Optimization Based Profitability Management Tool for Cloud Broker

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Abstract

This paper shows the development of an optimization based profitability management tool for a cloud broker with a particular business model organized as following: On behalf of a governing telecommunication holding company this cloud broker integrates, aggregates and customizes software and storage services of third-party internet software vendors (ISVs). The cloud broker neither pays license fees to ISVs nor gets payments from the sales of the service bundles. The cloud broker solely receives both a fixed and a subscription based commission fee from the telecommunication company. The cloud broker faces a limited amount of human resources that are necessary to deal with the legal, technical and economic activities that are required for this kind of endeavor. Moreover, sales numbers, service prices and resource usage cannot be estimated with certainty, which implies the risk of missing financial and operational targets. In order to run its business efficiently, the cloud broker needs to determine which services and service bundles improve the profitability and reduce the financial risk. This information is needed in order to support the negotiations concerning the fixed and variable commission as well as the prioritization of services and service bundles to be provided. For this situation, we develop an optimization model that can be used to select the service program with the highest profit-versus-risk potential.

Keywords: Cloud Broker, Cloud Services, Portfolio Optimization, Risk Analysis

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1 Introduction

In this paper, we report the development of a service portfolio and profitability management tool for a cloud service broker. Generally, a cloud service broker is an entity that negotiates relationships between cloud service customers and internet software vendors (IOS/IEC 17788, 2014). A cloud broker can be established on the grounds of different business models with respect to type of service (platform, infrastructure and software), type of customers (businesses, households), functions carried out (identity management, accounting and billing, location, etc.), degree of rebranding, degree of service aggregation and other criteria. Because of this variety, different cloud brokers have different attitudes towards which decisions are particularly relevant for running their business. These can be pricing, capacity planning and utilization, coupled with issues like quality of service, security, scalability among others (Filiopoulou et al. 2017, Wang et al. 2017, Shawish and Salama 2014). In this paper, we focus on a cloud broker that mediates software as a service (SaaS) to private households and small to medium sized enterprises.

One of the key decisions that such a cloud-service broker has to face is the choice of the services and service bundles to offer to its customers. Integration, aggregation and customization of such services from different internet software vendors can be a time consuming and therefore costly endeavor. Furthermore, both the time and resources used to create service offerings and the demand generated for these services is subject to uncertainty. Hence, a cloud broker needs to channel its time and human resources into the most beneficial service portfolio.

The contribution of this paper is therefore the development of a model that helps a cloud broker to make superior decisions concerning its service portfolio. The model draws from ideas found in other research domains than cloud computing and brokering. From the point of view of cost accounting the proposed model supports product-mix (output) decisions under scarce resources (capacity constraints) (McLaney and Atrill, 2010, pp. 335-337; Horngren et al., 2012, pp. 427-428). The model also fits the class of knapsack problems (Rardin, 1998; Gaivoronski and Lisser, 2010) because the entities of our model are represented by binary numbers. On the other hand the model can be seen as a financial portfolio problem where service bundles and services generate wealth while the implementation and maintenance of service utilizes scarce factors of different nature like financing, labor time, competency and others. Markowitz (1952) has pioneered modern financial portfolio theory and in the recent years financial portfolio optimization has developed into a rich body of models and applications (Elton et al. 2014, Zenios 2007). In the context of modern communication and information services the portfolio theory approach and business optimization has been used by Gaivoronski and Zoric (2008), Nesse et al. (2013) and Gaivoronski et al. (2013).

The development of the model described below is the outcome of a research process with case study characteristics (Yin, 2009). In order to understand the cloud service providers' role in the value chain, to identify relevant cost and income objects and their hierarchy, to elaborate the model structure, and to finally assign relevant financial data we conducted several semi-structured interviews with key persons both at the superior telecommunication company and the cloud service provider. More particularly, we have conducted several telephone and face-to-face interviews with the business manager, financial manager and service designers at the cloud service provider as well as product manager and product specialists at the telecommunication operator. In addition, we collected secondary data containing of product specifications, the companies web sites and annual reports.

The sequel of this paper is structured as follows: The next session describes the type of the cloud broker that we have studied. In section 3, we describe the base model for deterministic input data. Section 4 focuses on the implementation of uncertainty and risk. A numerical example is provided in section 5, and section 6 concludes the paper.

2 Description of our Particular Cloud Broker Firm

The cloud broker in our case is a fully owned subsidiary of a larger telecommunication holding company. It leases a platform from a third party platform provider. This platform facilitates the connection between users and services offered by internet service providers. By means of this platform, the cloud broker integrates, maintains and composes service bundles on request of other affiliated firms of the same telecommunication holding company. Let us refer to these subsidiaries as the service sellers. The platform run by the cloud broker also provides the infrastructure needed for service provision like identity and access management, pricing, billing, web design, and other features. The services to be integrated, maintained and bundled on the platform are provided by third party internet software vendors (ISVs). The service sellers sell the services and service bundles to the end customers.

The constellation of the cloud broker and its clients is illustrated in Figure 1. The peculiarity of the cloud broker is that it neither directly makes decisions concerning the composition of service offers nor decides the prices or marketing of the services or service bundles. Furthermore, the cloud broker does not directly pay any license fees to the internet software vendors. Although mediated through the platform, the service sellers receive payments from customers and pay license fees to the ISVs. For integrating services and generating service bundles and delivering the corresponding infrastructure, the cloud broker receives a commission from the service sellers. This commission is partly fixed and partly based on the number of subscriptions to the services. This commission is negotiated by the cloud broker and the telecommunication company, where the cloud brokers power of negotiation rests basically on well-founded arguments concerning its own profitability and cost effectiveness.

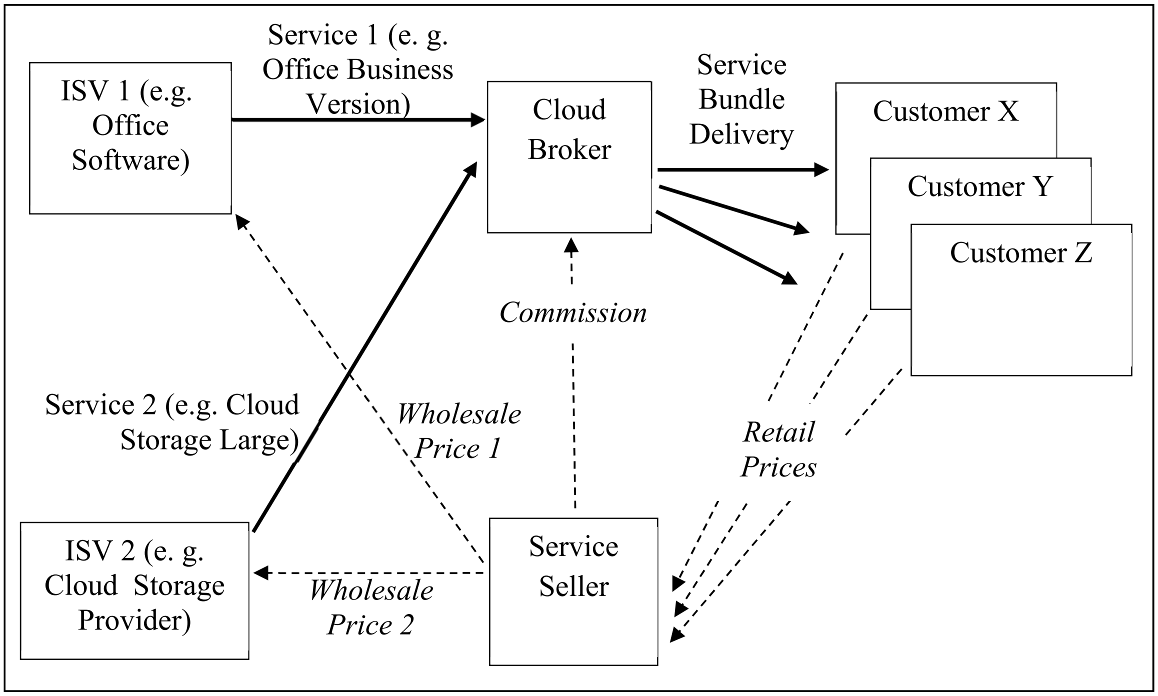

Figure 1: Flow of Services and Pricing

On one side, the cloud broker is requested to run its business in an economic feasible way and on the other hand it has a restricted influence on marketing, pricing and service portfolio composition, i. e. the cloud broker's decision space consists of cost management and negotiation of commission. For the latter the cloud broker needs a reliable way to assess the profitability of the service portfolio and the parts therein.

The model developed in the next section is intended to provide the following support to the cloud broker. First, it provides a suggestion about what the optimal cloud service portfolio should be if the cloud broker could autonomously control its service portfolio. Since the cloud broker integrates services and bundles on behalf of its clients (service sellers) the model highlights the mismatch between what ought to be provided and what indeed is provided. The model then can be used to derive indications about target numbers on costs, time usage, and commission payments. It provides incentives for cost reduction measures, re-negotiation of brokering or commission fees and re-negotiation of service integration. This enables the management to communicate incentives to the service sellers as well as to their developer teams or employees.

