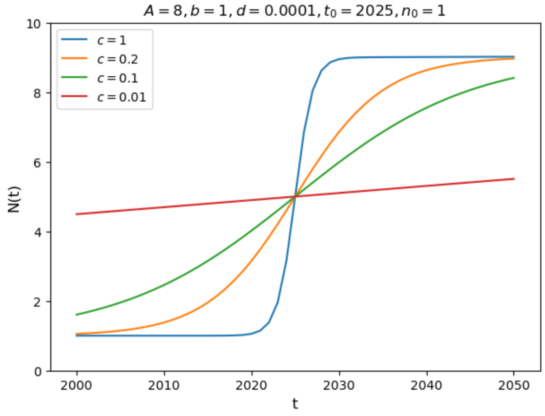

Fig. 3 Effect of c.

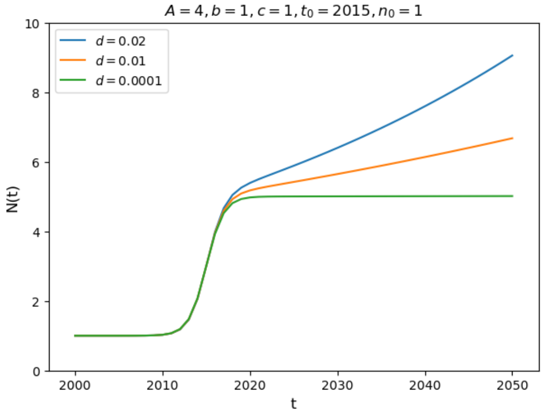

Fig. 4 Effect of d.

Figure 5 shows three different forecasts using this model for the number of objects launched over the next 30 years. The data shown on the graph for previous years come from DISCOSWeb *. These are the total number of individual payloads, rocket bodies, and mission related objects launched each year. The blue curve shows a scenario where the number of objects launched does not continue to increase as rapidly as it has since 2019 and only gradually increases over the next 30 years. The green and black curves give alternative scenarios where the launch rate continues to increase more steadily in the future.

The proportion of each object class in the total number of launched objects has also changed as a result of New Space. Individual launches can now contain many payloads and it is common to have smaller satellites "piggyback" on launches for larger missions. This is highlighted in Fig. 6, which shows the proportion of payloads, rocket bodies, and mission related objects launched to LEO since 2013. Payloads clearly take up a far greater share of object launches, which must be accounted for in launch forecasts. An additional set of parameters that can be controlled in this model is the proportion of object classes launched in a given year, with the potential to increase or decrease the relative number of payloads per launch.

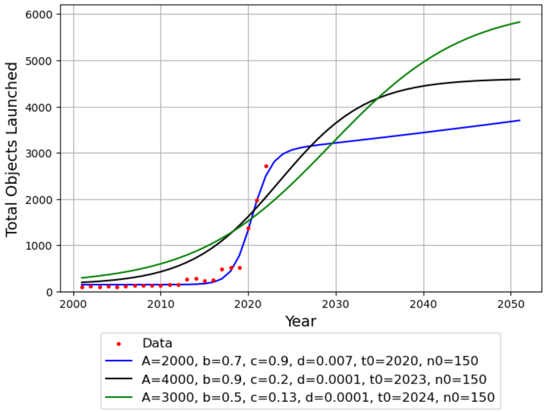

Fig. 5 Number of objects launched to LEO each year with different forecasts shown.

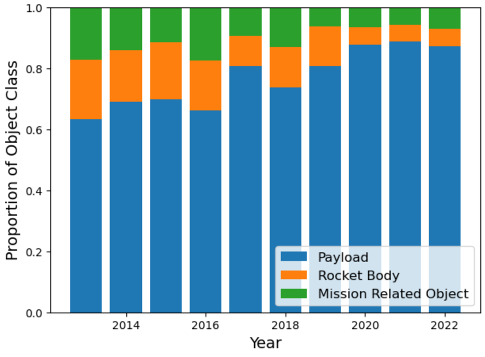

Fig. 6 Proportion of each object class launched to LEO for the previous ten years.

