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Winning the Internet: A tool for simulating the competitive strategies of satellite-based internet providers

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Abstract

New satellite operators, a changing technological landscape, and increased user demand are poised to remake the current satellite-based internet landscape. Estimation of long-term revenues under various market and competitive assumptions is of interest to operators, customers, and investors. This paper presents an algorithm for simulating the competitive interactions between satellite operators as they compete for a heterogenous, global market.

The theoretical underpinnings of the algorithm are presented with reference to economic and aerospace principles. The algorithm's implementation is then discussed in detail with critical numerical steps and assumptions outlined. A low-order example using representative satellite operators, customers, and contracts is used to illustrate the use of the tool. Results from the low order model agree with prevailing market opinions and show consistent growth for the sector over the upcoming decade.

The focus of this paper is on the algorithm and its implementation. A follow-up paper will provide more specific market predictions through enumeration of individual customers and operators.

Keywords: satellite communications, telecommunications economics, low earth orbit,

1. Introduction

Satellite-based internet has the potential to bring real-time communication to a truly global market, stimulating growth, creating jobs, and connecting heretofore unconnected populations. From 2020 to 2030 the satellite telecommunication industry's annual revenue is expected to grow from $2.9 to $18.6 billion [1]. Operators compete to supply internet connectivity to geographically distributed customers using on-orbit global satellite constellations (Fig. 1). Understanding how investment, corporate strategy, and changing consumer habits affect an operator's long-term revenue is an important – yet underexplored – area for investigation. The objective of this article is to develop and demonstrate a high-performance algorithm for use in study of these interactions.

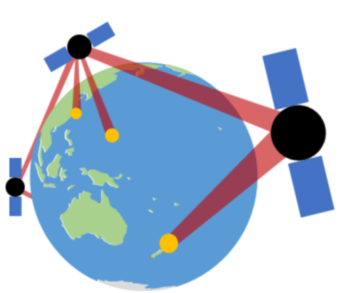


Fig. 1. Operator satellites (black) supplying data connectivity (red) to geographically distributed customer terminals (orange).

1.1 Revenue estimation

Predicting satellite constellation revenues is an essential component of investing in or studying new and existing constellations. Models to study these networks are often simplistic, assuming a homogenous distribution of demand comprised of a single customer class, and neglecting to incorporate the effects of competition [2]–[4]. Effectively, they assume that revenue is directly proportional to the capacity of the network. Clearly this is untrue; satellites passing over oceans use very little of their total capacity, while those over cities may be overwhelmed by demand. As high-capacity mega-constellations from Starlink, OneWeb, Telesat, and Amazon come online, it is likely that the market will be flooded with supply in the coming decade, with significant implications for price. The assumption that demand can increase indefinitely to match capacity is a central uncertainty in predicting future revenues. If multiple suppliers exist within a market then their behaviour and revenue will differ from if they were operating as a monopoly. Winsberg [5] and Cleopas [6] caution about the validity of overly simplistic approaches to revenue forecasting.

There is a precedent for more sophisticated modelling of satellite constellation revenues. Guerster [7] considers capacity allocation with geographically heterogenous customer distribution. Guerster provides an algebraic model for the power budget of a satellite network, validated against industrial data. Major satellite-based internet customer segments are identified although their purchasing characteristics are not used for revenue estimation. Guerster is also only concerned with only a single operator rather than the entire market.

In their 2021 paper [8], Ogutu and Oughton develop a supply-side engineering system model to estimate the revenue of satellite-based internet networks, studying the networks of three different competitors. Only a single class of residential customer paying a fixed price for a single level of service is considered and the authors only consider each network in isolation, without accounting for competition with terrestrial or other space-based operators. Customer distribution is modelled by regional population density. The model is used to determine the average bandwidth users will experience in the region although is not an input into the revenue calculation.

Market segmentation is the process of dividing a market into broadly similar groups who can be targeted with similar product offerings and is an important feature of academic research and business practice [9], [10]. Segmentation of the satellite-based internet market has been proposed by the ITU [11], NSR [12], [13], Euroconsult [14], and Grand View Research [15]. These segments have different uses for satellite-based internet and have correspondingly different willingness-to-pay for different internet products. Critical categories are residential broadband; cruise ships; oil and gas; airlines; backhauling/trunking; and government. Residential broadband addresses a single terminal consumer to connect their house with the internet especially in remote regions with limited or no wired internet and can be sold to directly or through an internet service provider (ISP) who bundles together multiple households. Cruise ships are characterized by large crews and passenger count demanding access to the internet from a mobile moving platform. Oil and gas are fixed offshore customers where satellite communication is the only option. Airlines are even more mobile, providing connectivity to the passengers onboard a commercial aircraft. Backhauling and trunking connect a subnetwork to the broader internet or to supplement existing connections during temporary demand spikes. Government is the broadest segment with aspects of all users described since the terminals can range from small sizes on UAVs to larger terminals on a remote base. Unique contracting and security requirements make this a separate group.