3 The Base Model in Case of Certain Input Data

Our optimization model requires a realistic and consistent picture of the cause-effect relationships between costs and revenues on one side and the cost objects like services, service groups, ISVs, service bundles and markets on the other side. In terms of cost accounting, we have to classify *variable* and *fixed revenues and costs* or *direct* and *indirect costs and revenues*. Variable costs are costs that vary with the production volume of the related cost object. Accordingly, fixed costs do not vary with production volume. Direct costs can be traced directly to a cost object such as a product, market or a department while indirect costs cannot. In the first place our model requires an appropriate cost object (or revenue object) hierarchy and the identification of the direct costs of each cost object. For our cloud broker we identified the following entities as most relevant:

- Global internet software vendors (like *Microsoft*, *F-secure*, *Jotta*, etc.)
- Local or market related internet software vendors on particular markets (like Microsoft in Denmark, Microsoft in Sweden, etc.)
- Service families or groups (like *Office 365 Suites*)
- Single services (like *Lync Online* or *Office 365 Business Essentials*)
- Service bundles (Mobile subscription with a particular Office 365 and Cloud storage and Internet Telephony)
- Markets (Denmark, Sweden, etc.)
- Clients (Sellers of service bundles)

The identification of these entities and their relationships may not only depend on purely financial reasons but can rest on juridical or technological characteristics as long as they cause resource usage and respective costs. The reason for differentiating global and local or market specific ISVs is the following: A service provided by some global ISV can be essentially the same on different markets with respect to installing the service on the platform, generating interfaces, integration and interoperability of the service with other services. However, with respect to other factors, the same service provided to different markets can require market specific (local) activities. For example, contracts between ISVs and the cloud broker need to be adjusted to country specific legal codes; payments may be specified in the respective country's currency. Furthermore, country or area specific legal requirements need to be fulfilled concerning data portability, location of processing and storage of data.

Figure 2 gives an overview on the entities in our model and indicates the relationships between them. In what follows, we represent the mathematical representation of these relationships. Let us start with the cloud broker itself. We introduce a binary variable x_O that indicates if the cloud broker offers services ($x_O = 1$) or if the cloud broker does not offer services ($x_O = 0$). All overhead expenses that cannot be traced to any other entity will be linked to this variable. Hence, there will be no overhead expenses if $x_O = 0$ meaning that the cloud broker should not carry on with its business. During the optimization the value of x_O tells if the cloud broker is profitable or not. It is a trivial variable in the sense that all other binary variables will be zero if $x_{\mathrm{O}} = 0$. Only if $x_{\mathrm{O}} = 1$, some or all other variables may become active (equal to 1).

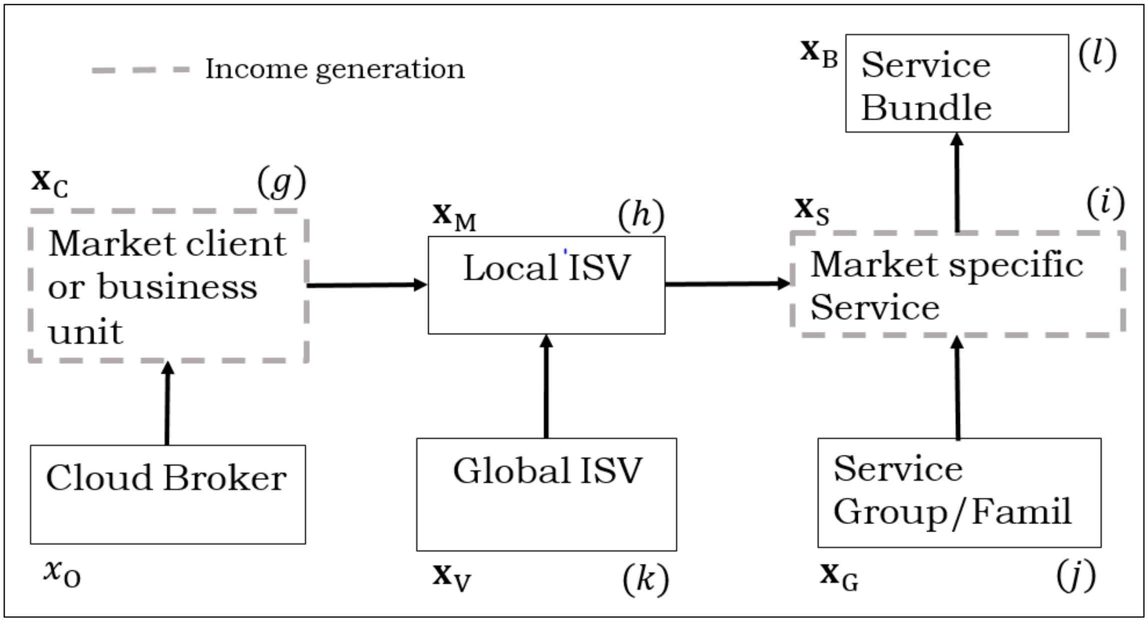

Figure 2: The Relationships between the Entities of the Cloud Broker

Let there be N_{C} service sellers that sell the service bundles generated by the cloud broker. Binary variables $x_{\mathrm{C},g}$ indicate whether a service seller $g = 1, \dots, N_{\mathrm{C}}$ will be served by the cloud broker or not. The following constraints assure that the clients cannot exist if the cloud broker is not active:

$$x_{\mathrm{C},g} \le x_{\mathrm{O}} \quad \text{or} \quad x_{\mathrm{C},g} - x_{\mathrm{O}} \le 0 \quad \text{for all } g = 1, \dots, N_{\mathrm{C}}$$

The cloud broker mediates or bundles services of the ISVs. There are two perspectives to be considered when integrating an ISV on the platform. On one hand, the ISVs services need to be made available on the platform. On the other hand, in order to sell services in different markets, legal, contractual and other market specific requirements need to be met. We therefore consider these perspectives separately in the model and refer to it as “technological ISV” and “market ISV”.

Let there be N_{M} local ISVs. In the case of our cloud broker, markets overlap with service sellers in the sense that there is only one service seller per market. We can therefore enforce that a local ISV will only be implemented if a particular market will be served. This is done by the following constraints:

$$x_{\mathrm{M},h} \le x_{\mathrm{C},g} \qquad \text{for all } h \in X_{\mathrm{MC},g} \quad \text{and for all} \quad g = 1, \dots, N_{\mathrm{C}}$$

where $X_{\mathrm{MC},g}$ is the set of set of market ISVs that theoretically can be part of the service portfolio on market g.

Let there be N_{V} technological ISVs. The market ISVs would not be available if the ISVs were not technologically integrated on the platform. We therefore impose the following constraints:

$$x_{\mathrm{M},h} \leq x_{\mathrm{V},k} \qquad \text{for all } h \in X_{\mathrm{MV},k} \text{ and for all } k = 1, \dots, N_{\mathrm{V}}$$

where $X_{\mathrm{MV},k}$ is the set of local ISVs that can be formed from the global ISV indexed by k.

The ISVs provide the services that will be bundled and sold to the clients (markets). Market specific services will not be available if the market specific local ISV is not implemented on the platform. Let there be N_{S} particular services like office software, backup, storage, connectivity, security, communication, e-mail, etc. Let $x_{\mathrm{S},i}$ be a binary variable that indicates if a service i ($i = 1, .., N_{\mathrm{S}}$) will be implemented or remains on the platform; $x_{\mathrm{S},i} = 1$ indicates that service i will be either integrated or kept on the platform, and $x_{\mathrm{S},i} = 0$ indicates that service i will either not be integrated on the platform or dismissed from the platform.

$$x_{\mathrm{S},i} \leq x_{\mathrm{M},h} \qquad \text{for all } i \in X_{\mathrm{SM},h} \text{ and for all } h = 1, \dots, N_{\mathrm{M}}$$

where $X_{\mathrm{SM},h}$ is the set of services that the market ISV h provides.

Services often come in different versions that address different market segments like private user, student, small business or large enterprise versions. If the same software is offered in different versions, then we treat these versions as different services with their specific $x_{\mathrm{S},i}$. However, the implementation of different versions of the same software or internet software vendor often causes joint costs. Therefore, we treat this kind of services as a group of services. Once the software group is successfully integrated on the platform it can be distributed in different versions to different customers and different markets. Once software is implemented on the platform the offering of different versions often adds little costs to each version.