The data shown in Fig. 5 and Fig. 6 include all constellation payloads, which constitute the majority of recent launch traffic. These payloads can also be considered separately from other launched objects and added based on proposed or approved launch plans. There are several different sources that detail these planned constellations. For example, the

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*https://discosweb.esoc.esa.int/

LEO Satcom Report from Prime Movers Lab, which lists over 200,000 satellites as parts of large constellations [9] and a report from the MITRE corporation that lists over 136,000 planned constellation satellites [10]. Figure 7 shows some example launch trends fit to historical launch numbers excluding constellations. While the number of objects launched each year is significantly lower, there is still an increase over the past few years that is captured by the model. The distribution of object classes also changes substantially when excluding constellations as shown in Fig. 8. Constellation launches tend to have more launches per rocket body and so excluding constellations results in a greater share of rocket bodies in total launched objects.

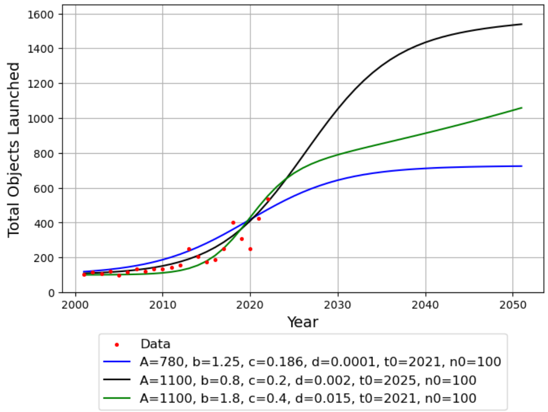


Fig. 7 Number of objects excluding constellation payloads launched to LEO each year with different forecasts shown.

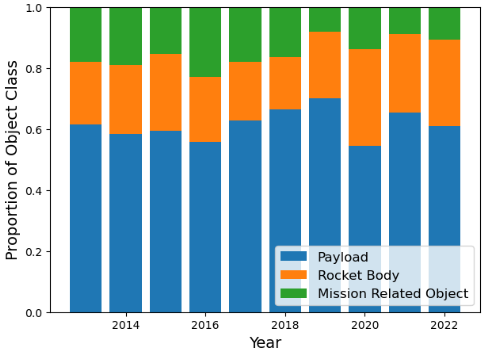


Fig. 8 Proportion of each object class launched to LEO for the previous ten years excluding constellation payloads.

B. Distributions of Orbital and Physical Parameters

In addition to the number of objects launched, it is necessary to model the orbits into which objects are launched since certain regions in LEO experience higher traffic than others. Furthermore, to predict the evolution of objects' orbits it is useful to model their physical properties. This is achieved by fitting a distribution to previous object launches with separate models defined for payloads, rocket bodies, and mission related objects. The distribution of orbital parameters models the semi-major axis, eccentricity, and inclination of previous launches. RAAN, argument of perigee, and mean anomaly are assumed uniformly distributed across objects. A separate distribution for the physical parameters models the cross-sectional area, mass, and characteristic length of each object class. The distribution used here is a Gaussian Mixture Model (GMM), which has the following form:

$$p(x) = \sum_{i=1}^{K} w_i \varphi(\boldsymbol{\mu}_i, \boldsymbol{\Sigma}_i), \tag{2}$$

where K is the number of components, φ is a multivariate normal with means $\boldsymbol{\mu}$ and covariance $\boldsymbol{\Sigma}$, and w_i is the weight of the i^{th} component. This distribution models the orbital and physical characteristics of previous object launches. When simulating future launch scenarios, objects are sampled from these distributions to obtain their relevant parameters. Figures 9 and 10 show examples of the historical launch data and samples from distributions fit to those data points. In Fig. 9 this is done for the area, mass, and length of payloads, excluding constellation payloads, launched to LEO between 2013 and 2022. The distribution is a 6 component GMM fit using expectation maximisation. In the case of the physical parameters, the fit is to the log values of each as this gives a clearer relationship between the parameters. Similarly, Fig. 10 shows the semi-major axis, eccentricity, and inclination of rocket bodies launched to LEO over the same time period fit to a 10 component GMM. These examples show that the GMM samples effectively capture the distributions of true objects.