Information on the economic modelling tools in use by those within the industry is not publicly available. It is understood that regression modelling (i.e., trend following) has seen high adoption although its usefulness has been brought into question in today's rapidly changing competitive landscape.

Outside the field of satellite-based internet networks, industrial modelling is more advanced. Henderson [16] observes that a business' success depends on how its management conducts competitive analysis and takes on these results into their marketing strategy. Hanssens et al. [17] infer that this analysis should being their highest priority, directing all other operations of the business. Porter [18] implores managers to understand what is driving competition, what decisions competitors are likely to make, and how the industry will evolve over time in order to best determine how the business must behave.

This theoretical basis has encouraged the development of analytical models for competition. Schmalensee [19] examines competitive behaviour in monopolies, oligopolies, and pure competition. Due to the high barriers to entry of satellite-based internet providers the market under study here is a case of oligopoly where there is a limited number of large suppliers. Jain and Rao [20] develop such a model for the effect of price on the adoption of durable goods through a diffusion process. This is an important consideration in the adoption of internet for consumers who are not yet connected to any existing network. Dutta and King [21] develop a metagame analysis of competitors in an oligopoly where operators repeatably optimise their strategy to each obtain maximum profit. Lise and Hobbs [22] describe a recursive dynamic simulation of the European gas market to predict how growth in demand combined with significant investment from both incumbent operators and new market entrants affects the revenue of different operators. Several sub-models are combined to explore the interaction of five suppliers and six customer classes under three different scenarios.

From these studies we may infer that while determining future revenue of satellite-based internet operators is an important and common practice, existing models lack the fidelity to inspire confidence. Applying more advanced techniques employed by other industries should shed light on the competitive dynamics that are likely to take place in this market.

2. Method

An algorithm to simulate the satellite-based internet market was developed. Illustrated in Fig. 2, this algorithm creates a synthetic representation of the market which accepts user-defined competitive strategies and market assumptions to predict long-term operator outcomes. A conceptual market model, shown in Fig. 3, was used as the basis for the algorithm, depicted in Fig. 4. Customers and operators are considered individually, and thus many thousands of agents must be considered in each simulation. The following subsections layout the development of each component of the algorithm.

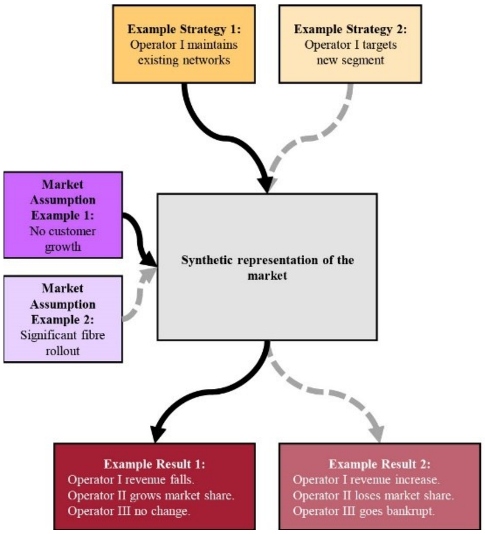


Fig. 2. Model overview. The goal of this model is to create a synthetic representation of the market (grey) which accepts strategy (orange) and assumption (purple) inputs to give results pertaining to operator outcomes (red). Two potential scenarios are shown.

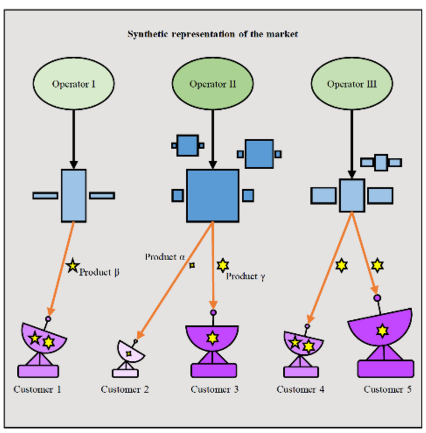


Fig. 3. Conceptual market model. Operators (green) use satellite constellations (blue) to supply customers (purple) with their desired internet product (yellow star). An allocation strategy (orange arrows) determines which customers are supplied by which operator with which product.

