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Determining the pricing strategy for different preference structures for the earth observation satellite scheduling problem through simulation and VIKOR

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Abstract

This paper presents a method by which decision-makers of the Earth observation satellite operations can coordinate pricing and operational decisions. The pricing of satellite images is complex due to uncertainty and high combinatorial complexity in the scheduling, and the high number of evaluation criteria associated with the customers' image requests. Likewise, any price changes will change the final schedule due to the complex scheduling procedure and preference reflected in the scoring, and understanding how is challenging. In addition, the changes can be very scenario-specific, so a change that seems beneficial in one scenario can lead to other outcomes in others. Therefore, this paper poses a method with which the satellite operator through simulation can investigate the robustness and combined effect of preference and pricing in order to select the pricing strategy that emphasizes the chosen preference structure the best while still finding a compromise on conflicting objectives related to profit, quantity, quality, etc. More specifically, the proposed method allows the satellite operators to take advantage of the scheduling flexibility through the decisions they control, i.e., price and preference structure.

Keywords Earth imaging satellite · Pricing · Simulation · Scheduling · Multi-criteria decision-making

Mathematics Subject Classification 90B50 · 90B35 · 90C59

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1 Introduction

The Earth Observing Satellite (EOS) industry has seen a significant increase in interest (https://ec.europa.eu/growth/tools-databases/dem/monitor/sites/default/files/DTM_Big%20Data%20in%20Earth%20Observation%20v1.pdf) in the last decade due to the increased affordability and utilization of EOS imagery in a vast number of fields, such as climate change, business, monitoring surveillance, agriculture, and even for recreational purposes (Intelligence 2020). Throughout history, government organizations funded these ventures, but with the increasing interest, a notable increase in capital investments for space tech startups has happened during the last decade (https://ec.europa.eu/growth/tools-databases/dem/monitor/sites/default/files/DTM_Big%20Data%20in%20Earth%20Observation%20v1.pdf; Dehqanzada et al. 2000; Peng et al. 2020b), and as new actors appear, the market will move towards a fragmented market type (Intelligence 2020). This transition period is leading to satellites being jointly operated and funded by governmental and commercial organizations, most likely leading to a high number of conflicts in preference and pricing strategy, as the commercial actors would be more concerned with maximizing profit relative to the governmental organizations seeking to maximize quality and priority of customers (Williamson 1997). One apparent conflict of interest is the American governments' ability to impose its shutter control policy, restricting commercial satellite imaging completely (Prober 2003). However, the innovation and adaptability driven by commercialization are necessary for the market to continue improving. Similarly, new actors need to define their preferred structure. With the increased competition, satellite operations need to improve the robustness of their decision process to take advantage of the flexibility in the scheduling, and in turn, yield the best possible images for their customers (Buzacott and Mandelbaum 2008; Chica et al. 2019; Berger et al. 2020).

Many sectors are experiencing change, and innovation is both driving it and required for actors to follow the change. In order for stakeholders to take advantage of the inherent flexibility offered by new technologies, they need to determine a pricing strategy and a preference structure that best streamline and prioritize different objectives. One of the main reasons for the interest in doing this stems from the growing demand for flexibly meeting customer expectations, for boosting customer satisfaction, and for building a pricing strategy that incorporates this flexibility. In the EOS scheduling, the system must consider many factors. These are cloud coverage, sun elevation, depointing angle, uncertainty, manoeuvrability, etc. To do this, the EOS scheduling (EOSS) problem generally comprises three main phases: pre-processing, scoring, and a scheduling phase. Lastly, one could also include an evaluation phase, but that is more concerned with photogrammetry properties of the individual image acquisitions than the actual schedule; thus, we neglect this phase in this paper. The pre-processing phase establishes each problem scenario as it combines the information of satellite path, satellite capabilities, the planning horizon, a granularity parameter, and the customer database in order to establish all feasible image acquisition for that particular planning horizon given the time-step length of the satellite path (granularity). The scoring phase evaluates each image attempt according to the objectives/preferences of the satellite operation to determine a value that reflects all viewpoints. Some preferences result in very complex objectives or preference structures, e.g., if a customer request expires after a said period, then to avoid not delivering, that particular attempt should at some point be valued substantially higher relative to other requests. In the literature, most research focuses on the scheduling phase as the entire EOSS problem is required to be solved in near real-time. This is because information such as cloud cover should be integrated as late as possible to ensure the reliability of the information and allow for late emergency requests to be incorporated. Additionally, the scheduling is of NP-hard complexity, and the advent of efficient scheduling methods is therefore of high interest (Malladi et al. 2017). This trend has partly neglected the explainability of the decision process and omitted the advantage of incorporating a flexible and transparent decision process. Consequently, this paper is investigating that process.

When the system (scoring and scheduling methodology Vasegaard et al. 2020b) is in place, one can make the decisions governing the final schedule. For any satellite operation, these decisions are the preference structure and the pricing strategy. The preference structure is incorporated through the scoring phase and the objective function in the scheduling phase. Still, due to incompetence in eliciting, defining, and incorporating it therein, there is often a correction or verification procedure where operators ensure the quality of the final schedule. In Fig. 1, one can visualize the intrinsic dependencies within the system relative to the final schedule. Note, the pricing strategy affects the size of the problem scenarios (number of customers in

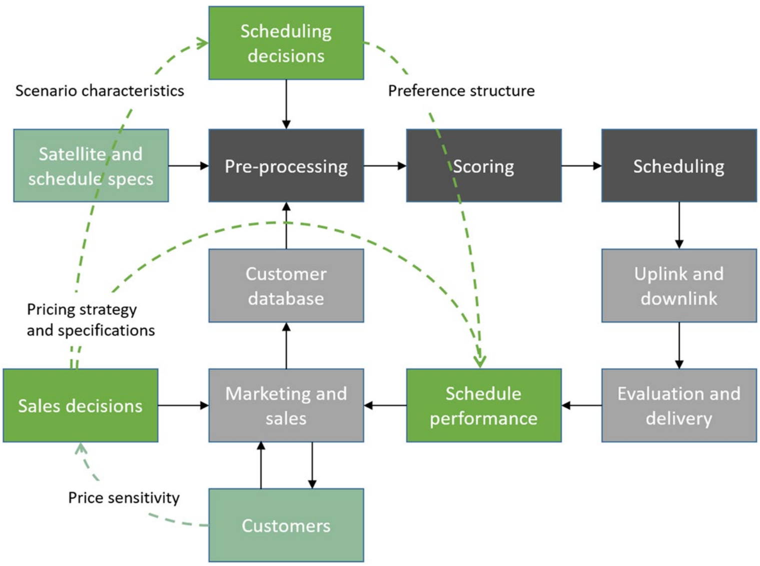

Fig. 1 Overview of the general solution approach for the satellite imaging process

the customer database) through their sensitivity to price changes. For this reason, the output (schedule) reflects the combined effects of the three inputs (preference structure, pricing, customer sensitivity). Additionally, any operational updates to the satellite capabilities will also change the problem scenario and the schedule. The point is, any changes in decision input have a collaborative effect on the outcome, and whenever any decision input changes, the decision-maker should modify the other inputs accordingly.