C. Time-Varying Distributions

The steps described previously capture the distribution of previous launches, but do not account for potential changes in these distributions, such as having more launches to certain regions or decreasing payload sizes. To capture such

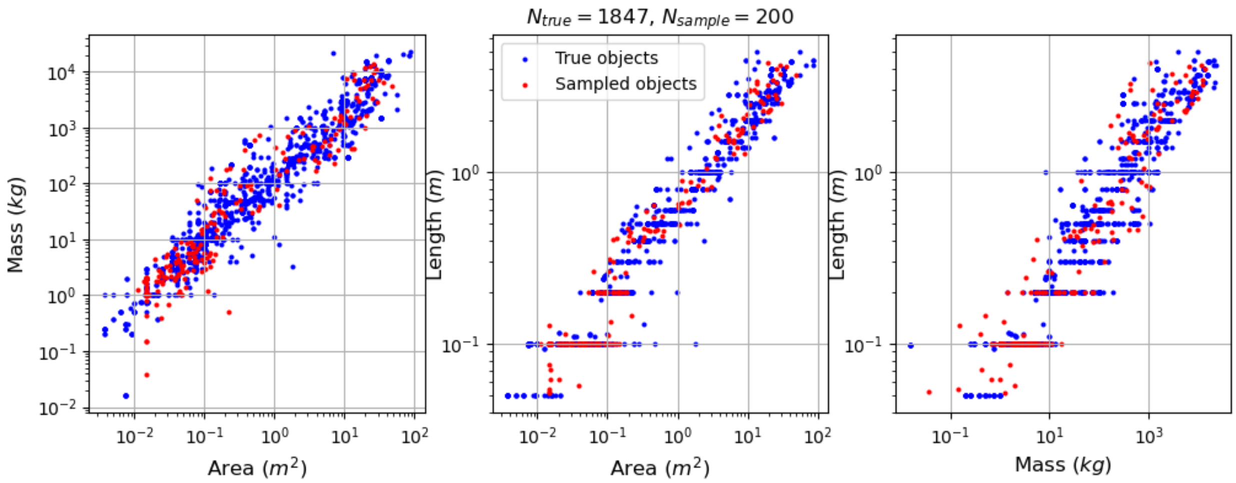


Fig. 9 Physical parameters of payloads, excluding constellation payloads, launched to LEO and samples from a distribution fit to these data.

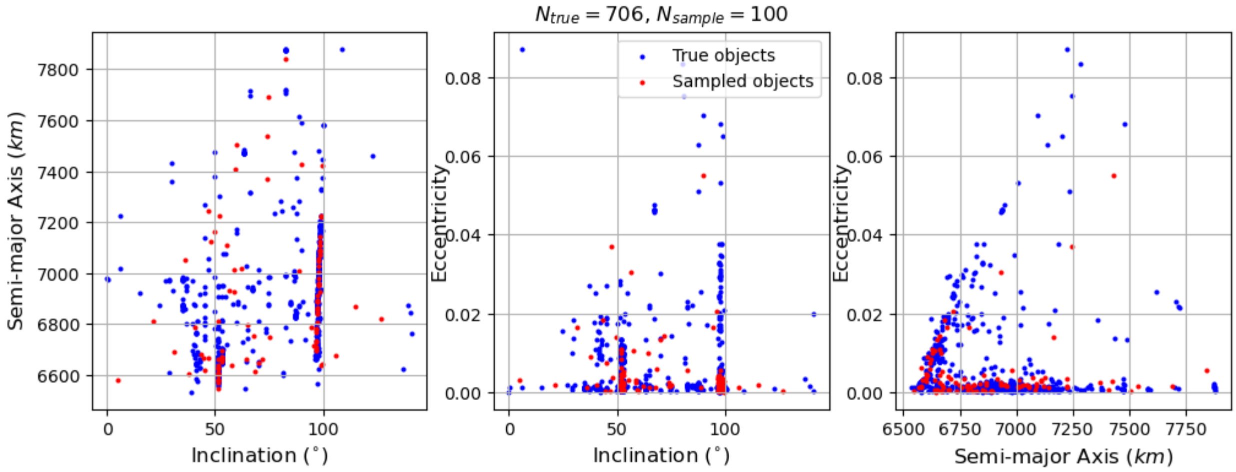


Fig. 10 Orbital parameters of rocket bodies launched to LEO and samples from a distribution fit to these data.