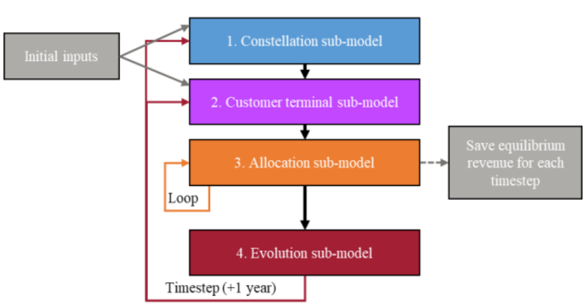


Fig. 4. Simplified code view showing inputs, intermediary sub-models, and incremental outputs.

2.1 Constellation sub-model

For a customer to use the network they need to be in view of the network's satellites and the satellites must have sufficient power to service that customer's demand. This sub-model, shown diagrammatically in Fig. 5 and assumptions given in Table 1, identifies which regions are serviced by which satellites for each of the operators, the distance to these satellites, and capacity of each satellite.

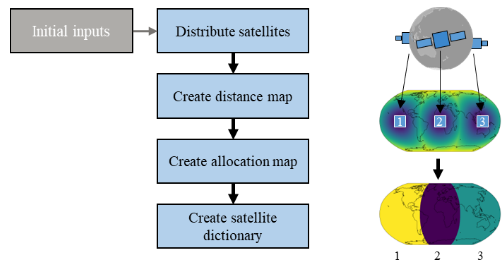


Fig. 5. Simplified constellation sub-model code.

Table 1. Constellation model assumptions

Assumption	Discussion
Each constellation is comprised of identical satellites evenly distributed within many planes at a single altitude.	This is appropriate. While satellites are unique, they have the same standard bus. They are positioned within a narrow band and orbits have low eccentricity.
Low-order model evaluated at day-long granularity. Satellites are fixed in position with constant power usage.	Assessing capacity over the entire orbit is a high-dimensionality problem impractical both for this paper and for the operator when actually selling capacity.
Satellites supply the closest customer to their sub-satellite point.	This assumption provides a worse-case scenario as compared to AI-based allocation studied by [23].
Satellites have a maximum capacity which is reached when all satellite power is allocated.	Spectrum allocation and maximum spectrum per unit area are important but not considered in this model.
Model resolution of 1° x 1° with a spherical Earth.	This resolution gives cells of size 110 km x 110 km, much smaller than a satellite's typical 1500 km field of view.

2.1.1 Implementation

Constellation information is sourced from data concerning current and planned satellite launches available in spectrum filing and shareholder information. Described in Table 2, for this small-scale study the representative operators are SES, Intelsat, and Starlink. By annual revenue SES and Intelsat are the two largest incumbents while Starlink has the largest amount of planned capacity growth of any operator, putting it in a good position to upset existing markets.

Table 2. Operators modelled. Price is in $ / terminal / year.

Operator	Description	Constellation	Price
SES equivalent	Incumbent with a MEO network of good satellites and GEO network of excellent satellites. Goodness factor is maximum revenue per watt of capacity	One constellation of eight satellites in a single equatorial plane of altitude 8,000 km. Each with 1,200 W of available power and 40 dB gain at 3900 MHz. Additional constellation of four satellites in a single equatorial plane of altitude 35,800 km. Each with 3,000 W, 40 dB, 4000 MHz.	Slow: $700 Fast: $900 CIR: $12,000
Intelsat equivalent	Incumbent with a MEO network of good satellites. Goodness factor is maximum revenue.	Five planes of 15 satellites at an inclination of 75° at an altitude of 700 km. 1,000 W of available power at a 2,600 MHz with 30 dB gain.	Slow: Not sold Fast: Not sold CIR: $8,000
Starlink equivalent	New entrant with a large LEO network of poor satellites. Goodness factor is maximum revenue per watt of capacity	50 planes of 25 satellites per plane at an altitude of 500 km and 50° inclination. 500 W power at 37,600 MHz with a gain of 50 dB.	Slow: $500 Fast: $700 CIR: Not sold

Constellations for each operator are created independently. Shown in Fig. 6, these are made of several planes (n_p) with some characteristic plane inclination (i) comprising of a set number of satellites (n_s). Since the planes and satellites within each plane are assumed to be evenly distributed with zero eccentricity, the remaining Keplerian coordinates can be easily enumerated. These are then converted into Cartesian coordinates through the appropriate matrix rotation.