Ultimately, this problem can be considered a multi-criteria evaluation problem. The decision-maker seeks to choose one alternative (combination of pricing and preference) from a set of alternatives (any feasible/examined combination). The goal of this paper is to:

1. Show that the collaborative effect of preference structure and pricing strategy must be considered collectively.
2. Present a methodology for evaluating the pricing strategy and the preference structure of the satellite operation.
3. Indicate the potential of compromise solutions obtained in jointly operated systems when there is conflicting preferences.

The paper is organized as follows; Sect. 2 reviews the literature, Sect. 3 describes pricing strategies for satellite imaging, Sect. 4 describes the applied theory of the paper, Sect. 5 defines the problem and solution approach more rigidly. Section 6 presents the results, while Sects. 7 and 8 discusses and concludes on the solution approach and findings of the paper, respectively.

2 Literature review

The literature for this paper is three-fold. The first part investigates changes and trends in the EOS market. The second part considers the literature on solving the EOSS problem while including the effect of pricing, and the third part investigates relevant evaluation methods within the Multi-Criteria Decision-Making (MCDM) field.

2.1 Trends on EOS market

Since the beginning of the 2000s, politicians have pushed for more commercial EOS imagery in order to improve quality, innovation, and pricing (Intelligence 2020; Williamson 1997). Since the first commercial EOS in 1982, Spot 1, laid the foundation for future business ventures for image distribution, a large number of start-ups and big web actors have been attracted to initiatives in space tourism, access to space, small satellites, internet connectivity through space, and it seems that new activities are on the way (Denis et al. 2020). Services like google earth were in 2005 completely democratizing access to archived low-resolution space imagery based on their virtual globe system (Denis et al. 2017). Today, most satellite systems have their designated ground stations; however, due to the growing interest and thereof growing number of satellites, it is expected that these ground stations will function as communication links for multiple satellites and potentially could be a bottleneck in the operation of future satellite constellations (Krupke et al. 2019).

All these new services are disrupting the market of EOS (the wave has been denoted, new space), and therefore a new balance between start-ups and legacy players within commercial and governmental operators needs to be found in order to ensure a trusted continuation of e.g., the emergency response services (Denis et al. 2016). The dual system Pleiades can provide imagery to both commercial and military users, and after now five years of operations, it is considered a success—now other actors are mimicking that service (Denis et al. 2017). Naturally, this dual ownership will lead to a conflict of interest, and this paper seeks to investigate and support the operation of such systems.

2.2 Trend on EOSS and pricing

The EOSS problem, also refered to as the Satellite Orbit Problem (SOP) (Cordeau and Laporte 2005) or Satellite Image Acquisition Scheduling Problem (SIASP) (Malladi et al. 2017), is shown to be a generalization of the knapsack problem (Vasquez and Hao 2001) as well as equivalent to that of the piecewise linear cluster restricted maximum weight clique problem (Malladi et al. 2017). A great deal of different operational constraints has been imposed on the problem, e.g. due to stereo or strip acquisitions, increased maneuverability, energy, and memory capabilities. It has been formulated as a mathematical programming problem (Vasegaard et al. 2020b; Bensana et al. 1996), graph-based problem (Vasegaard et al. 2020a; Gabrel and Vanderpooten 2002), constraint satisfaction problem (Lemaître et al. 1999), and the knapsack problem (Vasquez and Hao 2001), as well as solved through heuristics and meta-heuristics. The exact methods are for the most cases too slow to have any real chance at obtaining a solution, but some show promise for smaller scenarios such as the adaptive-directional dynamic programming with decremental state space relaxation (Peng et al. 2020a). Similarly, integrating the impact of cloud coverage and the corresponding stochasticity is an important issue of the EOSS. Often, the uncertainty is either considered in the scoring, by weighting scenarios, by stochastic programming or by some sample average approximation model (Vasegaard et al. 2020b; Valicka et al. 2019; Wang et al. 2020, 2016). We refer to the works of Álvarez et al. (2015) for a detailed discussion on the various aspect of the Earth observation satellite (EOS) scheduling problem.

Over the last twenty year period, the EOSS problem has been increasingly seen in the light of the multi-objective framework; however, due to the complexity of the problem, solution methods that search Pareto fronts are not competitive in solution speed. Therefore, the multi-objectivity is being incorporated a priori through scoring methods that take different aspects into account. E.g profit or marginal profit(Cordeau and Laporte 2005), cloud coverage (Wang et al. 2018), fairness (Tangpattanakul et al. 2015), and utility (Bianchessi et al. 2007; Vasegaard et al. 2020b).

There is very little research on the influence of different pricing strategies for the EOSS problem. Krupke et al. (2019) proposed an auction based scheduling approach to maximize the value of downloaded data from the perspective of the ground stations. Other than this, the only other price investigation for the EOSS problem is the piecewice linear marginal profit function derived by Cordeau and Laporte (2005) to emphasize the completion of strip or stereo acquisitions in the scheduling. Consequently, this research investigates the effect of different pricing strategies on the schedule.

2.3 Trends on multi-criteria evaluation methodologies

Multi-criteria evaluation problems are well researched with application purposes in many different fields (Toloie-Eshlaghy and Homayonfar 2011; Stojčić et al. 2019). In general, the evaluation problems can be split into different types of problems, namely choice, ranking, sorting, or classifying a set of explicitly known alternatives. For the EOSS problem, we are interested in a method for choosing between a high number of alternatives while gaining managerial insights into the decision-making process. For this purpose, the Analytical Hierarchical Process, TOPSIS, ELECTRE, PROMETHEE, and VIKOR have been widely applied as well as extended upon to incorporate uncertain, fuzzy, or crisp data characteristics (Corrente et al. 2017; Chang 1996; Roszkowska 2011; Sanayei et al. 2010). In order to gain managerial insight and ensure robustness in a stochastic environment, we could also apply the Stochastic Multi-Attribute Analysis (SMAA) framework (Lahdelma et al. 1998). However, we choose to utilize the VIKOR method (Opricovic 1998) that yields decision robustness through its stability and advantage conditions, as well as being relatively simple. Additionally, the findings of Opricovic and Tzeng (2007) showcased the robustness and comparison of VIKOR relative to TOPSIS, ELECTRE, and PROMETHEE, as well as their similar evaluation structure. The problem of evaluating business process changes has earlier been investigated by Sarkis and Talluri (2002) where they similarly developed a framework to evaluate these improvements. We are, however, interested in the effects of such changes when the results are governed by a complex optimization problem, and this paper, therefore, seeks to get managerial insights on the problem rather than impose them.

3 Pricing strategies

There are two main product types on the EOS market: newly acquired images (requested), and images that have been acquired earlier (archived). The development in pricing strategies for EOS images has seen very little innovation, where the advent of subscription based models to archived imagery (such as google earth) yields the most significant changes. Most research has since been done on the management of spatial data infrastructure with regards to archived data and how that market behaves (Jabbour et al. 2019).