changes, the weights of the GMMs used to model physical and orbital parameters can be controlled with time-varying values. The weights vary according to Eq. 1 and are then normalised such that their sum is 1. This is shown for a 6 component GMM fit to only mass and cross-sectional area of payloads in Fig. 11. Varying the weight w_3 of this distribution according to Eq. 1 with $A = 0.4$, $b = 1$, $c = 2.5$, $d = 0$, $t_0 = 2025$, and $n_0 = w_3$ gives the normalised weight trend shown in Fig. 12. Figure 13 then shows how the associated probability density function of this model varies over 10 years, where the weight w_3 associated with the lowest mass and area increases and so the density of this component increases. This can be used to model different orbits or sizes of satellite becoming more or less frequently launched in future.

III. Launch Scenarios

The parametric model of launches introduced above gives a highly flexible method for simulating future launch traffic. This is demonstrated here by showing some example launch scenarios using this model.

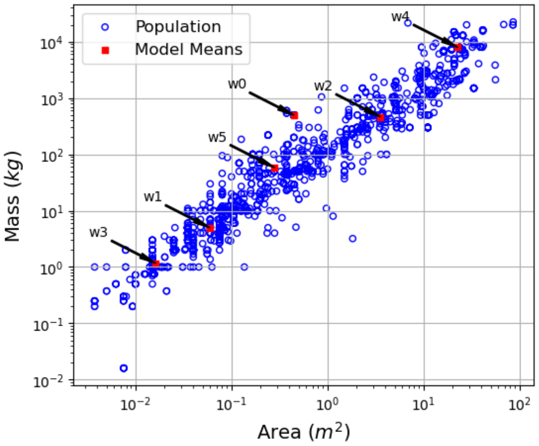


Fig. 11 Area and mass of previous payload launches and the means of a GMM fit.

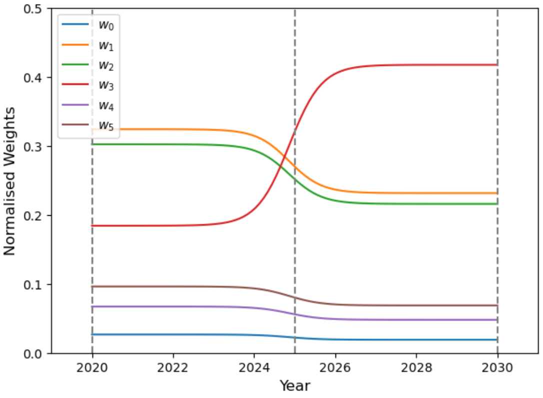
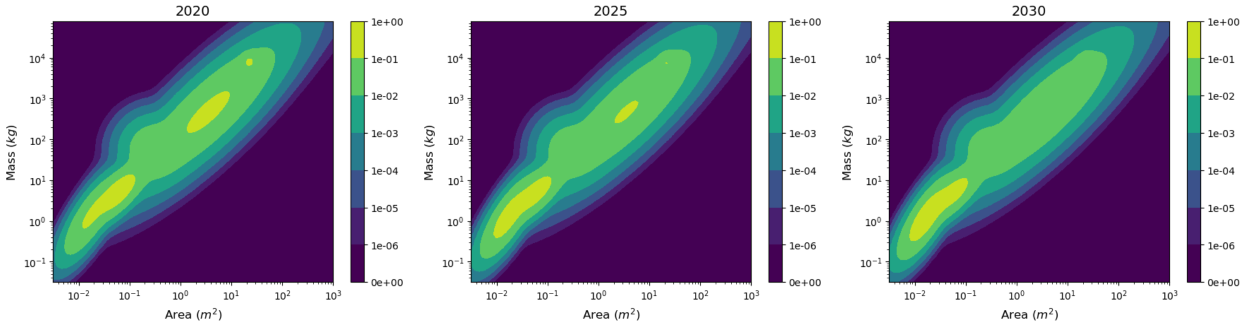


Fig. 12 Variation in GMM weights over time for area and mass of payloads.



