A Novel Methodology for Capitalizing on Cloud Storage through a Big Data-as-a-Service Framework

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***Abstract*—The Big Data-as-a-Service (BDaaS) framework exploits the elastic scalability and analytical data processing capabilities delivered via the cloud, minimizing the complexity and capital expense of on-premises data infrastructure. Since the cloud can be considered as a marketplace, small and large enterprises lease storage and computing capacity based on a negotiated cost approach. In this context, this research work examines a novel methodology for capitalizing earnings on cloud storage level through a big data-as-a-service framework and proposes cloud-inspired quantitative cost and benefits analysis models under the assumption that the demand curves are linear. The proposed modelling approach is evaluated against the conventional high-performance data warehouse appliances on the necessity of possible upgradation of the storage.**

Keywords—cloud storage; big data-as-a-service; data warehouse; linear modelling; cost-benefit analysis; mobile cloud computing

I. Introduction

Since the resource-intensive mobile applications produce large amounts of data, more computing power and storage should be provided by the cloud computing platforms (e.g., multimedia-rich applications). The mobile cloud computing technology [1] enables the augmentation of computing capabilities of mobile devices towards a more rich computing experience [2]. In this direction, mobile big data and location data should be harnessed effectively towards the optimization and personalization of mobile services. The big data-as-a-service (BDaaS) framework encompasses multiple data processing techniques to handle any type of data and analytical workload, from batch processing to interactive data visualization and real-time streaming data analysis, at an optimal performance level from an outside cloud provider along with reduced costs by freeing up organizational resources [3]. In mobile cloud marketplaces [4], leasing resources of mobile cloud-based service-oriented architectures entails paying a negotiated cost, whereas the pay-as-you-go cost model involves metering usage and charging based on actual use, such as network-accessible data storage priced by the gigabyte-month or computing capacity priced by the CPU-hour [5].

In this context, this paper proposes a methodology for capitalizing earnings on cloud storage level through a big data-as-a-service framework, which achieves to maximize the return on investment. The cloud-inspired quantitative models are formulated considering the lease of storage and a predicted linear increase in the demand for storage capacity. The comparison of big data-as-a-service business models against the conventional high-performance data warehouse appliances (DWH) proves that the adoption of the former will bring earnings, initiating the reinvestment of these on the additional storage needs in the long run.

The reminder of this paper is organized as follows: Section II presents related research work and the research gap that motivates the need for the evaluation of big data-as-a-service business models. Section III proposes the quantification models, while Section IV provides an evaluation analysis of three different case scenarios and Section V concludes this paper.

II. Related Work And Research Motivation

The big data-as-a-service technology enables the effective storage, data management and processing from an outside cloud provider. A number of research efforts have been devoted considering big data-related issues and challenges [6]. More specifically, the authors in [7] introduced a user experience-oriented big data-as-a-service architecture, while an overview of service-generated big data and big data-as-a-service is presented in [8] towards the proposal of an infrastructure to boost efficiency and provide functionality for storing, managing and analyzing different types of service-generated big data. On the other hand, the development of cloud-supported big data mining [9] and big data analytics [10] platforms is essential, which will consist of the infrastructure, virtualization, data processing and services layers, enabling the collaboration between different stakeholders.

As a result of the big data and analytics growth [11]–[13], small and large enterprises consider the big data-as-a-service technology as the solution to bridge both the storage and processing gap [14]. The deployment of big data in the cloud can be achieved by introducing big data provisioning services [15], which incorporate hierarchical and peer-to-peer data distribution techniques to speed-up data loading into the virtual machines used for data processing. Likewise, the authors in [16] propose a big data-as-a-service solution based on Hadoop, which achieves to extract data from the social networks, while an admission control and resource scheduling algorithm is presented in [17], which satisfies the Quality of Service requirements of requests, reduce costs and maximize profits for the Analytics-as-a-Service (AaaS) providers. Finally, the Magnetic, Agile, Deep (MAD) methodology is proposed in [18], attempting to replace conventional enterprise data warehouses and business intelligence solutions, exploiting data parallel algorithms for sophisticated statistical methods.