As mentioned in the literature review, the EOS market has been strongly affected by regulations and pricing policies rather than regular pricing schemes, this has led to the following pricing strategies being utilized:

- free data for all users;
- marginal cost price for all users;
- market driven, realisable prices for all users;
- full cost pricing;
- two tier pricing;
- information content pricing;
- access key pricing

Most of these are referring to archived images, while others are only applicable in a standardized market. See Harris (2000) for a further explanation of the different policies and the corresponding implications. However, as the EOS market becomes more fragmented, regular pricing schemes will take over. The interesting part of selecting a pricing strategy for requested images on the EOS market is that the product price is not affected by a limited quantity in the same manner as other products. This is because, the upper limit for number of acquisitions are dependent on each individual scenario, as well as each individual request having an expiry date. Additionally, there is a lot of uncertainty regarding the expected acquisition of each request as the pool of competitive requests can change instantaneously due to incoming emergency requests, bad cloud coverage, etc. A more elaborate understanding of why specific pricing strategies succeed and struggle in large companies are researched in Lancioni et al. (2005). They found that the company's internal political system, reflected in interdepartmental coordination and rivalry, has an impact upon the price setting. Their findings indicated that it is important that the organization shares the same belief of what the pricing strategy exhibits (Lancioni et al. 2005). As a consequence, this must mean that the success of the pricing strategy is further dependent on the preference structure of the satellite operation (Vasegaard et al. 2020a).

In general, pricing strategies can be categorised dependent on the objective of the firm and the consumer characteristics, that is the pricing strategy can either be differential, competitive, or be based on the product line (Tellis 1986). For the EOS market this means that the following pricing strategies would be applicable for the product of requested images:

- price segmentation (quality, operational specifications),
- service time,
- peak user pricing,
- time of purchase,
- changing conditions (demand over time, etc)

For this paper, we are focusing on price segmentation strategies, as the others require extensive information on the customer behaviour. We are therefore investigating the collaborative effects of price segmentation and preference structures to produce the schedule. The pricing schemes investigated for this paper are

Table 1 The different pricing schemes incorporated into the evaluation procedure of this paper

Strategy focus	Strategy	Description
No focus	Random	Price randomly drawn from U(800,1200)
	Uniform	1000 € for any request
	Cloud cover	1200 € for $cc \leq 20$ and 800 € for $cc > 20$
Quality	Depointing angle	1200 € for $angle \leq 15$ and 800 € for $angle > 15$
	Area	2 € per km^2
Quantity	Volume discount of area	1.5 € per km^2 for requests with areas larger than 500 km^2, and 1.5 € per km^2 for smaller

presented in Table 1. Note, the split of 800–1200 € for the good quality/large request is chosen for simplicity.

4 Background

4.1 VIKOR

The VIKOR method (VIseKriterijumska Optimizacija I Kompromisno Resenje) is developed by Serafim Opricovic (1998) and is intended to solve multi-criteria evaluation problems where a finite set of alternatives with conflicting and non-commensurable criteria are posed. The VIKOR method ranks all alternatives based on the measure of regret (i.e., closest-to-ideal), as of why it is similar to the TOPSIS method, however it introduces the compromise between maximum group utility and minimum individual regret. Additionally, it posses two conditions to ensure that there is both an acceptable advantage of the chosen alternative relative to the others and acceptable stability of the decision making. Given N alternatives and M criteria, the performance of alternative i for the jth criterion will be denoted by $f_{i,j}$ The procedure of the method can be described through the following five steps:

1. Determine the best f_j^* and worst f_j^- value of all criteria performances for each criteria $j \in \{1, 2, \dots, M\}$. If the ith criteria is beneficial then $f_j^* = \max_i f_{i,j}$ and $f_j^- = \min_i f_{i,j}$, and if it is not beneficial then $f_j^* = \min_i f_{i,j}$ and $f_j^- = \max_i f_{i,j}$
2. Compute the maximum group utility, S_i, and minimum individual regret of the opponent values, R_i, for all alternatives $i \in \{1, 2, \dots, N\}$

$$S_i = \sum_{j=0}^{M} W_j \frac{f_j^* - f_{i,j}}{f_j^* - f_j^-} \tag{1}$$

$$R_i = \max_j \left[\sum_{j=0}^{M} W_j \frac{f_j^* - f_{i,j}}{f_j^* - f_j^-} \right] \tag{2}$$

where w_j expresses the relative importance of the jth criteria.

3. Compute the value Q_i for each alternative

$$Q_i = \nu \frac{S_i - S^*}{S^- - S^*} + (1 - \nu) \frac{R_i - E^*}{R - R^*} \tag{3}$$

where $S^* = \min_i S_i$, $S^- = \max_i S_i$, $R^* = \min_i R_i$, $R^- = \max_i R_i$, and ν yields the compromise weight of the strategy between S_i and R_i.
4. Rank the alternatives by decreasing value relative to S, R, and Q values.
5. If the following two conditions are satisfied propose alternative a' as the best compromise solution:

   – C1—Acceptable advantage: $Q(a'') - Q(a') \geq \frac{1}{M-1}$
   – C2—Acceptable stability in decision making: Alternative a' is also ranked best by S and/or R. This condition reveals whether the compromise solution is stable within a decision process of 'voting by majority rule' (when $\nu > 0.5$), 'by consensus' (when $\nu \approx 0.5$), or 'with vote' (when $\nu < 0.5$).

Note, if one of the conditions are not satisfied, then it is possible to find a set of compromise solutions:

– If only condition C2 is not satisfied, then the compromise solutions are alternative a' and a''.
– If condition C1 is not satisfied, and alternative $a^{(h)}$ in the sorted list of alternatives is the first to follow: $Q(a^{(h)} - Q(a') \geq \frac{1}{M-1}$, then the compromise solution are alternative $a', a'', \ldots, a^{(h)}$.

4.2 Shannon entropy

For determining weights multiple different methods exist, and most of them seek to obtain as objective weights as possible. In general there are two different type of methods for determining weights (Milosavljević et al. 2018; Guiaşu 1971), these are:

– Obtaining weights through decision makers, e.g. the Delphi method
– Obtaining weights through data, e.g. Shannon entropy

In general it is recommended for decision makers to utilize a combination of these (Vasegaard et al. 2020a). For this paper, we are incorporating the Shannon entropy method, which is based on the measurement of uncertain information in the different criteria of the decision matrix. The method consists of three steps (Guiaşu 1971), i.e.

1. Normalize decision matrix with respect to each criteria j:

$$p_{i,j} = \frac{x_{i,j}}{\sum_{i=0}^{N} x_{i,j}} \quad \forall \{i,j\} \in \{1,..,N\} \times \{1,..,M\} \tag{4}$$

2. Compute entropy measure for each criteria j:

$$E_j = -k \sum_{i=0}^{N} p_{i,j} log(p_{i,j}) \quad \forall j \in \{1,..,M\} \tag{5}$$

where $k = \frac{1}{ln(M)}$

3. Define weights for each criteria based on the degree of divergence d_j:

$$d_j = 1 - E_j \tag{6}$$

$$W_j = \frac{d_j}{\sum_{j=0}^{M} d_j} \quad \forall j \in \{1,..,M\} \tag{7}$$

Note, the constant k ensures that $0 \leq E_j \leq 1$, and the range of the degree of divergence is therefore equal, as of why the weights can be computed through a simple additive normalization.