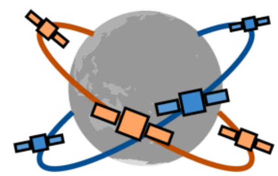


Fig. 6. Satellite distribution within a constellation. In this case there are two planes (blue and orange circles) of three satellites per plane with the planes inclined at 45°. Note how satellites are evenly distributed within a plane (360 ÷ 3 = 120°) and that planes are also evenly distributed (360 ÷ 2 = 180°).

The distance between each satellite and every 1° x 1° region on the Earth's surface are determined. As the model is calculated with day-long granularity only a single time is used. As illustrated in Fig. 7, the algorithm saves a matrix indicating the distance from surface of the Earth to the nearest satellite (i, ii) and the index of that satellite (iii, iv).

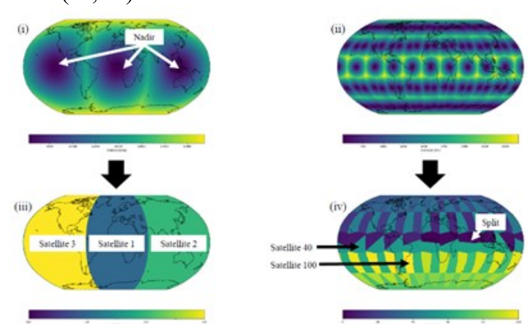


Fig. 7. Distance-based identification method for a three (i, iii) and 100 (ii, iv) satellite constellation.

2.2 Customer terminal sub-model

This algorithm considers all customers as separate agents. Customers are heterogeneous, meaning they form several different classes. The customer terminal model is illustrated in Fig. 8 with assumptions in Table 3.

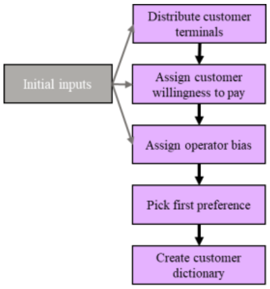


Fig. 8. Simplified sub-model code.

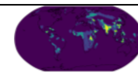
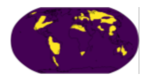
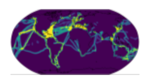
Table 3. Customer model assumptions

Assumption	Discussion
The market can be divided into multiple segments within which customer properties can be described through a probability distribution.	Industry segmentation is well established [24], [25] but it is hard to establish probability with low number of customers per segment.
Customers prefer one or more operators. They are sticky and somewhat resistant to changing operator.	Proprietary equipment increases stickiness while pricing and performance differences encourage changing operators.
Customers have a maximum budget for products. If the cost of the product is more than they are willing to pay, then they will not purchase it.	Basic economic theory, however predicting the maximum a customer is willing to pay is challenging.
Customers will reconsider satellite internet if a higher speed (fibre, copper) service is available – even if they previously purchased satellite-based internet.	Fibre and copper lines have much higher uptake than satellite internet [26]. These networks are constantly expanding, thus taking away from the potential customer pool.

2.2.1 *Implementation*

In this small-scale study, customers considered are oil and gas platforms; residential internet service providers (ISPs); and cruise ships. Customers are described in Table 4. These are significant customer segments by annual revenue and incorporate the main types of terminals. These are respectively fixed single-terminal, fixed multi-terminal, and moving multi-terminal mechanics required to code the remaining customer classes.

Table 4. Customers modelled. Willingness to pay is a normal distribution of $ / terminal / year.

Customer class	Distribution	Terminals	Willingness-to-pay
Residential internet service provider	 Underserviced populations	150 residential ISPs on selling to 1,000,000 households each. These use 30 dB gain fixed antennas.	Slow: $N(\$700, \$100^2)$ Fast: $N(\$700, \$150^2)$ CIR: Not desired 0.4 bias for I, 0.2 II, 0.4 III
Oil and gas	 Oil and Gas reserves	5,000 fixed single-terminal customers with 50 dB gain antennas.	Slow: Not desired Fast: Not desired CIR: $N(\$15{,}000, \$500^2)$ No bias for any operator
Cruise ship	 Cruise ship routes	30 customers with 40 dB gain mobile antennas. Each customer has 10 terminals where each terminal is a cruise ship.	Slow: Not desired Fast: $N(\$1{,}000, \$100^2)$ CIR: $N(\$10{,}000, \$500^2)$ 0.4 bias for I, 0.3 II, 0.3 III

Customers are generated by randomly distributing one or more terminals across a region. Fixed users with a single terminal are given by a single point, while those with multiple terminals (e.g., an internet service provider with 100,000 customers) include multiple points. A customer with moving terminals (e.g., the cruise ship segment) is modelled as several points where capacity must be reserved for all positions. These positions are used to connect each customer to the relevant operator satellite.