(a) 2020

(b) 2025

(c) 2030

Fig. 13 Variation in densities of payload area and mass over 10 years.

A. Including Constellations Separately

As discussed above, constellations can be included in the overall launch model or defined separately. Table 1 shows 6 of the largest current and planned constellations, including missions that already have a substantial number of operational payloads. The deploy start gives the approximate date when the satellites begin launching, assumed to be the first of January of that year, and the mission start is when all satellites in the constellation are assumed to be launched and operational. Based on the number of spacecraft in a constellation and lifetime of each spacecraft, it is possible to estimate the necessary number of objects launched per year to maintain the constellation from the mission start date. Combined with the modelled launches excluding constellations, this gives an estimate of the total number of objects launched in future.

Figure 14 shows the assumed total number of payloads launched per year from the constellations in Table 1, excluding the ramp up time from deployment start. This only considers the average number of launches each year to replace spacecraft at the end of their lifetime. After 2027, the number of constellation payloads launched remains constant at 2243 per year, assuming the constellations remain operational and continue to replace satellites. These launches can be added to a model of launches excluding constellations as shown in Fig. 15 to get an estimate of the future trend in total number of objects launched.

B. Adjusting Distributions based on Other Forecasts

The model can also use short-term forecasts from different entities of launches of certain satellite types to inform its long-term model. SpaceWorks [11] and nanosats.eu [12] are two examples of entities that recently published such forecasts. It is possible to compare these forecasts to outputs of the launch model for the same satellite classes and adjust

Table 1 Parameters of some planned constellations.

Name	Number of Spacecraft	Deploy Start	Mission Start	Lifetime (years)	Mass (kg)	SMA (km)	Ecc.	Inc. (°)
OneWeb	648	2020	2023	10	147	7578	1e-4	87.9
Starlink	8064	2020	2023	5	386	6938	1e-4	53
Spire Global	110	2020	2023	2	5	6868	1e-4	51.6
Amazon Kuiper	3264	2024	2025	7	650	6988	1e-4	51.9
Telesat	300	2026	2027	10	700	7626	1e-4	50.88
Boeing	147	2026	2027	10	3000	7463	1e-4	50

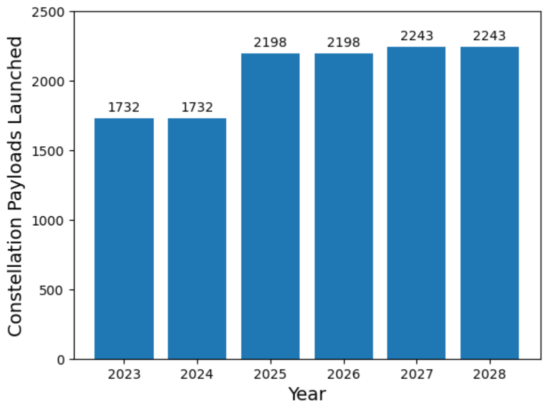


Fig. 14 Forecast number of constellation payload launches.

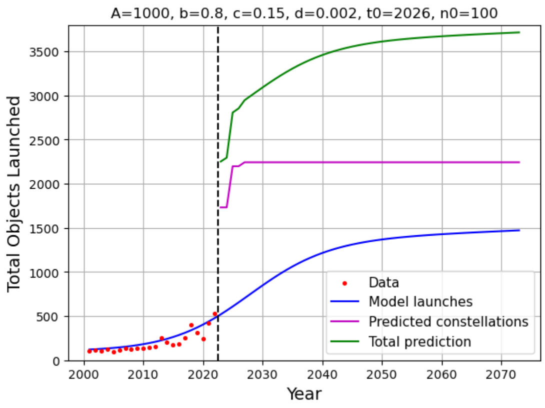


Fig. 15 Launch model without constellation payloads plus constellation forecast.

the model accordingly to better match these forecasts. As an example, consider the trend in total number of launches shown in Fig. 16 and a 6 component GMM fit to the physical parameters as illustrated in Fig. 17. The launch model only considers data up to 2021 and predicts the trend from 2022 onwards. Its output can be compared to the nanosats.eu forecast for 100g-10kg satellites and SpaceWorks' forecast for 1-50kg satellites as shown in Fig. 18. The proportion of payloads in the total number of launched objects is assumed to be 80%.