Let $x_{\mathrm{G},j}$, $j = 1, \dots, N_{\mathrm{G}}$ denote a binary variable that indicates that service group j will be implemented on the platform. The value $x_{\mathrm{G},j} = 1$ indicates that the service group j will be either deployed or kept on the platform, and $x_{\mathrm{G},j} = 0$ indicates that service group j will either not be integrated on the platform or dismissed from the platform. Single services belong to service groups that incur joint costs when integrated on the platform. Single services are not available if the corresponding service group is not integrated on the platform. The constraints representing this relationship are the following.

$$x_{\mathrm{S},i} \leq x_{\mathrm{G},j} \qquad \text{for all } i \in X_{\mathrm{SG},j} \text{ and for all } j = 1, \dots, N_{\mathrm{G}}$$

where $X_{\mathrm{SG},j}$ is the set of services that are contained in the service group j. Once a service is successfully integrated on the platform it can be distributed solely or can become part in different service bundles.

Finally, services are bundled into potential service bundles. In our application, service bundles are market specific. Let $x_{\mathrm{B},l} = 1$ describe the decision that service bundle j will be offered to customers ($x_{\mathrm{B},l} = 0$ means that a particular service bundle j will not be composed or dismissed). Service bundles can consist of one or many services. A service bundle cannot exist if the necessary services are not installed on the platform. Let $X_{\mathrm{BS},i}$ be the set of potential bundles that a service i can contribute to. The following constraints describe the necessity of having installed services for the corresponding service bundles:

$$x_{\mathrm{B},l} \leq x_{\mathrm{S},i} \qquad \text{for all } l \in X_{\mathrm{BS},i} \text{ and for all } i = 1, \dots, N_{\mathrm{S}}$$

The profit of the cloud broker is given as follow:

$$\Pi = \pi_{\mathrm{O}} \cdot x_{\mathrm{O}} + \sum_{i=1}^{N_{\mathrm{C}}} \pi_{\mathrm{C},g} \cdot x_{\mathrm{C},g} + \cdots + \sum_{i=1}^{N_{\mathrm{S}}} \pi_{\mathrm{S},i} \cdot x_{\mathrm{S},i} + \sum_{l=1}^{N_{\mathrm{B}}} \pi_{\mathrm{B},l} \cdot x_{\mathrm{B},l}$$

Here the dots represent a placeholder for the remaining entities shown in Figure 2. Both the objective value Π and the coefficients $\boldsymbol{\pi} = [\pi_{\mathrm{O}}, \pi_{\mathrm{C},g}, \dots]$ may net income consisting of revenues and costs or present values based on cash inflows and cash outflows. Taking costs and revenues as an example, these figures can furthermore be split down into fixed or variable costs with respect to certain cost/revenue drivers. Such drivers may be working time, processing time, number of subscriptions or users, and others.

The cloud broker may face several financial or operational constraints. In the case of the cloud broker studied here, we had to consider constraints concerning the human resources that deal with technical and juridical aspects of service bundling. In other words we had to deal with one critical resource related to the time needed for integrating and maintaining services on the platform. Let the amount of the limited resource be denoted by Q_{T} and let q_i denote the usage of this resource by some entity i. Then the following resource constraint is added to our optimization problem:

$$q_{\mathrm{O}} \cdot x_{\mathrm{O}} + \sum_{i=1}^{N_{\mathrm{C}}} q_{\mathrm{C},g} \cdot x_{\mathrm{C},g} + \cdots + \sum_{i=1}^{N_{\mathrm{S}}} q_{\mathrm{S},i} \cdot x_{\mathrm{S},i} + \sum_{l=1}^{N_{\mathrm{B}}} q_{\mathrm{B},l} \cdot x_{\mathrm{B},l} \leq Q_{\mathrm{T}}$$

Summarizing, the constraints and the objective from above, the decision problem becomes the following:

$$\begin{aligned}
\underset{\mathbf{x}}{\text{maximize}} \quad & \Pi = \pi_{\mathrm{O}} \cdot x_{\mathrm{O}} + \sum_{i=1}^{N_{\mathrm{C}}} \pi_{\mathrm{C},g} \cdot x_{\mathrm{C},g} + \cdots + \sum_{i=1}^{N_{\mathrm{S}}} \pi_{\mathrm{S},i} \cdot x_{\mathrm{S},i} + \sum_{l=1}^{N_{\mathrm{B}}} \pi_{\mathrm{B},l} \cdot x_{\mathrm{B},l} \\
\text{subject to} \quad & x_{\mathrm{C},g} - x_{\mathrm{O}} \leq 0 \quad \text{for all } g = 1, \dots, N_{\mathrm{C}} \\
& x_{\mathrm{M},h} - x_{\mathrm{C},g} \leq 0 \quad \text{for all } h \in X_{\mathrm{MC},g} \text{ and for all } g = 1, \dots, N_{\mathrm{C}} \\
& x_{\mathrm{M},h} - x_{\mathrm{V},k} \leq 0 \quad \text{for all } h \in X_{\mathrm{MV},k} \text{ and for all } k = 1, \dots, N_{\mathrm{V}} \\
& x_{\mathrm{S},i} - x_{\mathrm{M},h} \leq 0 \quad \text{for all } i \in X_{\mathrm{SM},h} \text{ and for all } h = 1, \dots, N_{\mathrm{M}} \\
& x_{\mathrm{S},i} - x_{\mathrm{G},j} \leq 0 \quad \text{for all } i \in X_{\mathrm{SG},j} \text{ and for all } j = 1, \dots, N_{\mathrm{G}} \\
& x_{\mathrm{B},l} - x_{\mathrm{S},i} \leq 0 \quad \text{for all } l \in X_{\mathrm{BS},i} \text{ and for all } i = 1, \dots, N_{\mathrm{S}}
\end{aligned}$$

$$q_{\mathrm{O}} \cdot x_{\mathrm{O}} + \sum_{i=1}^{N_{\mathrm{C}}} q_{\mathrm{C},g} \cdot x_{\mathrm{C},g} + \cdots + \sum_{i=1}^{N_{\mathrm{S}}} q_{\mathrm{S},i} \cdot x_{\mathrm{S},i} + \sum_{l=1}^{N_{\mathrm{B}}} q_{\mathrm{B},l} \cdot x_{\mathrm{B},l} \leq Q_{\mathrm{T}}$$

$x_{\mathrm{B},l} \in [0,1]$ for all l
$x_{\mathrm{C},g} \in [0,1]$ for all g
$x_{\mathrm{G},j} \in [0,1]$ for all j
$x_{\mathrm{M},h} \in [0,1]$ for all h
$x_{\mathrm{S},i} \in [0,1]$ for all i
$x_{\mathrm{V},k} \in [0,1]$ for all k

Before we continue with our analysis we will write this problem in more compact and more general form. Let $\boldsymbol{\pi} = [\pi_{\mathrm{O}}, \boldsymbol{\pi}_{\mathrm{C}}, \boldsymbol{\pi}_{\mathrm{V}}, \boldsymbol{\pi}_{\mathrm{M}}, \boldsymbol{\pi}_{\mathrm{G}}, \boldsymbol{\pi}_{\mathrm{S}}, \boldsymbol{\pi}_{\mathrm{B}}]$, $\mathbf{x} = [x_{\mathrm{O}}, \mathbf{x}_{\mathrm{C}}, \mathbf{x}_{\mathrm{V}}, \mathbf{x}_{\mathrm{M}}, \mathbf{x}_{\mathrm{G}}, \mathbf{x}_{\mathrm{S}}, \mathbf{x}_{\mathrm{B}}]$ and $\mathbf{q} = [q_{\mathrm{O}}, \mathbf{q}_{\mathrm{C}}, \mathbf{q}_{\mathrm{V}}, \mathbf{q}_{\mathrm{M}}, \mathbf{q}_{\mathrm{G}}, \mathbf{q}_{\mathrm{S}}, \mathbf{q}_{\mathrm{B}}]$. Let $\mathbf{A}_{\mathrm{x}}$ be the matrix that describes the assignment of the entities to each other, i. e. $a_{\mathrm{x},hi} = 1$, $a_{\mathrm{x},hj} = -1$ and $b_{\mathrm{x},h} = 0$ have the meaning that entity i depends on the installation of entity j. Then the problem can be compactly formulated as:

$$\underset{\mathbf{x}}{\text{maximize}} \quad \Pi = \boldsymbol{\pi} \cdot \mathbf{x}^{\mathrm{T}}$$

$$\text{Subject to} \quad \mathbf{A}_{\mathrm{x}} \cdot \mathbf{x}^{\mathrm{T}} \leq \mathbf{0} \tag{1}$$

$$\mathbf{q} \cdot \mathbf{x}^{\mathrm{T}} \leq Q_{\mathrm{T}} \tag{2}$$

$$\mathbf{x} \in [0,1] \tag{3}$$

4 Consideration of Uncertainty and Risk

The model developed so far assumes that all data is given in a deterministic way. In practice, however, most of the data that drive the parameters $\boldsymbol{\pi}$ and $\mathbf{q}$ are not known with certainty. The diffusion of services and service bundles in different market segments cannot be perfectly forecasted. Among other factors a lack of commitment from the service sellers to achieve demand targets or unforeseen competitive forces can degenerate demand. Also the time usage for integrating and maintaining entities like services, service bundles and ISVs cannot be predicted with absolute certainty. Another factor are the labor cost rates which can vary with the level of sick leave, substitution of employees, salary adjustments, etc.