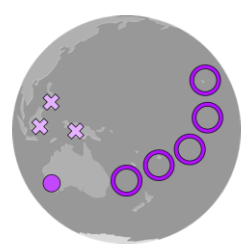


Fig. 9. Terminal placement for a single-terminal (dot), multiple-terminal (cross), and moving-terminal (open circle) customer.

Customers apply for different products. These are defined by the customer's maximum willingness to pay, the sale-price by the operator, and the amount of data rate that must be reserved by the operator to supply that product. This allocated capacity is a function of some base data rate (what is sold) and an overbooking factor (how many times the same capacity can be sold). Summarised in Table 5, in this model we consider slow broadband, fast broadband, and guaranteed service. These have progressively more capacity that must be reserved on the satellite. A residential customer is willing to pay more for faster broadband but does not have an interest in the guaranteed service product, whereas an oil and gas customer places a high value on the guaranteed service product but does not want the other two.

Table 5. Products modelled

Product	Description	Base data rate	Overbooking factor
Slow broadband	Low-cost product ideal for residential customers	5 Mbps / terminal	50
Fast broadband	Medium-cost product ideal for residential customers	20 Mbps / terminal	10
Committed information rate	High-cost product ideal for business customers	10 Mbps / terminal	2

The maximum price each customer is willing to pay for a given product is generated from a probability distribution. Each individual customer has a fixed maximum price. As illustrated in Fig. 10, these are approximated as normal distributions through the reverse calculation of customer surveys of equivalent internet products. In this small-study only a single survey is consulted per customer, but more will be incorporated for larger-scale results.

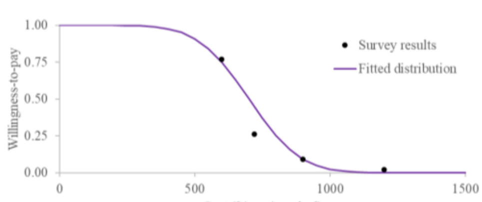


Fig. 10. Annualized willingness-to-pay for residential internet. Original survey by Wetrz [27] for customers in San Francisco, USA. The fitted distribution has a normal of $700, standard deviation of $150, and R^2 of 0.96.

Customers do not necessarily behave logically when purchasing internet products and may preferentially purchase from one operator over another even if products are identical. Similarly, some operators have more customers than other operators. To take these into account a “bias” system has been implemented which describes the probability that a customer will seek their internet product from one operator as opposed to another. This bias value is a set of input priors set by the authors initially applied on a segment-by-segment (e.g., if SES has an agreement with Indian ISPs then these ISPs will have a bias toward selecting SES as their supplier) but is modified on a customer-by-customer basis to account for stickiness factors (e.g., if a customer has previously been supplied by Intelsat then they are likely to stay with Intelsat).

In the model, customers “apply” for their preferred operator at their willingness-to-pay price. The operator is chosen randomly but weighted by the previously described bias characteristic. For a sample of 100 ISP customers with biases of 0.5 for SES, 0.4 for Intelsat, and 0.1 for Starlink we would expect 50 apply for SES, 40 for Intelsat, and 10 for Starlink.

2.3 *Allocation sub-model*

The allocation sub-model assigns customers to operators according to customer and operator preference. Operators can choose to rank customers by the highest price, highest price per watt capacity, or some other characteristic which represents their competitive strategy. The strategy is selected by the author based on inferring strategy by competitor behaviour.

The process repeats for a fixed point in time until all customers are allocated or all capacity it used. The allocation model is illustrated in Fig. 11 with assumptions in Table 6.

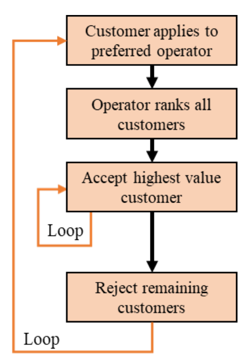


Fig. 11. Simplified sub-model code.

Table 6. Allocation model assumptions

Assumption	Discussion
Operators decide to accept a customer based on some objective goodness metric such as maximum revenue or maximum revenue per allocated capacity.	We expect profit-seeking businesses are mostly rational actors. Watts are calculated using the link budget equation across the satellite-to-customer downlink path [28].