Although there are related work approaches in the literature presenting the benefits of the infrastructure in the cloud [19] or the challenges in big data research, there is still a research gap on the evaluation of different big data-driven business models. Since the evaluation results should be meaningful for both technical and non-technical stakeholders, this research paper investigates a novel methodology for capitalizing earnings on cloud storage level through a big data-as-a-service framework. The cloud-inspired quantitative modelling is based on a cost-benefit appraisal under the assumption that the demand curves for storage capacity are linear. The approach is evaluated against the conventional high-performance data warehouse appliances on the necessity of possible upgradation of the storage. The proposed model formulation is a substantial extension of previous research works conducted by Skourletopoulos et al. in [20]–[24] from the big data-as-a-service viewpoint.

III. Model Formulation

The proposed methodology intends to prove the benefits gained due to the selection of big data-as-a-service business models instead of conventional data warehouse appliances. The quantification models were formulated considering that the demand curves for storage capacity are linear (i.e., symmetry) and measuring the actual amount of profit not earned due to the underutilization of the storage capacity. The cost of selecting a business model and the predicted benefits stemming from the selection decision motivate the evaluation of different data-driven models, examining the option of reinvesting the earnings on cloud storage level (i.e., additional storage required in the long run) through a big data-as-a-service framework. Since the cloud storage and computing capacity are resources to be leased off, the following facts and assumptions are taken into account:

- The cloud storage is subscription-based and the charging vary over the period of *l*-years as the demand curves for storage capacity are increasing linearly (e.g., a sample pricing overview is shown in [25]).
- The predicted cost variations consist of data and document (unstructured) storage, maintenance services, network, on-demand I/O, operations (i.e., service requests), server and technical support costs.
- The total network cost consists of costs related to bandwidth usage and data transfer between regional and multi-region locations. As the cloud-based mobile services are usually sensitive to network bandwidth and latency [26], the additional network cost is expected to satisfy the outbound network traffic demands in order to avoid delays. The custom metadata headers are also accounted for in the monthly storage and bandwidth usage.
- The additional on-demand I/O cost intends to increase the throughput [27] when the content retrieval from a bucket should be faster than the default.
- The additional server cost consists of those costs associated with the additional CPU cores and the amount of memory required for processing.

In this direction, the cost analysis (CA) modelling from the conventional data warehouse appliance (DWH) perspective takes the following form [28] (the variables' definitions are presented in Table 1):

$$CA_i = 12 * \left(Cs_{/m} * S_{max}\right), 0 < i \leq l \text{ and } S_{curr} \leq S_{max} \quad (1)$$

where,

$$Cs_{/m} = Cs_{/m(max)} = C\alpha_{/m(max)} + C\gamma_{/m(max)} + C\eta_{/m(max)} + C\theta_{/m(max)} + C\kappa_{/m(max)} + C\lambda_{/m(max)} + C\mu_{/m(max)} + C\sigma_{/m(max)}$$

Since the elastic scalability of the cloud computing and the big data-as-a-service technology does not stand in conventional data warehouse appliances, the cost analysis modelling does not examine the storage capacity currently used (S_{curr}), which involves metering usage and charging based on actual use. In this case, no cost variations apply as long as $S_{curr} \leq S_{max}$, whereas the true benefits are always zero ($B = 0$) over the period of *l*-years. It is worthy of mention that in case of such an increase in the demand for storage capacity that $S_{curr} > S_{max}$, then incremental capacity should be added to the storage systems with overhead and downtime, triggering additional costs (i.e., there is charging for storage capacity that is not based on actual use).

On the contrary, the cost analysis (CA) and benefits (B) modelling from the big data-as-a-service (BDaaS) point of view would take the form shown below (the variables' definitions are shown in Table 1). The benefits calculation procedure is also presented in algorithm 1.