5 The proposed framework

As seen in Fig. 1, the decision process should in short be based on a five-phase analysis, which investigates:

1. The price sensitivity for the expected customers
2. The pricing strategies
3. The effects of changes to the pricing strategy specifications
4. The impact of changing scenarios characteristics
5. The effects of the preference structure

For this paper, we focus on the decision being made on pricing strategy and the system-imposed uncertainty that governs these. The framework of the analysis is based on a randomly chosen 4 h planning horizon within the interval between the 12th and 13th of October 2020 at 12:00, the satellite paths of Spot 6 and 7, a granularity of 10 s, maximum off-nadir angle of 30 degrees, minimum sun elevation of 15 degrees, 60 km swath, and satellite agility of 30/12 degrees per second. We consider in this study a 4-h planning horizon, which can be reduced or increased to demonstrate the effect. Optimally, one would utilize a rolling window approach to incorporate the effect of future scheduling horizons on the current one. As shown in the works of Küçük and Yıldız (2019), most scheduling approaches operate with scenarios of approximately 55 requests. In our case, we consider 1,000 customer requests. Note that a longer planning horizon would put additional requirements on the scheduling procedure. The satellites Spot 6 and Spot 7 were chosen because of their operational flexibility and specifications. These satellites are agile, high-resolution, new-generation satellites that can capture a high number of images (Perea et al. 2015). Therefore, developing a flexible system is more attractive because this would allow one to take advantage of the inherent flexibility of the satellites. Given this, these results should only become clearer as future generations of satellites become more agile. The sensitivity of the chosen settings in the framework is investigated through the computational complexity of the scenarios. In the next subsection, we illustrate this in detail (Fig. 2).

In this paper, the topology, or location of requests, mimic the population density in given areas. Therefore, there is a higher density of requests near urbanized areas, causing some scenarios to have extremely high complexity. Last, we neglect the effects of duty cycles and communication with the satellite, as we incorporate these in a 1-h buffering time zone. All scheduling is done based on forecasted information, but this is only relevant to account for cloud coverage (Wang et al. 2016).

5.1 Scenario generation

The problem scenarios are besides the satellite operational specifications and planning horizon affected by the customer database. In this paper, we are generating 1000 worldwide located customer requests with a higher density in urbanised areas. Each request is defined to be square area, thus the amount of multi-strip requests can be calculated. Note that we utilize actual cloud coverage data by integrating real-time forecast information from OpenWeather API (http://OpenWeatherMap.org) based on satellite locations (accessed through the TLEs found via www.n2yo.com). The obtained forecasts are only available for every third hour; that is, the utilized forecast information for each imaging attempt is that which is closest in time.

The characteristics for a single problem scenario generation can be seen in Table 2, while the behaviour for a single scenario and the collective group of 100 scenarios can be seen in Figs. 5 and 6, respectively.

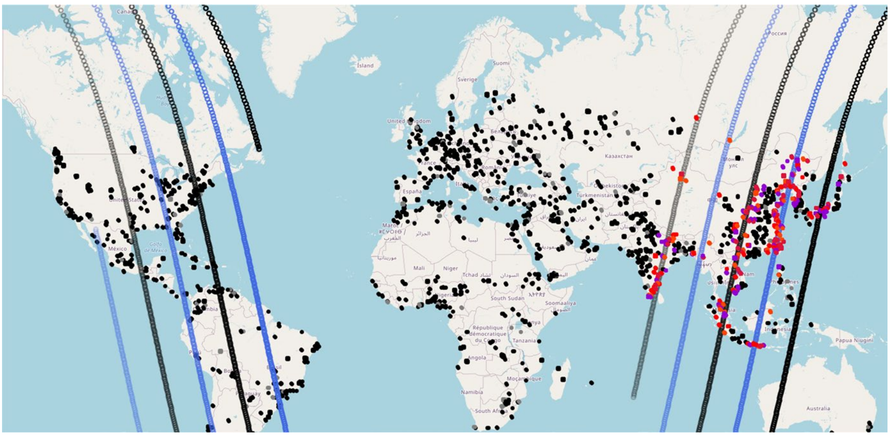

Fig. 2 A map representation of one of the generated problem scenarios

Table 2 The characteristics for the customer and scenario generation

Specification	Description
Area (km^2)	U(1,1000)
Priority	U(1,4) (1 is max)
Duration (s)	U(2,8)
Age (days)	U(1,14)
Stereo requests	10%
Emergency request	0.1%

5.2 Preference profiles

The three preference structures investigated though out this paper correspond to a profit-focused, quality-focused, and intermediate profile. They are realised through the ELECTRE-III approach presented in Vasegaard et al. (2020b). The weight setting for the different preference profiles can be seen in Fig. 3, and the threshold values can be seen in Table 8. Note the intermediate profile weighting w_3 is generated based on the weights of the two other profiles through $w_{3,i} = \alpha w_{1,i} + (1 - \alpha) w_{2,i}$. Here we assume $\alpha = 0.5$. This representation reflects the difference in preference e.g. for a governmental and commercial organization, and the corresponding compromise in a collaboration between the two.

The scoring is part of the general solution approach for the satellite scheduling problem. In essence this part assigns a weight to each image attempt that is considered in the scheduling procedure. Note that in the ELECTRE-III approach, each image attempt is considered as an alternative and an outranking index is built. Ultimately, the computed score for an image attempt is the average credibility that the specific alternative will outrank another alternative.

Fig. 3 Criteria weighting for the three different preference profiles

5.3 Problem formulation

The discrete version of the EOSS problem can be formulated as the following optimization problem:

$$\max_{x} \sum_{p=0}^{P} \sum_{i=0}^{N_p} w_{i,p} x_{i,p} \tag{8}$$

$$\begin{aligned} &\text{subject to} \\ &x_{i,p} + x_{j,p} \leq 1 \qquad \forall \{i,j,p\} : F_{i,j,p} = 1 \end{aligned} \tag{9}$$

$$\sum_{p=0}^{P} \sum_{i=0}^{N_p} B_{r,i,p} x_{i,p} \leq b_{r,p} \qquad \forall r \in \{1, \dots, R_p\} \tag{10}$$

$$\sum_{p=0}^{P} \sum_{i=0}^{N_p} A_{s,i,p} x_{i,p} = 0 \qquad \forall s \in \{1, \dots, S_p\} \tag{11}$$

$$\sum_{p=0}^{P} \sum_{i=0}^{N_p} E_{o,i,p} x_{i,p} \leq e_o \qquad \forall o \in \{1, \dots, \omega\} \tag{12}$$

$$\sum_{p=0}^{P} \sum_{i=0}^{N_p} C_{o,i,p} x_{i,p} \leq c_o \qquad \forall o \in \{1, \dots, \omega\} \tag{13}$$

$$\sum_{p=0}^{P} \sum_{i=0}^{N_p} D_{h,i,p} x_{i,p} = 1 \qquad \forall h \in \{1, \dots, H\} \tag{14}$$

$$\begin{aligned} &x_{i,p} \in \{0, 1\} \qquad\qquad \forall i \in \{1, ..., N_p\} \\ &\forall p \in \{1, ..., P\} \end{aligned} \tag{15}$$

See Table 3 for a description of the notation. The maneuverability constraint in Eq. (9) does not allow the acquisition of both of the two attempts when an infeasible maneuver between them exists. In the case of a maneuver being infeasible, the $F_{i,j,p} = 1$ will force maximum one of attempt $x_{i,p}$ or $x_{j,p}$ to be chosen, rather than both attempts. Note, for the regular acquisitions (only acquired once) b_r equals 1, for stereo acquisitions b_r equals 2, and for acquisitions that are too large to be acquired in a single strip b_r then equals the specific number of strips required. Therein intentionally approximating the real world problem by neglecting the decomposition and assuming the acquisition of the same area to be similar to that of acquiring decomposed areas that are in close proximity. Therefore, in the strip acquisition constraints