If a customer does not receive their first preference of operator, they will continue to seek out alternate suppliers for the same desired product.	Products are rarely unique to a single operator and customers are willing to look at different suppliers.
Operators cannot execute perfect market segmentation but instead sell commodified products with fixed prices.	The market seeks perfect segmentation, but this typically falls short [29]. It is not reasonable to assume that every customer always pays their maximum willingness to pay.
Operators can abandon a customer once they are accepted but prefer not to.	High costs associated with getting new customers mean that operators try to keep existing customers. This is partially countered by short term contracts.

2.3.1 Implementation

Customers are assessed by their respective first-preference operator and then ranked by the operator according to their desired preference characteristic. The default goodness metric is revenue per watt. Customers are accepted in rank order until either the operator's capacity has been exceeded or all first-preference customers have been serviced. Operators with multiple networks assess the preference characteristic for the customer across all their networks and assign the customer to the network which gives the highest goodness metric which still has sufficient capacity, and then assign capacity from this network.

Customers which did not receive their first preference then apply to their second preference operator. This is decided by recalculating their bias numbers for each remaining operator. This repeats until the revenues for the entire market have converged (less than 1% change between iterations) or there have been more than 25 iterations.

2.4 Evolution sub-model

As the market changes so to must the market model. The evolution algorithm updates network and customer characteristics to reflect these changes. The model is illustrated in Fig. 11 with assumptions in Table 7.

One critical use for this part of the tool is the study of how failing to meet certain deadlines affects the profitability of an operator. For example, if they fail to get a certain capacity launched by a certain date then they may lose spectrum licencing and thus have a drastically different final network. This evolution model allows such scenarios to be studied.

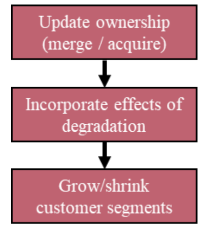


Fig. 12. Simplified sub-model code.

Table 7. Allocation model assumptions

Assumption	**Discussion**
Model evolution is based on multiple time-steps where underlying properties change and the system re-establishes equilibrium before moving to the next timestep.	It may not be reasonable to assume that equilibrium is always reached within a single time-step.
Customer segments grow by adding in new customers and shrink with the removal of old ones.	The focus is on evolution of the market under different growth conditions.
Operators add new satellites with capacity of existing satellites changing based on degradation losses and efficiency gains.	This allows the market to be compared as it grows rather than as if it were to appear all at once as with other papers [2]–[4], [26], [30], [31].

2.4.1 Implementation

The scenario studied covers a 5-year period representing significant growth in supply. This is driven by significant constellation build-out by the Starlink equivalent operator, achieving a final constellation of 75 planes of 30 satellites per plane by year 5. In this scenario we assume that the SES equivalent acquires the Intelsat constellation in year three of the simulation. The residential segment grows at a rate of 5% per year while oil and gas segment shrinks at 2% per year. Cruise ships remain constant.

Mergers and acquisitions are when an entire constellation is transferred between operators. For acquisitions the acquirer receives the target's constellation and customers while in a merger both party's constellations and customers are transferred to a new operator. In this small-scale test an acquisition is modelled where SES acquires Intelsat as a response to growth from Starlink.

Next, networks are grown with new satellites created. Existing satellites receive efficiency gains or degradation losses which are applied to each satellite separately. Illustrated in Fig. 13, Customer segments that shrink due to build-out of fibre or copper networks have customers deleted based on their position, while those that grow have new customer added in random positions according to the relevant distribution map. The allocation algorithm then repeats with these new assumptions and the system evolves.

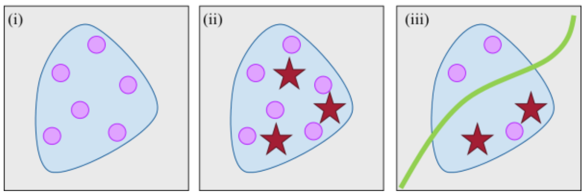


Fig. 13. Initial map of customers (purple circle) distributed within a region (blue) (i), new customers (red star) are added (ii), and then fibre rollout (green line) removes some of these customers (iii).

3. Results

A low-order problem was used for testing and benchmarking of the algorithm. Inputs, described in the preceding section, were based on known industry figures to better understand the heterogenous data characteristics of the real world. Resulting revenues are shown in Fig. 14.

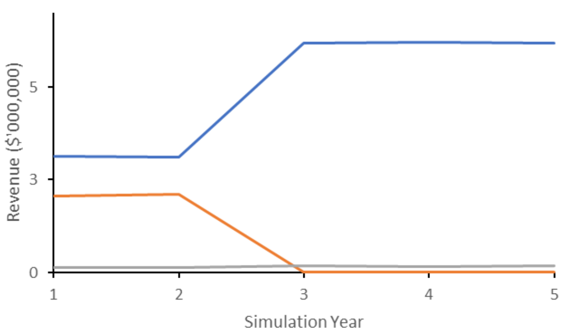


Fig. 14. Operator revenues over the five-year simulation, showing SES (blue), Intelsat (orange), and Starlink (grey).