The consequences of these uncertainties are that the resources denoted by Q_{T} can be insufficient for producing the service portfolio $\mathbf{x}$. Furthermore, the objective function value Π representing total income or value may be higher or lower than expected, in the worst case being below the break-even or some desired target value.

For modeling this uncertainty, we therefore apply a probabilistic framework. It is common to indicate the uncertainty by a random event ω from the set of possible future states Ω that happens with some probability α_ω. In what follows, we describe the process of developing the model that can treat uncertainty and risk. In a first step we will reformulate the model in such a way that the expected present value $\mathbb{E}_\omega[\Pi_\omega]$ is maximized. Furthermore, we assume that we aim at the expected resource usage (working time) being equal to the available resources Q_T.

$$
\begin{aligned}
\underset{\mathbf{x}}{\text{maximize}} \quad & \mathbb{E}_\omega[\Pi_\omega] = \mathbb{E}_\omega[\boldsymbol{\pi}_\omega] \cdot \mathbf{x} \\
\text{Subject to} \quad & \mathbf{A}_\mathrm{x} \cdot \mathbf{x}^\mathrm{T} \leq 0 \\
& \mathbb{E}_\omega[\mathbf{q}_\omega] \cdot \mathbf{x}^\mathrm{T} \leq Q_\mathrm{T} \\
& \mathbf{x} \in [0,1]
\end{aligned}
$$

In this formulation, the decision maker is neutral concerning both the financial risk and infringing the time constraint. The time constraint is only met in average, but will be violated in some of the possible future states. In the present formulation, if the time constraint is violated there will be no additional consequences like increased costs due to overtime or losses because of not being able to offer services on time. Note that costs related to resource usage are part of the $\boldsymbol{\pi}_\omega$ such that extra costs will come along with extra time usage, but the costs per unit time are the same with or without violating the time constraint.

If we focus on the uncertainty concerning the time resources required for implementing and bundling services then the negative consequences are delays in service offerings, postponed income, churn, and increased costs. We will therefore adjust our formulation in the following way. Let the per-unit costs (penalty) for constraint violation be denoted by φ. The violation of the resource constraint in the case of the event ω can be represented $\max\{\mathbf{q}_\omega \cdot \mathbf{x}^\mathrm{T} - Q_\mathrm{T}, 0\}$. The objective function of our optimization problem can then be extended by the expected penalty costs. Our problem then becomes:

$$
\begin{aligned}
\underset{\mathbf{x}}{\text{maximize}} \quad & \mathbb{E}_\omega[\Pi_\omega] = \mathbb{E}_\omega[\boldsymbol{\pi}_\omega] \cdot \mathbf{x} - \mathbb{E}_\omega[\varphi \cdot \max\{\mathbf{q}_\omega \cdot \mathbf{x}^\mathrm{T} - Q_\mathrm{T}, 0\}] \\
\text{Subject to} \quad & \mathbf{A}_\mathrm{x} \cdot \mathbf{x}^\mathrm{T} \leq 0 \\
& \mathbf{x} \in [0,1]
\end{aligned}
$$

In addition, one can restrict the overuse of resources by limiting, either in each state ω or in expectation. For example, with R_T being a user defined parameter the constraint $\max\{\mathbf{q}_\omega \cdot \mathbf{x}^\mathrm{T} - Q_\mathrm{T}, 0\} \leq R_\mathrm{T}$ restricts the expected exceedance of the resource constraint. In what follows the latter kind of constraint is neglected.

Finally, we also want to control the financial risk which is governed by the stochastic input parameters like demand, costs, cost driver quantities and penalties. The financial literature has suggested various different risk measures: Some of the most prominent are the variance or standard deviation (applied by Markowitz, 1952), the value at risk (Jorion, 1997) and the conditional value at risk (Uryasev and Rockafellar, 1999).

The selection of the right risk deserves some attention: First of all, a risk measure should sufficiently describe the users perception of risk. Second, a risk measure needs to support rational decisions. Finally, the choice of the risk measure affects the model properties, i. e linearity, convexity, differentiability, which are important for optimization software implementations.

In our analysis, we have chosen to apply two alternative risk measures. The first risk measure is the mean negative deviation, a risk measure that is based on Baumol (1963). With respect to financial portfolio optimization it has been used by Zenios (2007). This risk measure is a special case of the more general lower partial risk measures introduced by Fishburn (1977). The second risk measure is the conditional value at risk. Unlike other measures like the variance (standard deviation), mean absolute deviation, or negative (semi lower) deviations, this kind of risk measures prevents irrational decisions in the context of our model. We will illustrate this by means of an example. The following table contains the expected costs of two entities (or cost objects) as well as three risk measures, the standard deviation (StDev) the average deviation from then mean (MAD) and the one-sided negative deviation from the mean (NAD). The last column of this table shows the objective of the form $\pm(1-\lambda)\cdot\text{Performance}-\lambda\cdot\text{Risk}$. Assume that entity 1 is somehow necessary for the cloud broker because it is required for other entities that provide revenues to the cloud broker. Entity 2, however, does not contribute any value to the cloud broker, and its absence would not involve any negative consequences. Hence, in an optimization model this entity should be eliminated.

	Expected Costs, to be minimized	Standard Deviation	Mean Abs. Deviation from Mean (MAD)	Negative Abs. Deviation from Mean	(1-0,9)*Expected Costs + 0,9*MAD
Entity 1	10 700	5 934	6 202	2 650	6 652
Entity 2	3 019	1 185	1 237	530	1 415
Entity 1 and 2	13 719	4 750	4 965	2 121	5 841

As can be seen in the last row and first column in this table, the pure minimization of expected costs would eliminate Entity 2 because it adds costs. A pure risk minimization, however, would not eliminate this entity because all three risk measures indicate that the risk is reduced by including entity 2. Even the use of an objective function that contains a linear combination of expected costs and risk will lead to the inclusion of entity 2, although it only provides negative consequences in all possible future states as indicated in Figure 3. With lower partial risk measures or the conditional value at risk, this undesired effect can be avoided.

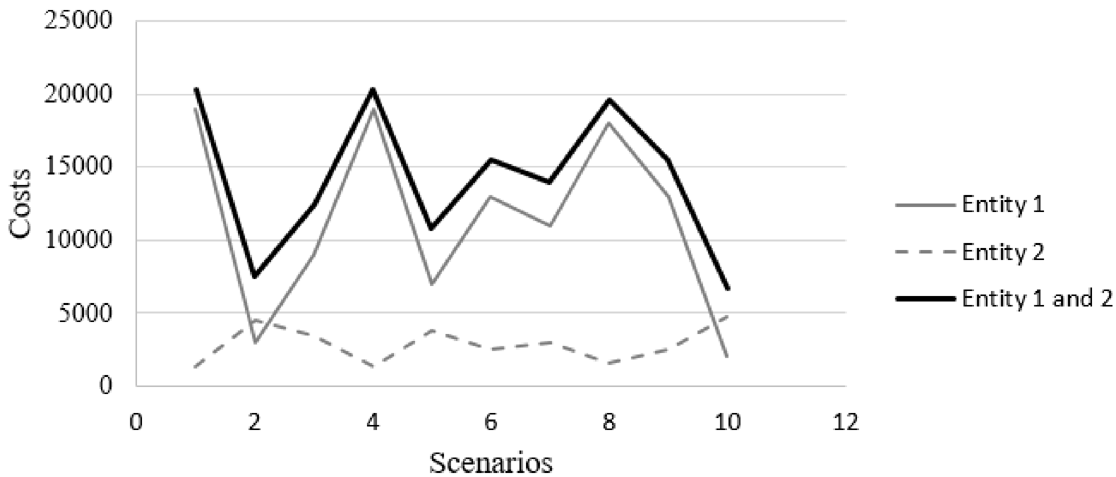

Figure 3: Mean Absolute Deviation and Standard Deviation as Risk Measures

Beside supporting rational decisions, both CVaR and MAD can be implemented in a way such that the optimization problem remains a linear program (See Zenios 2007). In the following, we show the integration of these risk measures in our optimization model.