Table 3 Notation table for problem formulation

Indices	
P	Number of regions where each region p is independent from the others with respect to maneuverability, interdependency, and allowance ($p \in \{1, \dots, P\}$)
N_p	Number of attempts in region p ($i \in \{1, \dots, N_p\}$)
R_p	Number of unique requests in region p ($r \in \{1, \dots, R_p\}$)
S_p	Number of complete pairs of stereo requests in each region p ($s \in \{1, \dots, S_p\}$)
H	Number of emergency requests ($h \in \{1, \dots, H\}$)
ω	Number of satellites ($o \in \{1, \dots, \omega\}$)
Parameters and matrices	
$w_{i,p}$	the relative value of image attempt i in region p with respect to all the other attempts and criteria
$F_{i,j,p}$	Binary matrix that represents all infeasible maneuvers between any two attempts $\{i, j\}$ of region p
$B_{r,i,p}$	Binary matrix that for any unique request r yields which attempts that represent particular request for each region p
$b_{r,p}$	Maximum number of acquisition per request r in region p
$A_{s,i,p}$	Matrix yielding which pairs of attempts that can be acquired in order to complete a stereo request, i.e. a request of two attempts acquiring the same area where the convergence angle between these two attempts are between 15^o-20^o. (Value of 1 indicating first acquisition in the pair s in region p, -1 indicating second attempt, and 0 indicating attempt that are not part of the sth pair)
$E_{o,i,p}$	The energy consumption for satellite o on attempt i in region p
e_o	Maximum energy capacity for satellite o
$C_{o,i,p}$	The memory consumption for satellite o on attempt i in region p
c_o	Maximum memory capacity for satellite o
$D_{h,i,p}$	Binary matrix representation of all attempts i in region p that represent emergency request h. Note an emergency request can under no circumstances be omitted from the schedule. Anytwo emergency requests cannot have all its image attempts to be completely conflicting, and this should be checked in the pre-processing
Decision variables	
$x_{i,p}$	Binary variable that represents either an included or excluded ith acquisition for that particular region p

in Eq. (10), a maximum of b_r acquisitions can be made. This formulation allows the inclusion of multi-strip acquisition by the constraints in Eq. (10), as certain constraints can be acquired more than once. In reality, these acquisitions will be composed of different segments, but for simplicity we will omit the photogrammetry properties of splitting each request. That is, requests that are too large to be captured in a single strip should be decomposed into smaller strips relative to the satellite path. Additionally, for long strips, this is mimicked by having the acquisition duration be additionally long. See Vasegaard et al. (2020b) for a deeper explanation of this. The stereo acquisition constraint in Eq. (11) ensures that a stereo request is either completely acquired or not at all acquired. Both the energy and memory constraint in Eqs. (12) and (13) ensures that the cumulative capacity is not exhausted within the planning horizon. The emergency request constraint in Eq. (14) ensures that the emergency requests are acquired.

5.4 Solution approach for scheduling

As the weight of each image attempt in Eq. (8) represents the relative value with respect to all the other image attempts and the criteria of interest, we are employing the ELECTRE-III scoring method applied in Vasegaard et al. (2020b). ELECTRE-III is a fuzzy outranking method that utilizes a pairwise comparison of the criteria performance for each alternative. It does so by assessing the criteria performance through the indifference and preference threshold to compute the outranking degree, as well as the veto threshold in order compute the discordance and concordance index for each alternative. These two indexes are then combined to form the credibility index that states the trust in which one alternative outranks the other. Lastly, the alternatives are ranked based on two pre-orders that are made through either an ascending or descending distillation process (Corrente et al. 2017). However, the last step is omitted in the scoring approach, as the score is computed based on the average credibility for each alternative outranking the other alternatives (Vasegaard et al. 2020b). This method yields the possibility of employing a high number of criteria e.g. cloud coverage, area, depointing angle, price, priority, sun elevation, as well as the ability to discriminate between requests through the veto threshold and introduce different levels of uncertainty through the indifference and preference value. It is within the scoring approach, that the preference structures is imposed. That is, see Fig. 3 for the utilized weighting and Table 8 for the utilized threshold values for each preference profile.

Additionally, we are employing the extended longest path algorithm (ELPA) represented in Vasegaard et al. (2020a), as the method serves as a fast and good approximation to the optimal solution. The method builds on the assumption that the satellite network can be formulated as a directed acyclic graph with interdependent and allowed nodes, where these type of nodes represent attempts being made of either the same requests or stereo requests. Moreover, the explainability of the method allows decision-makers to understand the consequences of the decisions being made, and uncover problems in the preference structure if these should exist. Note that the attempts (nodes) must be topologically sorted first by satellite and then by time per satellite. By doing this, there won't be any discrepancies when utilizing the extended longest path algorithm (ELPA), as it iteratively corrects any interdependent or allowed nodes that are acquired when linearly searching the graph. Although the ELPA does not incorporate the energy and memory constraints of Eqs. (12) and (13) directly, those impacts are nonetheless ensured through post-processing checking. More specifically, this check is performed where the solutions found by the ELPA from the longest path to the shortest path iteratively are verified. If they do not follow the energy and memory constraints, they are forced to fit by a greedy approach decreasing the solution's length. The first solution found to be valid and longer than the following path to be checked or longer than any other valid path is chosen as the path (schedule) that accommodates all constraints (with energy and memory constraints incorporated). Similarly, the emergency request constraint of Eq. (14) is incorporated in the pre-processing phase (Elkjaer Vasegaard and Nielsen 2021).

6 Simulation and strategy determination

This section investigates the average behaviour of the system given the specified pricing strategy and the stated preference profile through simulation. Of the stated pricing strategies presented in Table 1, this section investigates firstly those pricing strategies and secondly the pricing strategy specifications. The strategy determination is conducted through the VIKOR methodology with criteria weights derived from the Shannon entropy method, which utilized the available performance data and 0.5 as the corresponding compromise weight.

6.1 Determining the pricing strategy

To investigate the pricing strategy 100 different scenarios are generated and for each scenario the different pricing strategies and different preference profiles are interpreted through the schedule computed by the ELECTRE-III and extended longest path methodology. The results can be seen in Table 4, where a number of findings become apparent.

It is clear that the quality-focused preference profile is relatively indifferent to changes in pricing strategy, and similarly the profit-focused profile selects the image attempts that allows for a higher profit. Not surprisingly, the profit-focused and quality-focused profiles are much less prone to integrate attempts that does not perform within their respective focused criteria. However for the medium preference profile, one surprise is that the gain in the other criteria is much bigger than expected. E.g. the Average number of acquisitions for the quality-focused profile is 108.41–108.48 while for the profit-focused it is between 109.33 and 110.25, and then surprisingly the medium preference profile delivers between 110.84 and 111.10 acquisitions on average per four hour schedule horizon. Additionally, the medium profile does not fall far behind from the focused profiles on the criteria that these are focused on. E.g. for the total profit and avg angle, the medium profile are much closer to the respective focused preference profiles performances relative to the profile that are not focused on these criteria. Ultimately, the medium preference profile serves as a very good compromise between the two conflicting viewpoints.