To better understand the computational requirements simple benchmarking was conducted. The algorithm was written in the Julia Programming Language and executed on a Microsoft Surface-book Laptop with a Intel(R) Core(TM) i7-1065G7 4-core 1.30 GHz CPU and NVIDIA GeForce GTX 1650 MHz GPU. Execution time for each sub-model is shown in Fig. 15.

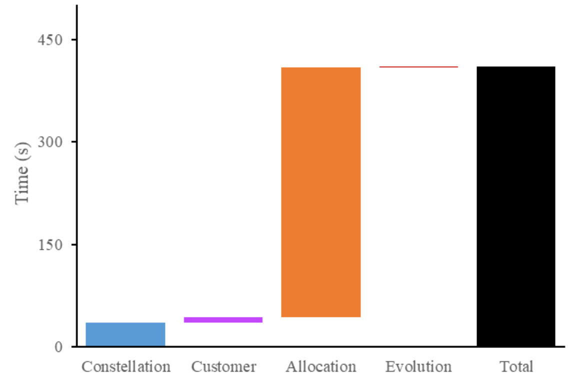


Fig. 15. Waterfall chart showing time for each key stage in the simulation.

4. Discussion

The simulation shows that the initial market leader, SES, maintains their position throughout the five-year simulation (Fig. 14). As expected, the acquisition of Intelsat's network results in a corresponding increase in SES' revenue. Excluding this acquisition, SES and Intelsat have generally static revenues, representative of their fixed-size networks. Meanwhile, Starlink experiences a revenue growth rate of 8.8%, p.a. slightly behind their capacity growth of 15.8% p.a.. This suggests that the market is not yet saturated with supply and that new competitors can enter the market without disrupting incumbents or needing to aggressively compete. The difference between added capacity and observed revenue increase is expected under this model since around half of the added capacity occurs in regions lacking in customers.

Analysis of the revenue sources found that the CIR product was driving the majoring of operator income. The Starlink operator was modified to provide a low-cost ($800 p.a.) CIR product. By considering only market share to net out any market growth effect and then isolating each of the factors in turn we can get insight into the state of the market, shown in Fig. 16 - Fig. 19. Fig. 16 is the market in steady state with no growth. As expected, market share is static. Significantly increasing the capacity of the Starlink operator in Fig. 17 causes little change in revenue; suggesting that in this market formulation all customers have already been serviced at the existing price-point. Curiously, dropping the prices of the SES service in Fig. 18 does not result in enough additional customers to counteract the price drop and thus revenue and market share fall. The fall in revenue is less than the fall in price; suggesting that many new customers were acquired – even if these do not entirely counteract the loss of high-paying customers. This points

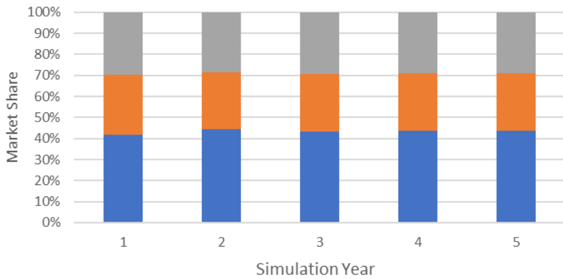


Fig. 16. Operator market share over each year of the simulation in control scenario with no acquisition or constellation growth. SES (blue), Intelsat (orange), and Starlink (grey).

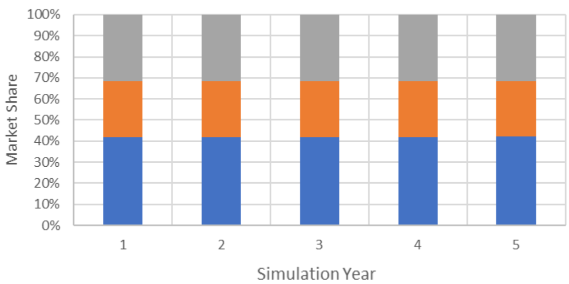


Fig. 17. Operator market share as Starlink (grey) increases capacity by 10x over the course of the simulation.