Modeling the Negative Deviation from Target: Let there be a target present value (for example the break-even): Q_F. A negative deviation from this target profit can be measured by the expression $\max\{Q_\mathrm{F} - \boldsymbol{\pi}_\omega \cdot \mathbf{x} - \varphi \cdot \max\{\mathbf{q}_\omega \cdot \mathbf{x}^\mathrm{T} - Q_\mathrm{T}, 0\}, 0\}$. In what follows we limit the expected shortfall below the target Q_F:

$$\underset{\mathbf{x}}{\text{maximize}} \quad \mathbb{E}_\omega[\Pi_\omega] = \mathbb{E}_\omega[\boldsymbol{\pi}_\omega] \cdot \mathbf{x} - \mathbb{E}_\omega[\varphi \cdot \max\{\mathbf{q}_\omega \cdot \mathbf{x}^\mathrm{T} - Q_\mathrm{T}, 0\}] \tag{4}$$

$$\text{Subject to} \quad \mathbf{A}_\mathrm{x} \cdot \mathbf{x}^\mathrm{T} \leq 0$$

$$\mathbb{E}_\omega[\max\{Q_\mathrm{F} - \boldsymbol{\pi}_\omega \cdot \mathbf{x} - \varphi \cdot \max\{\mathbf{q}_\omega \cdot \mathbf{x}^\mathrm{T} - Q_\mathrm{T}, 0\}, 0\}] \leq R_\mathrm{F} \tag{5}$$

$$\mathbf{x} \in [0,1]$$

Again, R_F is a parameter that needs to be defined by the user.

In the present form, the objective function (4) is not linear because of the maximum operator. For the same reason the left hand side of constraint (5) is not linear. The problem becomes simpler if we assume that the random parameters have finite support defined by a finite number of scenarios. Suppose that we have S scenarios and each scenario $s = 1, \ldots, S$ has probability α_s. Then the problem can be written in the follow form (See also Zenios, 2007: Chapter 5):

$$\underset{\mathbf{x},\mathbf{v},\mathbf{w}}{\text{maximize}} \quad \mathbb{E}_s[\Pi_s] = \sum_{s=1}^{S} \alpha_s \cdot (\boldsymbol{\pi}_s \cdot \mathbf{x} - \varphi \cdot v_s) \tag{6}$$

$$\text{Subject to} \quad \mathbf{A}_\mathrm{x} \cdot \mathbf{x}^\mathrm{T} \leq 0 \tag{7}$$

$$\mathbf{q}_s \cdot \mathbf{x}^\mathrm{T} - v_s \leq Q_\mathrm{T} \quad \text{for all } s = 1, \ldots, S \tag{8}$$

$$\boldsymbol{\pi}_{\mathrm{s}} \cdot \mathbf{x} - \varphi \cdot v_s + w_s \geq Q_{\mathrm{F}} \quad \text{for all } s = 1, \dots, S \tag{9}$$

$$\sum_{s=1}^{S} \alpha_s \cdot w_s \leq R_{\mathrm{F}} \tag{10}$$

$$\begin{aligned} &\mathbf{x} \in [0,1] \\ &v_s \geq 0, w_s \geq 0 \quad \text{for all } s = 1, \dots, S \end{aligned} \tag{11}$$

In constraint (8), the variables v_s measure any exceedance of the restricted resource Q_{T} in scenario s. In constraint (9) the variables w_s measure any negative deviation from the target profit Q_{F} in scenario s. We now have a linear optimization problem with binary variables **x** and non-negative real-valued variables **v** and **w**. This problem is solvable with standard software for mixed-integer linear problems. The computational efforts, of course, depends mainly on the size of **x** (the number of entities to consider) and the number of scenarios.

In praxis, the parameter R_{F} may be hard to identify generally by the user, particularly if input data is changed or if the number of entities to consider is increased or reduced. It is more convenient to further reformulate the problem by introducing a composite objective function that is a linear combination with weight λ between the performance measure (6) and the risk value from the left hand side of expression (10). The problem becomes:

$$\underset{\mathbf{x},\mathbf{v},\mathbf{w}}{\text{maximize}} \quad (1-\lambda) \cdot \sum_{s=1}^{S} \alpha_s \cdot (\boldsymbol{\pi}_{\mathrm{s}} \cdot \mathbf{x} - \varphi \cdot v_s) - \lambda \cdot \sum_{s=1}^{S} \alpha_s \cdot w_s \tag{12}$$

$$\text{Subject to} \quad \mathbf{A}_{\mathrm{x}} \cdot \mathbf{x}^{\mathrm{T}} \leq 0 \tag{13}$$

$$\mathbf{q}_s \cdot \mathbf{x}^{\mathrm{T}} - v_s \leq Q_{\mathrm{T}} \quad \text{for all } s = 1, \dots, S \tag{14}$$

$$\boldsymbol{\pi}_{\mathrm{s}} \cdot \mathbf{x} - \varphi \cdot v_s + w_s \geq Q_{\mathrm{F}} \quad \text{for all } s = 1, \dots, S \tag{15}$$

$$\begin{aligned} &\mathbf{x} \in [0,1] \\ &v_s \geq 0, w_s \geq 0 \quad \text{for all } s = 1, \dots, S \end{aligned} \tag{16}$$

In fact, one can prove that under mild technical assumptions any solution of problem (12) to (16) for any fixed $\lambda \in [0,1]$ is also a solution of problem (6) to (11) for some specific R_{F} which depends on this solution. In the theory of financial portfolio management this transformation is widely used, see for example Zenios (2007: Chapter 3).

Modeling the Conditional Value at Risk: The formulation with the CVaR as risk measure is very similar. The only adjustment to be made is the risk-part of the objective function, i. e. expression (12) needs to be adjusted to:

$$\underset{\mathbf{x},\mathbf{v},\mathbf{w}}{\text{maximize}} \quad (1-\lambda) \cdot \sum_{s=1}^{S} \alpha_s \cdot (\boldsymbol{\pi}_{\mathrm{s}} \cdot \mathbf{x} - \varphi \cdot v_s) - \lambda \cdot \left(V + \frac{1}{\alpha_{\mathrm{VaR}}} \cdot \sum_{s=1}^{S} \alpha_s \cdot w_s \right) \tag{17}$$

Subject to constraints (13) to (16).

5 Practical Implementation and Modification of the Model

In this section, we will show the results, which one can obtain from the model by presenting a numerical example. We furthermore illustrate our approach with fewer service bundles, which allows us to compute and visualize all possible production combinations with the computational resources at hand. The original practical case contained 154 entities (ISVs, service groups, etc.) from which 47 are service bundles. This implies that there are $2^{N_{\mathrm{B}}} = 2^{47} \approx 1.41 \cdot 10^{14}$ possible service-bundle combinations, both feasible and infeasible with respect to the constraints of the optimization problem. Although the optimization model can still be solved in negligible time (less than 1 second on a standard PC), it is computationally expensive to evaluate all combinations. In the following illustrative example we shall therefore reduce the number of entities (binary variables) to 79: these are 1 overhead department, 3 markets, 5 technological ISVs, 10 market-ISV's (not all ISVs deliver services to all markets), 7 service groups, 35 services and 18 service bundles. In this case we have $2^{N_{\mathrm{B}}} = 2^{18}$ =262,144 possible service-bundle combinations, both feasible and infeasible with respect to the constraints. For each entity of the model, the expected present value, the variation of the present value, the working time and working time variations are input data to our model. All values of these input data are given in Table 1: . Like in the original practical case, this present value is based on the cash flows for the forthcoming three years. These cash flows consist of fixed, variable costs and revenues. For example, in the case of the service bundles, these cash flows are driven by the number of subscriptions and the compensation per subscription. Since, the constituents of the cash flows (i. e. costs, revenues, sales, working hours) are not given with certainty we allowed deviations from the expected value. Based on these data, we generated 2 000 scenarios. Figure 5 shows the standard deviation of the present value and the resource consumption, which are result of this simulation.

In model (12) to (16) and (17) the variables $\{\boldsymbol{\pi}_{\mathrm{s}}\}_{s=1,\ldots,S}$ and $\{\mathbf{q}_{\mathrm{s}}\}_{s=1,\ldots,S}$ contain these 2 000 present values and resource consumption values respectively.

Entity (Cost or Income Objects)	Expected NPV	NPV Variation	Expected Time	Time Variation
Overhead	-2498	100	121	30
Market 1	2002	608	160	101
Market 2	2366	982	199	97
Market 3	2399	405	120	92
ISV 1	-200	98	22	51
ISV 2	-302	218	88	225
ISV 3	-405	397	44	24
ISV 4	-397	191	91	103
ISV 5	-301	280	26	83
ISV 1 - Market 1	-89	37	59	21
ISV 1 - Market 2	-35	22	35	109
ISV 2 - Market 1	-24	46	36	113
ISV 2 - Market 2	-23	157	60	15
ISV 2 - Market 5	-87	12	82	8
ISV 3 - Market 1	-59	113	93	101
ISV 3 - Market 2	-23	45	56	73
ISV 4 - Market 1	-24	385	56	26
ISV 5 - Market 1	-23	11	71	129
ISV 5 - Market 3	-13	82	51	101
Group 1	-81	76	104	82
Group 2	-72	58	103	5
Group 3	-61	88	73	35
Group 4	-43	21	50	124
Group 5	-7	35	62	7
Group 6	-51	39	19	79
Group 7	-24	13	28	101
Bundle 1	702	479	75	71
Bundle 2	695	33	72	22
Bundle 3	706	1066	72	7
Bundle 4	468	33	59	74
Bundle 5	412	55	27	15
Bundle 6	120	35	71	118
Bundle 7	360	864	35	20
Bundle 8	658	241	17	7
Bundle 9	111	355	93	79
Bundle 10	180	19	14	26
Bundle 11	512	242	27	54
Bundle 12	203	167	56	29
Bundle 13	503	695	33	30
Bundle 14	698	1011	73	30
Bundle 15	112	310	23	105
Bundle 16	427	110	51	22
Bundle 17	420	799	94	65
Bundle 18	469	195	38	14