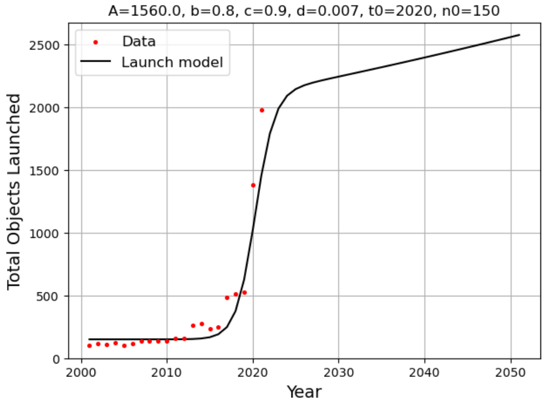


Fig. 16 Example launch trend for all object classes launched to LEO.

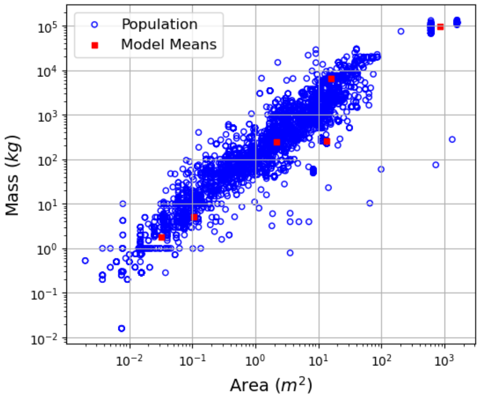


Fig. 17 Locations of GMM means of a distribution fit to mass, area, and length.

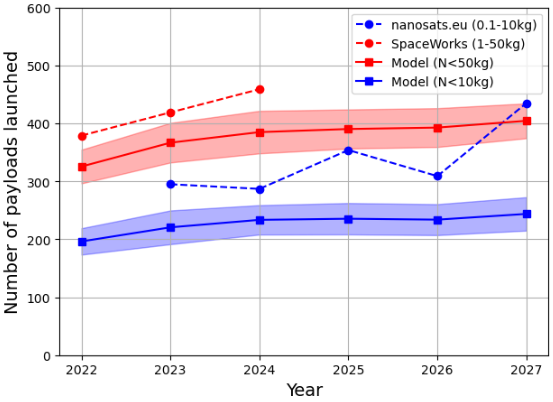


Fig. 18 Comparison of model outputs to short-term launch forecasts. Forecast data from [11, 12].

In this case, the model tends to predict a lower number of payloads launched in this size range than the forecasts. Without changing the trend in total number of launches, it is possible to improve the agreement between the model and forecasts by increasing the weight of one of the GMM components, as shown in Fig. 19. This results in better agreement with the forecasts as can be seen from Fig. 20.

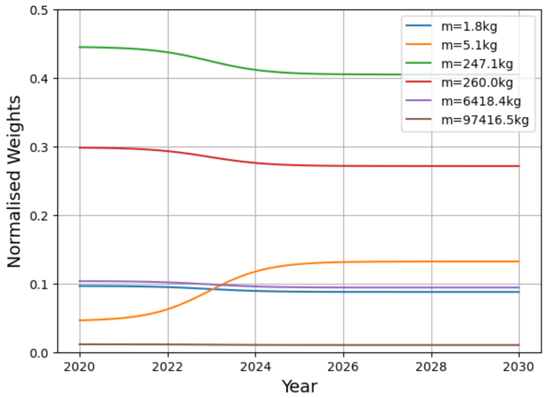


Fig. 19 Variation in GMM weights over time of a distribution fit to area, mass, and length of payloads launched.