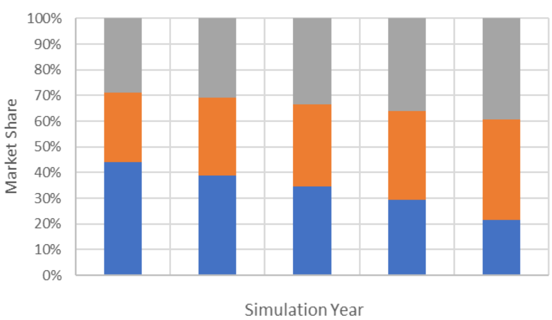


Fig. 18. Operator market share as SES (blue) reduces their service price by a factor of 10.

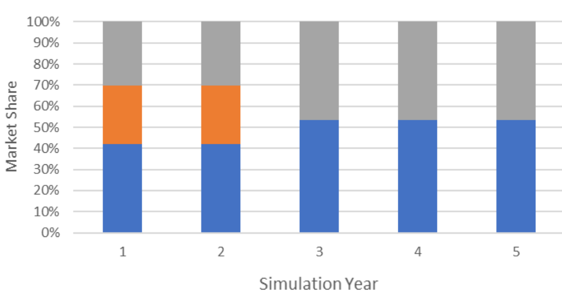


Fig. 19. Operator market share over each year of the simulation if SES (blue) acquires Intelsat (orange) in the third year of the simulation.

toward the use of further market segmentation as a required strategy moving forward. As before, the biggest gains were seen by acquiring a competitor in Fig. 19; resulting in increased market share for all other operators in the market.

Since this scenario only considers three operators, adding in more operators to better represent the real world may simultaneously shift the market into a more competitive supply-saturated space. However, it does serve to illustrate some of the applications for the final model while providing insight into future scenarios to study.

Total calculation time for the entire five-year scenario was 2770 ± 170 s (approximately 46 minutes). This is an acceptable amount of time for one-off simulations but is limiting in the case of attempting Monte Carlo simulation. The initial calculation considering just the first-time step took 410 ± 26 s (approximately seven minutes) with most of the time being dedicated to the allocation sub-model (89.3%). This is reasonable since this is where all satellites and terminals must interact with each other multiple times to determine the result. It is also implemented only in series on the CPU. Meanwhile, other stages involve little interaction and only a single allocation. In the case of the constellation and customer sub-models both rely on the computers GPU and parallel processing which are a significant aid to calculation speed.

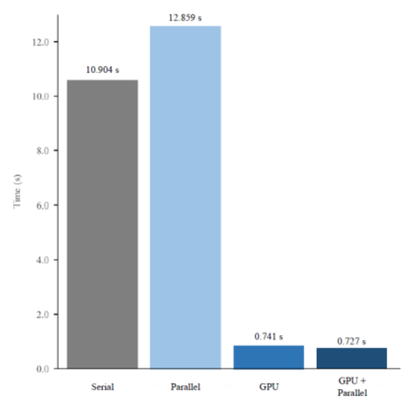


Fig. 20. Benchmarked execution of the constellation model showing serial, parallel, GPU, and parallel with GPU implementations.

If many more simulations are desired, then several approaches can be taken to improve calculation speed. The code itself could be optimised. In an early implementation of the code the constellation model was written with and without the benefit of parallelisation and the GPU and then benchmarked. As can be seen with the results shown in **Error! Reference source not found.**, the parallel GPU implementation resulted in a speedup of 15 as compared with this original serial implementation. This has the potential to reduce the original calculation time to under four minutes, a much more reasonable amount. With the advent of affordable cloud-computing solutions it may also be beneficial to perform some of the simulations remotely where much greater computing capacity can be dedicated to the problem. While one could continue to simulate small-scale market models this limits the usefulness of the results. The effect of changing the number of operators and customers should be studied to determine an appropriate level of approximation.

5. Conclusion

As new technologies become available and new capacities come online the satellite-based internet landscape will experience significant competitive changes. This paper has described and demonstrated a tool for the estimation of long-term operator revenues under various market assumptions, allowing operators to test and adjust their strategies while also providing investors with insight into future trends. Theoretical underpinnings and key assumptions are detailed with a low-order model used to illustrate how it is to be applied. Results suggest consistent growth for the sector over the upcoming five years while also serving to emphasise the strategic advantage of the acquisition of other competitors.

A key limitation of this model are its inputs. Operators and customers were generated with the intent to test the model's functionality rather than to accurately represent the true market conditions. As such results should not be used to inform strategic decisions but rather to illustrate the potential of the model. A follow-up paper will derive more realistic inputs through the detailed case-by-case analysis. Together, these two papers will provide a wholistic description of the future of the satellite-internet market.

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