Entity (Cost or Income Objects)	Expected NPV	NPV Variation	Expected Time	Time Variation
Market 1 - Service 01	-15	16	94	53
Market 1 - Service 02	-11	41	58	56
Market 1 - Service 03	-19	42	14	47
Market 1 - Service 04	-36	23	104	12
Market 1 - Service 05	-71	70	99	15
Market 1 - Service 06	-89	27	37	63
Market 1 - Service 07	-74	78	75	29
Market 1 - Service 08	-31	23	17	33
Market 1 - Service 09	-57	25	96	54
Market 1 - Service 10	-69	8	107	7
Market 1 - Service 11	-35	22	109	623
Market 1 - Service 12	-16	53	11	47
Market 1 - Service 13	-87	15	74	16
Market 2 - Service 01	-101	24	74	91
Market 2 - Service 02	-91	23	11	52
Market 2 - Service 03	-65	25	16	56
Market 2 - Service 04	-45	34	25	104
Market 2 - Service 05	-6	43	77	104
Market 2 - Service 06	-10	33	44	7
Market 2 - Service 07	-62	18	91	56
Market 2 - Service 08	-80	183	93	152
Market 2 - Service 09	-13	7	29	6
Market 2 - Service 10	-63	99	13	42
Market 2 - Service 11	-14	23	112	110
Market 2 - Service 12	-36	308	82	116
Market 3 - Service 01	-37	109	40	39
Market 3 - Service 02	-32	11	54	56
Market 3 - Service 03	-96	68	31	35
Market 3 - Service 04	-12	140	88	31
Market 3 - Service 05	-61	84	79	177
Market 3 - Service 06	-78	171	40	83
Market 3 - Service 07	-35	108	41	28
Market 3 - Service 08	-22	10	66	117
Market 3 - Service 09	-90	65	63	85
Market 3 - Service 10	-104	11	46	98

Table 1: Input Data to Our Model (79 entities from which 18 are service bundles)

Before we continue showing some numerical results, we have to point out one practical obstacle: As mentioned in the introduction the cloud broker receives two kinds of commission fees, namely a fixed commission per market and a variable commission per service bundle that depends on the number of subscriptions. In some cases, the costs of a service bundle together with up-stream services and ISVs may be greater than the revenues. In such case, the optimization model tends to implement markets (for which a large fixed commission is paid) without offering services (for which the contribution margin is negative). If we implement the model (17) without further constraint then we obtain the production program shown in Figure 4. This figure indicates that independent from the risk attitude all markets are implemented on the platform. This is because of the large fixed commission paid by telecommunication operator for each market served. However, for a risk seeking decision maker ($\lambda \leq 0.26$) there are service bundles offered only on one market (bundle 14 to 18), while a risk averse decision maker ($\lambda > 0.26$) does not offer any services bundles at all.

	Overhead	Market 1	Market 2	Market 3
λ ≤ 0.26	1	1	1	1
λ > 0.26	1	1	1	1

	Market 1 - Service 01	Market 1 - Service 02	Market 1 - Service 03	Market 1 - Service 04	Market 1 - Service 05	Market 1 - Service 06	Market 1 - Service 07	Market 1 - Service 08	Market 1 - Service 09	Market 1 - Service 10	Market 1 - Service 11	Market 1 - Service 12	Market 1 - Service 13
λ ≤ 0.26	0	0	0	0	0	0	0	0	0	0	0	0	0
λ > 0.26	0	0	0	0	0	0	0	0	0	0	0	0	0

	Market 2 - Service 01	Market 2 - Service 02	Market 2 - Service 03	Market 2 - Service 04	Market 2 - Service 05	Market 2 - Service 06	Market 2 - Service 07	Market 2 - Service 08	Market 2 - Service 09	Market 2 - Service 10	Market 2 - Service 11	Market 2 - Service 12
λ ≤ 0.26	0	0	0	0	0	0	0	0	0	0	0	0
λ > 0.26	0	0	0	0	0	0	0	0	0	0	0	0

	Market 3 - Service 01	Market 3 - Service 02	Market 3 - Service 03	Market 3 - Service 04	Market 3 - Service 05	Market 3 - Service 06	Market 3 - Service 07	Market 3 - Service 08	Market 3 - Service 09	Market 3 - Service 10
λ ≤ 0.26	1	1	1	1	1	1	1	1	1	1
λ > 0.26	0	0	0	0	0	0	0	0	0	0

	ISV 1	ISV 2	ISV 3	ISV 4	ISV 5	ISV 1 - Market 1	ISV 1 - Market 2	ISV 2 - Market 1	ISV 2 - Market 2	ISV 2 - Market 3	ISV 3 - Market 1	ISV 3 - Market 2	ISV 4 - Market 1	ISV 5 - Market 1	ISV 5 - Market 3
λ ≤ 0.26	0	1	0	0	1	0	0	0	0	1	0	0	0	0	1
λ > 0.26	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

	Group 1	Group 2	Group 3	Group 4	Group 5	Group 6	Group 7
λ ≤ 0.26	0	1	1	0	0	1	1
λ > 0.26	0	0	0	0	0	0	0

	Bundle 1	Bundle 2	Bundle 3	Bundle 4	Bundle 5	Bundle 6	Bundle 7	Bundle 8	Bundle 9	Bundle 10	Bundle 11	Bundle 12	Bundle 13	Bundle 14	Bundle 15	Bundle 16	Bundle 17	Bundle 18
λ ≤ 0.26	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1
λ > 0.26	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Figure 4: Optimal Service Bundle Combinations and their Components

Implementing markets without offering services is not intended. Therefore, a constraint is added to the optimization model that enforces a minimum number n_h of service bundles to be produced in each market h:

$$n_h \cdot x_{\mathrm{M},h} \leq \sum_{l \in X_{\mathrm{BM},h}} x_{\mathrm{B},l} \quad \text{for all } \ h = 1, \dots, N_{\mathrm{M}} \tag{18}$$

with $X_{\mathrm{BM},h}$ being the set of the bundles that are offered on market h. Depending on this minimum requirement the number of feasible combinations will be further reduced. In case of $n_h = 3$, for all h, we are left with 73,099 feasible combinations out of the initially 262,143 combinations. In what follows we look at these feasible and rational production combinations in a risk-value diagram. By rationality we mean that any upstream entity (ISV, service, etc.) will not be implemented if this does not contribute to a downstream entity (service bundles being the most down stream). Note, that there is no such constraint that prohibits this irrationality in the optimization problems above. For the reason described in section 4, the preferred risk measures to be applied is the conditional value at risk (CVaR) or a similar risk measure like the mean negative deviation from some target (MND). In what follows we solely present results for the CVaR. An equivalent analysis can be carried out with the MND. Nevertheless, we also show the results for standard deviation The reason for this is that the standard deviation normally produces more efficient production combinations. In our analysis we use $\alpha = 95\ \%$ for the computation of the CVaR. The following results are furthermore based on a penalty of $\varphi = 2$ for violations of the resource constraints. Furthermore, we require that the cloud broker produces at least 3 service bundles in each markets, if the respective market is served, i. e. $n_h = 3$ in constraint (18).

Figure 5 shows all the feasible (73 099) combinations of the service bundles in a risk-return diagram as commonly used in financial theory (Markowitz, 1952). However, instead of using the standard deviation and expected return we apply the CVaR as risk measure and the present value of the service bundle portfolio as performance measure. Surprisingly, there exist only very few efficient production points (5 points) relative to all feasible service bundle combinations (73,099). These points are numerically shown in Table 2. Moreover, Figure 6 is an excerpt of Figure 5 that zooms into the efficient service bundle combinations and shows a hypothetical efficient frontier. Note that only the efficient production points are achievable production bundles. Any other point on the efficient frontier is not achievable because of the non-divisibility of the decision variables. The same applies to Figure 7 that shows all efficient production points and a hypothetical efficient frontier for the standard deviation. Once more, it needs to be pointed out, that the standard deviation may give irrational decision. However, in the computation of all possible production combinations, irrational service bundle decisions were excluded.