The pricing strategy has almost no effect on the scheduling of the quality-focused profile, as the only change comes from the direct changes in pricing. Meanwhile, the profit-focused and medium profiles are being impacted as other imaging attempts are being considered to integrate preferences better. The cloud cover pricing strategy does not seem to elevate the cloud cover performance of the schedules. However, the angle pricing strategy highly increases the performance of the depointing angle in the final schedules, but from this follows a relatively large decrease in profits and cloud cover performance. The area pricing strategy leads to a high number of

Table 4 The average performance for different pricing strategies and preference profiles on 100 generated scenarios with the stated scenario and customer characteristics

Alternatives		Criteria				
Profile	Pricing strategy	Avg number of acquisitions	Total profit (€)	Avg cloud cover (%)	Avg angle (°)	Avg priority
Quality-focused	Random	108.48	110175	26.034	20.966	2.504
	Uniform	108.48	108480	26.028	20.987	2.504
	Cloud	108.48	109383	26.031	20.989	2.504
	Angle	108.48	97468	26.031	20.989	2.504
	Area	108.41	127352	26.032	20.941	2.504
	Volume	108.41	106623	26.027	20.966	2.503
Profit-focused	Random	109.92	114111	26.873	22.723	2.430
	Uniform	110.25	110247	26.964	22.706	2.429
	Cloud	110.25	110876	26.865	22.738	2.432
	Angle	109.98	99484	27.097	21.568	2.431
	Area	109.33	135328	26.997	22.671	2.458
	Volume	109.40	111417	27.068	22.583	2.442
Medium	Random	110.77	113917	26.727	21.545	2.465
	Uniform	111.03	111033	26.759	21.498	2.469
	Cloud	111.10	68416	26.716	21.597	2.471
	Angle	110.84	111975	26.676	21.308	2.463
	Area	110.97	134436	26.744	21.531	2.470
	Volume	110.97	111340	26.769	21.487	2.467

acquisitions, profits, and good cloud cover and angle performance. The volume discount pricing served as an extension to the regular area strategy, but performs worse.

In the case, that a much higher number of alternatives were given, i.e. pricing strategies and preference profiles, it would be much more unclear to which method to choose. To circumvent this, the VIKOR method and the objective weighting provided through the Shannon Entropy framework is utilized in this project.

The weights generated by the Shannon entropy method are seen in Table 5, and as a continuation the respective ranking produced by the the VIKOR methods S, R, and Q indexes can be seen in Table 6.

Table5 The generated weights through the shannon entropy method, where E_j, d_j, and w_j is the entropy, discriminabilty, and weights, respectively

Criteria	Avg. number of acquisitions	Total profit	Avg. cloud cover	Avg. angle	Avg. priority
E_j	0.99998	0.99860	0.99996	0.99983	0.99997
d_j	0.00002	0.00139	0.00004	0.00016	0.00002
w_j	0.00952	0.84898	0.02456	0.10339	0.01352

Table 6 The output for the VIKOR method on the different alternatives of pricing and preference profile, as well as the corresponding ranking

Alternatives	S_i	R_i	Q_i	$Rank_S$	$Rank_R$	$Rank_Q$
0	0.588	0.564	0.645	6	12	9
1	0.627	0.602	0.693	11	14	13
2	0.607	0.581	0.668	10	13	10
3	0.874	0.848	1.000	18	18	18
4	0.202	0.178	0.166	3	3	3
5	0.667	0.643	0.744	13	15	15
6	0.602	0.475	0.599	9	4	5
7	0.688	0.562	0.707	15	11	14
8	0.674	0.548	0.689	14	10	12
9	0.868	0.803	0.968	17	16	17
10	0.133	0.099	0.074	2	2	2
11	0.662	0.536	0.675	12	7	11
12	0.538	0.480	0.562	4	5	4
13	0.601	0.544	0.641	8	9	8
14	0.584	0.523	0.618	5	6	6
15	0.849	0.806	0.957	16	17	16
16	0.078	0.033	0.000	1	1	1
17	0.593	0.537	0.632	7	8	7

Note, S_i, R_i, and Q_i is the maximum utility of the majority, minimum individual regret of the opponent, and the weighted average with respect to the two, respectively

According to the VIKOR and Shannon entropy method the best compromise solution is alternative 16, where the medium preference profile and the area pricing strategy are selected. Here, both conditions of the VIKOR are met as of why the solution yields an acceptable advantage and has acceptable stability in the decision making. Note, we neglected the influence of price sensitivity, and it is therefore very possible that this does not reflect reality. Furthermore, as seen in Table 6, the Medium profile has significantly higher rankings for S, R, and Q indices of VIKOR across the board, therefore serving as good compromise between the two profiles for any of the pricing strategies.

6.2 Determining the pricing specifications

To investigate the pricing specifications, we are solely modifying the pricing strategy of the best compromise solution found in the previous section. That is, varying the price between 1.5 and 2.5 € per sqkm. Through the same procedure, we can see in Tables 9, 10, and 11 that both conditions are met and the best compromise solution is alternative 14, where the Medium profile selects a threshold of 2.5 € per sqkm. Note, that the compromise solution is not necessarily better for a higher profit, as this leads to decreases in the other performance metrics. Similarly, the customer sensitivity is here neglected, as of why this could change in the real world results.

Remark, that this is per 4 h planning horizon, so these results are expected to be replicated every 4 h, as of why an additional acquisition in the presented results could potentially lead to 42 additional acquisitions per week, as the satellite continuously is expected to average these type of results.

7 Discussion

7.1 Effectiveness of the method

The method in this paper clearly showcases the importance of considering the collaborative effects of pricing and preference structure. In addition, it shows that the problem of pricing in satellite scheduling ultimately can be seen as an MCDM evaluation problem as different pricing strategies for different preference profiles lead to substantially different outcomes.

In a satellite operation, there are multiple different objectives to consider, and it is therefore important to obtain a good compromise solution. Similarly, it is easy to introduce harmful bias when determining either the pricing strategy or preference profile, and the VIKOR method in this paper avoids just that by evaluating the decisions on simulated scenarios, as well as on an unbiased scale that is determined based on the best and worst ideal alternatives derived from the observed data. Additionally, the VIKOR method allows the decision maker to gain some insights in the advantage and stability of their decision when choosing the compromise solution by analysing the ranking of alternatives and considering the advantage and stability conditions imposed through VIKOR.

We are utilizing the Shannon entropy in order to avoid adding bias through weighting of the importance of the different criteria. However, if the data does not reflect the information or importance corresponding to each criteria, one should utilize a different weight elicitation method by having experts posing educated guesses on the weights, e.g. via Delphis method or via a combination (Vasegaard et al. 2020a).

7.2 Simulation and assumptions

The two biggest assumptions and shortcomings of this research is that we are neglecting the variability of both price sensitivity and scenario characteristics. However, when incorporated in industry, similar assumptions will also be derived, this will however be conducted with their expertise in order to minimize the errors of this shortcoming.