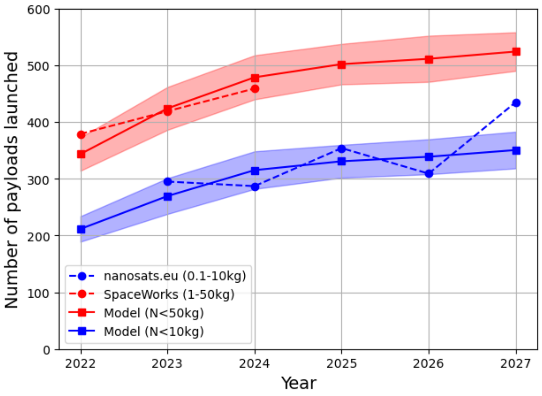


Fig. 20 Comparison of model outputs to short-term launch forecasts with varying weights. Forecast data from [11, 12].

IV. Application to Long-term Environment Modelling

Previous sections demonstrated the flexibility of this model for simulating different launch scenarios. Here we will show how the launch model can be incorporated into a more general space environment model which can in turn be used to estimate risk of collision for a new mission. The software used to simulate the evolution of the space environment is ESA's DELTA [3] which includes a force-based orbit propagator and facilitates adding new objects via launches.

A. Environment Model Parameters

The launch scenarios considered here are no future launches (NFL) and a moderate future increase in non-constellation launches with parameters $A = 1100$, $b = 0.8$, $c = 0.2$, $d = 0.002$, $t_0 = 2025$, and $n_0 = 100$ as shown in Fig. 21. NFL is not a realistic scenario for future traffic, but is often used as a baseline for the evolution of the space environment without the added uncertainty of launches. In the launch model scenario, constellation payload launches are included separately based on the planned constellations shown in Table 1. The initial population of objects is defined using

Table 2 Orbital parameters of example missions.

Orbit	SMA (km)	Ecc.	Inc. (°)
1	6780	0.0005	52
2	6650	0.002	41
3	7250	0.0001	80
4	7800	0.05	70

position data from SpaceTrack [†] and information on physical characteristics from DISCOSWeb. Objects are added to the environment as a result of launches as well as from fragmentation events modelled in DELTA. The mission lifetime for payloads is by default set to 8 years, after which point they enter a disposal orbit with a post-mission disposal success rate of 90%. Figure 22 shows the change in the number of tracked objects over 50 years for each scenario. Both start at the same value and, as expected, the number of objects in the launch model scenario increases steadily over time. The number of objects under NFL initially decreases then increases slightly due to in-orbit fragmentations.

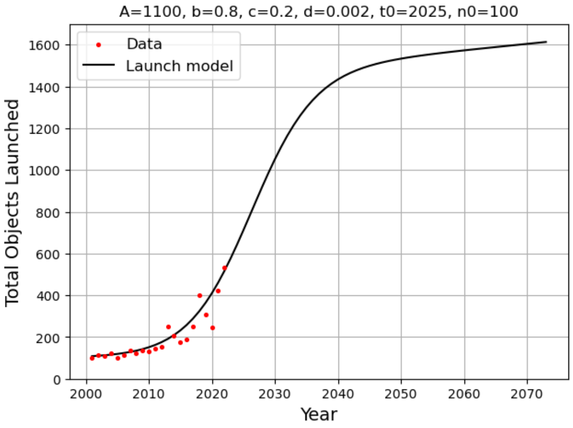


Fig. 21 Example future launch trend for calculating risk.

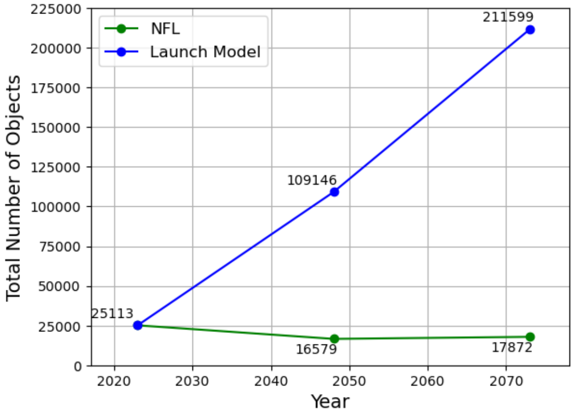


Fig. 22 Variation in total number of background objects over time in each launch scenario.