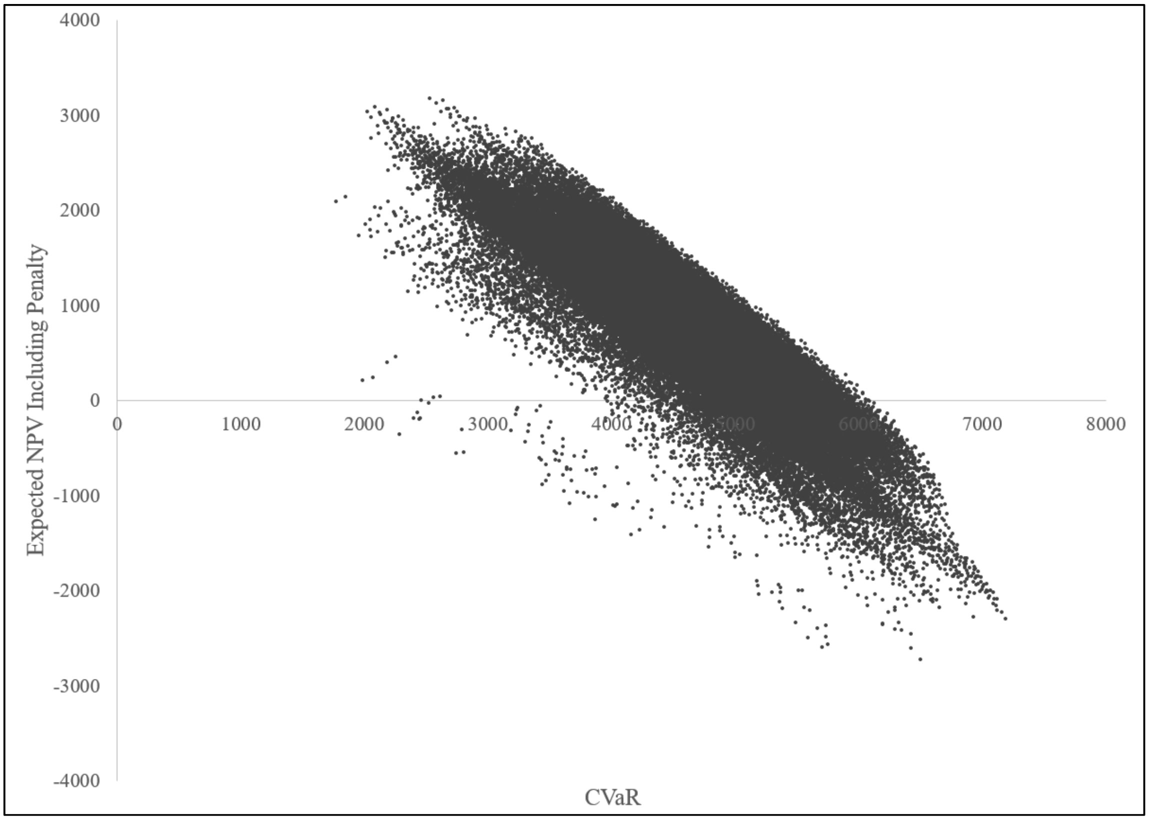

Figure 5: CVaR-Present-Value Diagram of all Feasible Service Bundle Combinations

	Present Value	Risk (CVaR 95 %)
Bundle Combination #1	2533.80	3178.89
Bundle Combination #2	2085.86	3081.52
Bundle Combination #3	2028.93	3035.19
Bundle Combination #4	1850.12	2136.07
Bundle Combination #5	1774.74	2086.91

Table 2: Efficient Service Bundle Combinations Expressed by Present Value and Risk