By incorporating the preference profiles through the ELECTRE-III approach, it is possible to mimic the complex behaviour of a real world schedule as satellite operators have the ability to integrate a more comprehensive preference structure into the scoring. That modification would for simple weighted average scoring approaches otherwise have been introduced in a posterior analysis or correction phase. The preference profiles are through the scoring approach determining the score and ultimately the schedule, so in the case that another weight elicitation method is preferred over the Shannon entropy method, it is important that a range of preference profiles are tested to find the optimal one.

A reason for this was the indications that analogue findings of Braess' paradox existed in the EOSS when increasing weight in one criteria of the preference profiles (Vasegaard et al. 2020a). Braess' paradox refers to the strange behaviour of a system for example adding a road to a road network would decrease the overall flow through that network(Frank 1981).

7.3 Results and managerial insights

The results emphasize that one should not only modify the pricing strategy to increase profits, as the collaborative effects of the preference structure on the stated pricing strategies must also be Incorporated. As an example, the ranking of compromise solutions in Tables 6 and 9 show that it is possible to obtain a better compromise solutions by modifying either one of the preference profile as well as the pricing strategy.

From a perspective of managing, the presented method can be utilized directly to evaluate the effects of small changes in pricing and preference, as well as support short and long term decisions on pricing and preference profile of companies. This can prove to be very valuable to understand the effects of changing market behavior, especially as the EOS market is transitioning into a higher market fragmentation.

7.4 Overview and application

The EOS imaging system is inherently flexible, but due to its scale, constraints, induced uncertainty and multiobjectivity, it is also extremely complex. The proposed framework investigates the effect of pricing strategies on the entire system in collaboration with the inherent preferences of satellite operation. In many ways, the scheduling system behind EOS imaging is very similar to that of any other manufacturing setting. This is especially the case, as manufacturing moves into the era of mass customization, where products, pricing, and customers all are being taken into account. That is, in any manufacturing setting a demand should be met through some utilization of resources. There is most likely also an optimization problem behind obtaining a solution that determines which demand is met in the given scheduling horizon. In a similar manner to that of EOS scheduling, decision makers of the manufacturing process have to determine a preference structure to then incorporate into the optimization problem. The developed method should not only be applicable to that of the satellite scheduling problem but could also be integrated in any other flexible service or manufacturing sector. What our research suggests, then, is that if the collaborative effect of the pricing strategy and the preference structure is not considered, the decision makers are missing out on potential gains relative to their actual preferences and objectives. The method we propose in this paper can help to determine the preference structure that best prioritizes gains. Figure 4 provides a holistic overview of the proposed system.

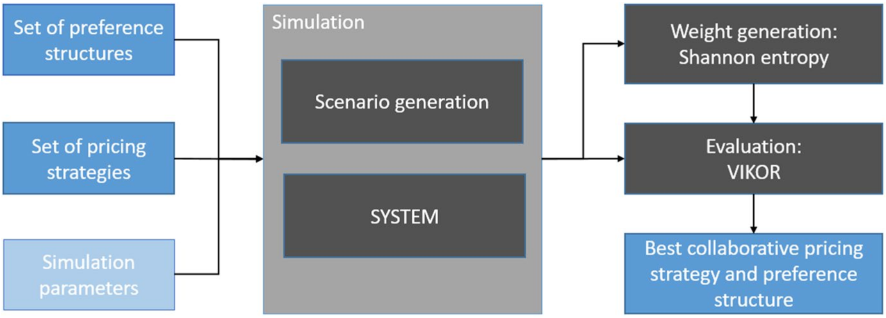

Fig. 4 Overview of the proposed system

Determining a pricing strategy and a preference structure should be done collaboratively. A high number of computations are required to simulate real-world effects on different schemes. This is shown specifically for the EOSs. In Table 7, the different computation times for different settings. Note, the effect of employing a different number of satellites is omitted due to the dependencies of the orbit of satellite paths and their position of each other in relation to the location of customer requests. We refer to the works of Álvarez et al. (2015) who perform a substantial analysis on the employment of multiple satellites, as well as the position and relationship between stations and number of satellites.

Other systems that could benefit from the added flexibility of this approach of determining a collaborative pricing strategy and preference structure include the following:

1. The specific case of vehicle routing problems in package delivery, as delivery decision makers not only seek to minimize delivery time but also have a higher preference for certain customer types that buy either high-quality products or perishable items, or some other specified merchandise. Often these customers have a lower threshold for being unsatisfied. Therefore, determining the combined preference structure and pricing in such situations would improve the long-term efficiency of that particular system (Golden et al. 2008).

Table 7 The runtime effects of different settings for granularity, planning horizon, and number of requests

Time gran. (s)	Avg. run time (s)	Time horizon (h)	Avg. run time (s)	Number of requests	Avg. run time (s)
5	56.37	1	0.20	500	5.05
10	14.21	2	4.55	750	8.51
15	5.92	4	13.94	1000	14.39
20	2.12	8	25.41	1250	16.94
25	0.56	12	45.93	1500	26.59

2. The integrated production and distribution planning of perishable foods. In this sector, it is important to distinguish between different types of foods and not to just consider the minimization of total waiting times. Similarly, determining a pricing strategy for this type of food delivery is extremely difficult as the pricing has an effect on the production and planning (Farahani et al. 2012). In the future, these decisions will likely be further intertwined, and it therefore will be of great value of high value to determine the effect of pricing strategies.
3. The pricing problem of customized products in large assembly manufacturing. This problem is also extremely difficult to solve, as different customer segments have different levels of importance, all while planners seek to produce as many products as possible. If, for example, one segment is emerging, then, the importance of planning is high. Lu et al. (2007), in their work, investigated the effect of customized product configurations; but clearly evaluating the pricing and preference structure in collaboration with this system would be of great help to managers and decision makers.

8 Conclusion and future work

In recent years, satellite imagery with good optical properties have been used extensively in various complex decision-making processes. Constellations of satellites have higher flexibility and therefore utility than single-operated satellites, but are also extremely complex and expensive to operate. As a consequence, these constellations are often dual owned (and operated) posing a challenge when defining the preference structure of the operators. Constellations of satellites are used to acquire images/data continuously (e.g., Spot, Sentinel, RapidEye) or according to on-demand (e.g., Spot, Quickbird), and the prices of those images are highly influenced by factors s.a. area for purchase, the optical quality, etc. However, the pricing and profitability of satellite images in perspective of scheduling is not well-discussed in the literature.

This study showcases a method to evaluate changing preference profiles and pricing strategies on the complex EOSS problem and the importance of considering the inherent multi criteria aspect of the problem. The presented methodology serves as a good decision support tool when the satellite operation defines or evaluates proposed pricing strategies or preference profiles for the future. Similarly, it greatly decreases the complexity of incorporating the EOSS in a multi-objective framework while giving managerial insight. In the generic scenarios considered in this research, the intermediate preference profile served as a very good compromise solution as the image quality results where similar to that of the Quality-focused profile, all while the obtained profits where close to that of the Profit-focused profile.

In the future, this work should be generalized to incorporate the effects of changing price sensitivity as well as a more diverse representation of the real world scenarios. Correspondingly, in order to account for the stochastic nature of the scenarios and the fuzzy weighting of group decision making, the VIKOR method could be extended further (Sanayei et al. 2010).

In addition, the effects of incorporating a much larger, diverse, and representable portfolio of real world preference profiles should be tested. Another important aspect that should be further investigated is the long-term effects of selecting a combination of pricing strategy and preference structure relative to another. Lastly, we hope that this paper will inspire other researchers to investigate and develop methods that not only evaluate different pricing strategies but derives them.