B. Example Risk Estimate for New Missions

In addition to observing the evolution and stability of the future space environment, this model can be used to estimate the risk of collision for a new mission. Here we show risk calculations for some example missions based on both launch scenarios. The procedure to estimate the likelihood of a collision uses the methodology presented in [13] which calculates the probability of intersection of two distributions of orbital parameters based on the minimum orbit intersection distance (MOID):

$$p(\text{MOID} < \nu) = \int\int_{\text{MOID}<\nu} \left(p(\mathbf{x}_{sat})p(\mathbf{x}_{bkgd})\right) d\mathbf{x}_{sat} d\mathbf{x}_{bkgd} \tag{3}$$

To account for multiple satellites in a mission of interest and the number of objects in the background population, the metric for collision risk is the product of the total number of tracked background objects and the probability of intersection calculated via Eq. 3. Table 2 shows the orbital parameters of the example missions considered here.

Figures 23 and 24 show the variation in collision likelihood over 50 years for each orbit in the NFL scenario and launch model scenario, respectively. The values of collision likelihood for each orbit in 2023 are the same in each scenario. Due to the lower number of objects, the collision risks for NFL in 2048 and 2073 are considerably lower than the scenario with launches. When launches are included, the collision likelihoods for orbits 1 and 2 increase substantially over the first 25 years but then decrease. This is due to the density of objects changing in this region

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[†] https://www.space-track.org/

since, despite the substantial increase in total numbers of objects, those in lower LEO will also decay more quickly. In contrast, orbits 3 and 4 see a sustained increase in their collision likelihood since these regions become more dense with increased launch traffic and fewer debris naturally decaying.

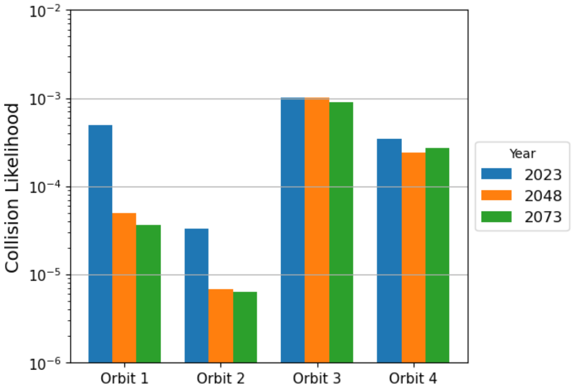

Fig. 23 Collision likelihood for four example missions over time assuming NFL.

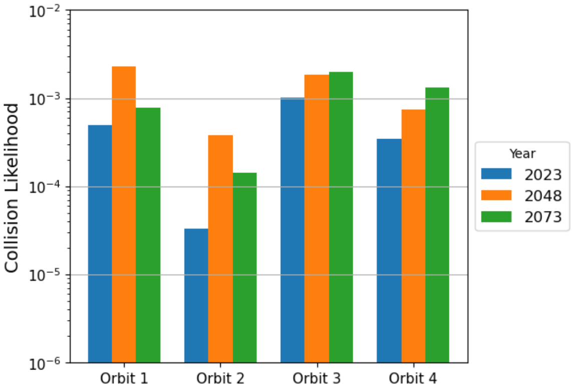

Fig. 24 Collision likelihood for four example missions over time under the launch model scenario.

V. Conclusions

This work presents a novel approach to modelling future launch traffic that can account for recent substantial shifts in launch trends. The model is suitably flexible to capture various potential changes in this traffic over time while exploiting historical data to determine likely future patterns in launches. This is useful for predicting the future space environment and associated risk for missions, which depends heavily on launch traffic. Here we have shown the effect of one example future launch scenario on the evolution of the space environment in LEO. Further investigation is necessary into the effect of different rates of launch traffic on the future space environment.

Acknowledgments

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