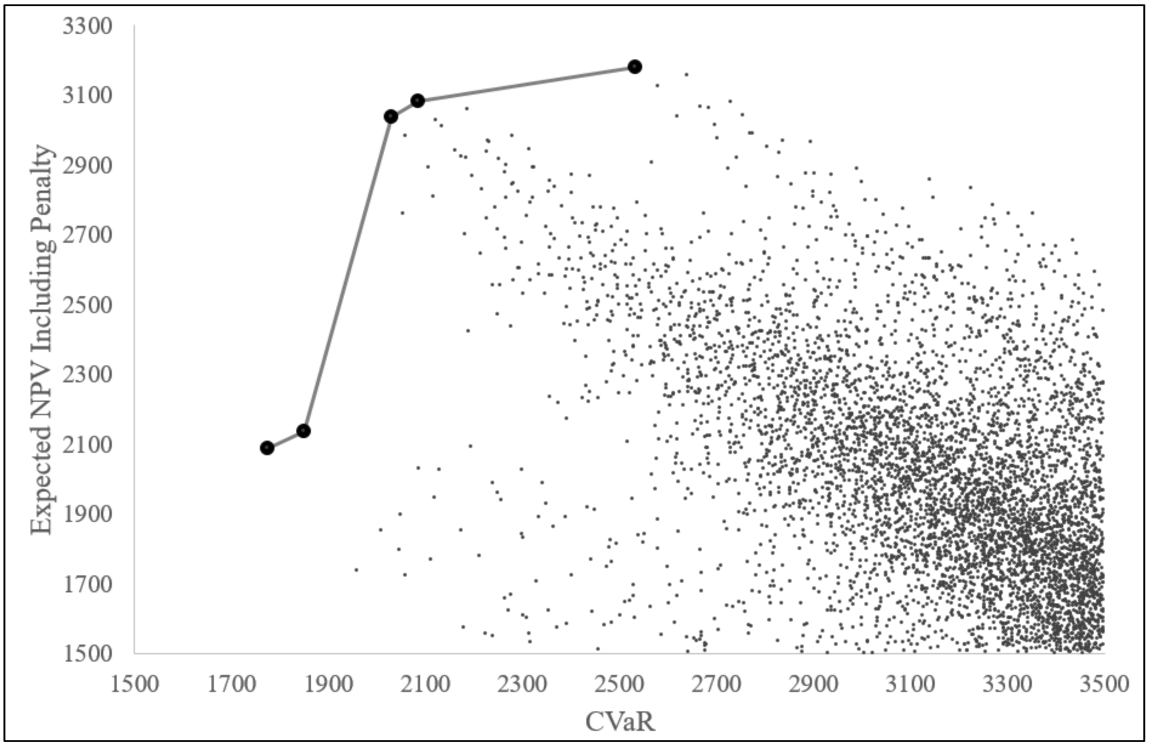

Figure 6: Efficient Service Bundle Combinations Based on CVaR

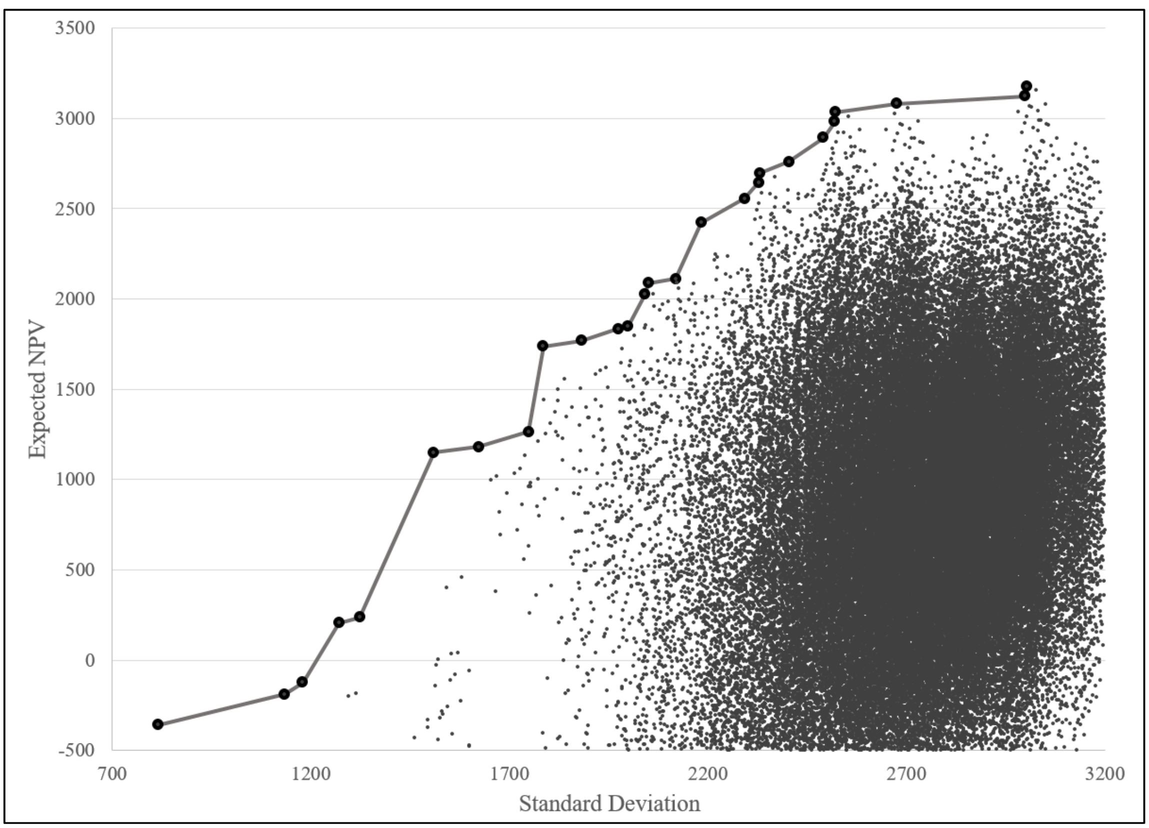

Figure 7: Efficient Service Bundle Combinations Based on Standard Deviation

The active entities within the efficient service bundle combinations of the cloud broker are schematically shown in Figure 8. This figure gives a clear indication about which markets and service bundles are definitely profitable or non-profitable (independent of risk attitude) or partly profitable (depending on risk attitude). For example, Market 1 and 3 should be served irrespective of the risk attitude of the cloud broker. The provision of service bundles to market 2 is a more risky endeavor. A cloud broker with a high degree of risk aversion should not provide services to this market. On market 1, the bundles 1, 2, 3 and 5 should definitely be provided. We also see that ISV 3 on market 1 is a clear value destroyer. This means that despite of having already incurred some of the common costs (for example for the market entry on market 1 or service groups) the costs for implementing this ISV are higher than the revenues or that its implementation does not contribute to a reduction of the risk. The same applies for bundles 6, 8, 9, etc. These bundles do not contribute to either profitability improvement or risk reduction. The provision of other bundles, like bundle 4 and 7, depends on the risk attitude of the cloud broker. Similar conclusions can be drawn for the other markets and bundles.

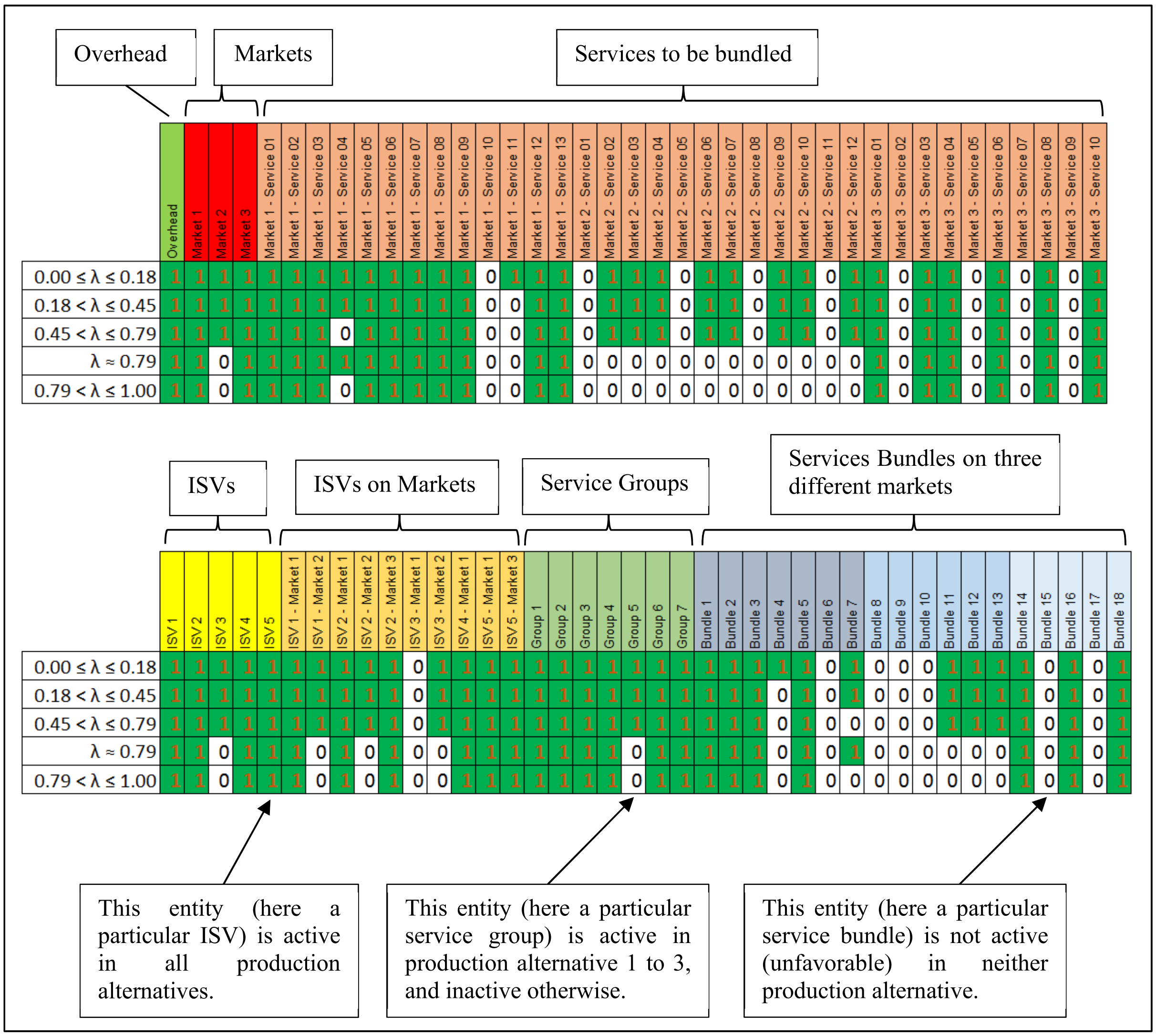

Figure 8: Efficient Service Bundle Combinations and their Components

After having implemented this model we can pursue further economic questions: For example how should the variable compensation of a particular service bundle be adjusted, such that this bundle will be prioritized, or how should the fixed compensation of a particular market be adjusted in order to reduce the risk and raise profitability of the cloud broker. The model contains several subjective parameters that can affect the decision. Two important parameters are the probability for which the CVaR is defined and the penalty-costs for resource expansion.

Before we want to conclude this section, we will shortly comment on the computational requirements for the model presented above. The computational resources needed to solve the problem depend on the size of the problem and the values of the parameter. The size of the problem is driven by the number of entities (i.e. service bundles, services, etc.), the number of scenarios and the number of heterogeneous resources. The most critical factor is the number of entities considered in the model because these drive the number of the binary variables. Let us depart from the total number of entities, no matter if these are service bundles, ISVs service groups, etc. Then the number of possible combinations, both feasible and infeasible is given by $2^{(N_\mathrm{C}+N_\mathrm{M}+N_\mathrm{V}+N_\mathrm{G}+N_\mathrm{S}+N_\mathrm{B})}$. In our numerical example with 154 entities this number becomes $2^{154} \approx 2.28 \cdot 10^{46}$. Being aware of other integer programming solution approaches (see for instance Bertsimas and Weismantel 2005) we will here discuss the size, scalability and computational requirements from the perspective of the Branch-and-Bound strategy. Although, it is beyond the scope of this paper to develop or represent a superior candidate of Branch-and-Bound algorithm, it is obvious that it can exploit the dependencies between the entities (services, service bundles, etc.) in the model. Because of service bundles depending on services, and services on ISVs, etc. the number of potential combinations to be analyzed can be reduced to $2^{N_\mathrm{B}} = 2^{47} \approx 1.41 \cdot 10^{14}$ where $N_\mathrm{B} = 47$ is the number of service bundles delivered to the customers. Branch-and Bound algorithms have the property to reduce the number of computed combinations because potentially infeasible and non-beneficial combinations will early be discarded. Infeasibility in our problem is mainly driven by the amount of resources Q_T (right hands side of constraint (8) or (14) compared to the number of services and their individual resource requirements (i. e. the coefficients $\mathbf{q}_s$ on the left hand side in constraint (8) or (14). Although it was beyond the scope of our paper to mathematically and empirically analyze the number of Branch-and-Bound iterations for the number service bundles, we can by means of a little example indicate what the growth behavior of the model will be. Imagine a more simplified non-stochastic production model with only one resource and one kind of product. Assume that the production capacity is K units. Assume furthermore that we have M potential products to be produced, each requiring exactly one unit of production capacity. Hence, there are $\frac{(M)!}{(M-K)! \cdot K!}$ production combinations. The binomial coefficient has a far less pronounced growth rate than 2^M. Furthermore, since some of the products will be less profitable, the branch-and bound strategy will not evaluate all of the possible combinations. Hence, the binomial coefficient represent the most pessimistic value concerning the increase of computational resources required for this problem. In our practical application, we cam still expect a considerable increase in the number of the entities before computational resources become exhausted.

6 Summary

In this paper, we have introduced a tool that helps to identify profitable combinations of service bundles to be produced by a cloud broker. More precisely, this tool identifies which combinations of service bundles are value contributors and which services are value destroyers. We have applied an optimization framework since traditional management accounting tools are insufficient for the complex and intertwined structure of production processes like for our cloud brokering case. In addition, and inspired by financial theory, we added risk control to the model. Hence, the decision maker can choose the service bundle combination that gives the best trade-off between risk and expected value. Although the model has been applied to cloud brokering services, it can be used for other kind of products and production processes, which have an intertwined structure described in this paper.

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