Appendix 1: Pre-processing of system

The pre-processing of the system is highly connected to the scenario generation as it ultimately converts the customer database and satellite information into a problem scenario. In short, it identifies all feasible imaging attempts for the satellite and defines the constraints between all attempts. It does this by converting the satellite path into a grid of satellite action points. Each point identifies which requests are reachable and feasible according to the satellite capabilities and customer requirements. After that, all other relevant information (sun elevation, angle, area, cloud coverage) is obtained. In Figs. 5 and 6 the average characteristics of the generated scenarios can be seen. In the works of Elkjaer Vasegaard and Nielsen (2021), an overview of how the pre-processing is improved can be seen.

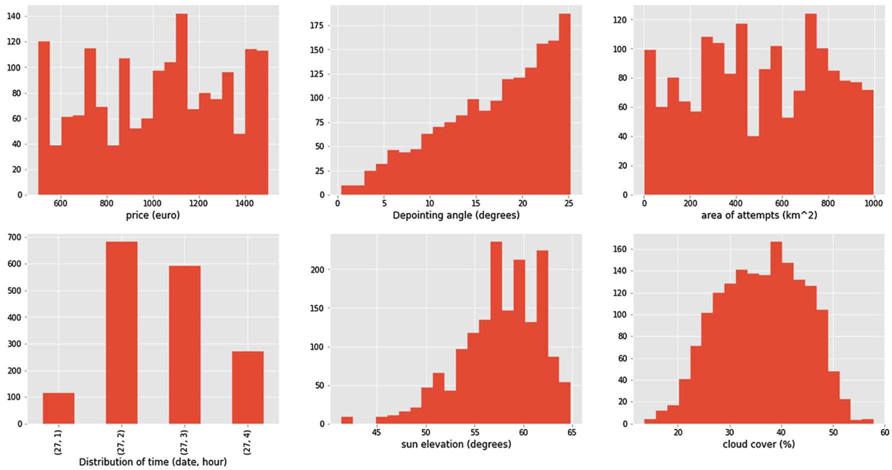

Fig. 5 Characteristics of a single scenario generated in the planning horizon at 12th October 2020 18:00–22:00

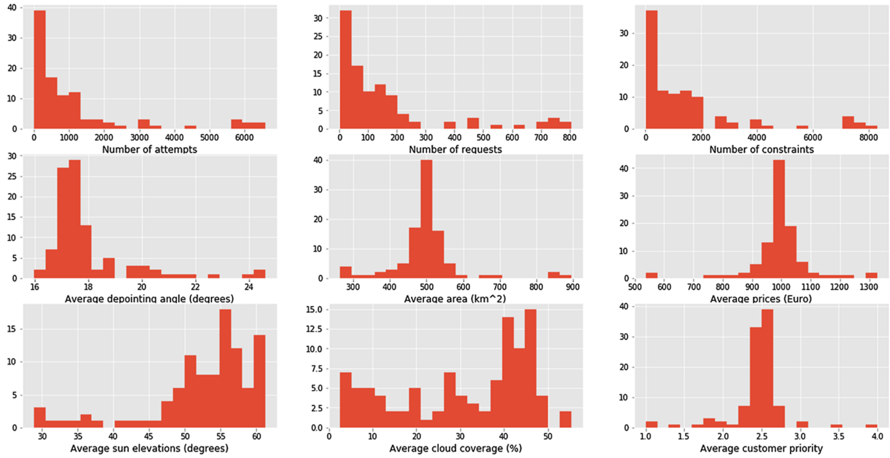

Fig. 6 Characteristics of 100 different scenarios generated between the 12th and 13th of October 2020 at 12:00

Appendix 2: VIKOR and Shannon entropy tables

See Tables 8, 9, 10 and 11.

Table 8 Threshold values for the three preference profiles utilized in the ELECTRE-III scoring approach. Note, q represents indifference, p represents preference, and v represents veto threshold

Criteria		Profiles	
Threshold (q, p, v)	Quality	Profit	Medium
Area	(0, 500, 1000)	(0, 0, 900)	(0, 250, 950)
Angle	(0, 0, 25)	(10, 20, 30)	(5, 10, 27.5)
Sun elev	(0, 0, 4)	(0, 10, 40)	(0, 5, 40)
Cloud cover	(0, 0, 30)	(10, 20, 50)	(5, 10, 40)
Priority	(0, 0, 4)	(0, 0, 2)	(0, 0, 3)
Price	(100, 500, 2000)	(0, 0, 1000)	(50, 250, 1500)
Age	(0, 0, 14)	(2, 10, 14)	(1, 5, 14)
Uncertainty	(0, 0, 1)	(0, 0.5, 1)	(0, 0.25, 1)

Table 9 S, R, and Q indices and the corresponding rank

Alternatives	S_i	R_i	Q_i	$Rank_S$	$Rank_R$	$Rank_Q$
0	0.930	0.920	1.000	15	15	15
1	0.742	0.732	0.788	12	12	12
2	0.553	0.542	0.575	9	9	9
3	0.363	0.352	0.361	6	6	6
4	0.168	0.154	0.141	3	3	3
5	0.894	0.824	0.925	14	13	14
6	0.688	0.618	0.694	11	10	11
7	0.483	0.411	0.462	8	7	8
8	0.277	0.205	0.231	5	4	5
9	0.071	0.045	0.024	2	2	2
10	0.873	0.834	0.920	13	14	13
11	0.667	0.627	0.687	10	11	10
12	0.465	0.426	0.461	7	8	7
13	0.256	0.217	0.225	4	5	4
14	0.049	0.022	0.000	1	1	1

Table 10 Weights for pricing specifications derived through Shannon entropy

Criteria	Avg number of	Total profit	Avg cloud cover	Avg angle	Avg priority
E_j	0.99997	0.99371	0.99983	0.99968	0.99995
d_j	0.00003	0.00628	0.00016	0.00031	0.00004
w_j	0.00432	0.92030	0.02351	0.04587	0.00598

Table 11 The average performance measures for the different pricing specifications of area pricing strategy found through simulation

Alternatives		Criteria				
Profile	Thresholds	Acquisitions	Profit	Cloud cover	Angle	Priority
Quality	1.50	108.48	92244	26.019	19.993	2.413
	1.75	108.48	107784	26.012	20.008	2.413
	2.00	108.56	123412	26.031	20.032	2.412
	2.25	108.56	139110	26.005	20.049	2.414
	2.50	108.64	155406	26.093	20.115	2.419
Profit	1.50	110.24	100177	27.938	22.172	2.323
	1.75	110.20	117146	27.924	22.127	2.328
	2.00	110.00	1342045	27.985	22.186	2.332
	2.25	109.96	151218	27.948	22.194	2.333
	2.50	109.92	168196	28.030	22.160	2.332
Medium	1.50	112.28	99293	27.269	21.060	2.357
	1.75	112.28	116392	27.222	21.089	2.361
	2.00	112.08	132989	27.266	21.055	2.361
	2.25	111.44	150230	27.208	21.043	2.356
	2.50	111.44	167396	27.215	21.093	2.359

Note each specification is a potential alternative (combination of pricing, specifications, and preference profile)

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