$$CA_i = 12 * \left[\left(1 + \frac{\Delta\%}{l}\right)^{i-1} * Cs_{/m} * (1 + \beta\%)^{i-1} * S_{curr}\right] \quad (2)$$

$$B_i = 12 * \left\{ \left(1 + \frac{\Delta\%}{l}\right)^{i-1} * Cs_{/m} * [S_{max} - (1+\beta\%)^{i-1} * S_{curr}] \right\} \quad (3)$$

$$with\ 0 < i \leq l\ and,$$

$$Cs_{/m} = Cs_{/m_{(curr)}} = C\alpha_{/m_{(curr)}} + C\gamma_{/m_{(curr)}} + C\eta_{/m_{(curr)}} + C\theta_{/m_{(curr)}} + C\kappa_{/m_{(curr)}} + C\lambda_{/m_{(curr)}} + C\mu_{/m_{(curr)}} + C\sigma_{/m_{(curr)}}$$

$$\Delta\% = \alpha\% + \gamma\% + \eta\% + \theta\% + \kappa\% + \lambda\% + \mu\% + \sigma\%$$

Two possible types of benefits calculation results are encountered, when leasing cloud storage:

- Positive numerical results: Underutilization of the storage capacity and probability to meet the needs of a possible increase in the demand in the long run.
- Negative numerical results: Need for upgradation, which triggers accumulated costs.

Algorithm 1. Pseudocode implementation of benefits modelling approach

```
// This algorithm aims to calculate the benefits of adopting
// a big data-as-a-service model under the prediction that the
//demand curves for storage capacity are increasing linearly.

1: procedure BENEFITSCALCULATION (S_max, S_curr, i,
Δ%, β%, l, Cs/m, α%, γ%, η%, θ%, κ%, λ%, μ%, σ%)
2:   sequential input (α%, γ%, η%, θ%, κ%, λ%, μ%, σ%)
       Δ% ← α% + γ% + η% + θ% + κ% + λ% + μ% + σ%
3:   return Δ%
4:   sequential input (S_max, S_curr, i, Δ%, β%, l, Cs/m)
5:     for i = 1 to l do  // Increasing the index of the year to
       // get the output element with respect to the year
       B[i] ← 12 * {(1 + Δ%/l)^(i−1) * Cs/m * [S_max − (1 + β%)^(i−1) *
       * S_curr]}
6:     end for
7:   return B[i]
8: end procedure
```

IV. Performance Evaluation And Numerical Results

This paper proposes a methodology that motivates the evaluation and comparison of big data-as-a-service models against conventional high-performance data warehouse appliances, adopting a cost-benefit appraisal and predicting that the demand curves for storage capacity are linear. The evaluation results prove that the adoption of the former will bring earnings, motivating the capitalization on cloud storage through a big data-as-a-service framework. In addition, the analysis indicates that the business model selection decision and the maximum storage capacity might affect the size of the accumulated cost.

Table 1. ABBREVIATIONS AND VARIABLE DEFINITION.

Symbol	Variable Definition
CA	The cost analysis calculations (in monetary units).
B	The benefits calculation results (in monetary units).
i	The index of the year.
l	The period of time that is examined.
$Cs_{/m}$	The initial monthly cost for leasing cloud storage (in monetary units).
S_{max}	The maximum storage capacity.
S_{curr}	The storage currently used.
$\Delta\%$	The total variation regarding the cost for leasing cloud storage for the *l*-year period of time.
$\beta\%$	The increase in the demand for cloud storage capacity per year.
C_α	The data storage cost.
C_γ	The document storage cost.
C_η	The maintenance services cost.
C_θ	The network cost.
C_κ	The on-demand I/O cost.
C_λ	The operations cost.
C_μ	The server cost.
C_σ	The technical support cost.
$\alpha\%$	The variation in the monthly data storage cost for the *l*-year period of time.
$\gamma\%$	The variation in the monthly document storage cost for the *l*-year period of time.
$\eta\%$	The variation in the monthly maintenance services cost for the *l*-year period of time.
$\theta\%$	The variation in the monthly network cost for the *l*-year period of time.
$\kappa\%$	The variation in the monthly on-demand I/O cost for the *l*-year period of time.
$\lambda\%$	The variation in the monthly operations cost for the *l*-year period of time.
$\mu\%$	The variation in the monthly server cost for the *l*-year period of time.
$\sigma\%$	The variation in the monthly technical support cost for the *l*-year period of time.

The need to consolidate data from different sources is examined throughout the performance evaluation, under the assumption that data-intense workloads of analytics should be managed at the storage level. In this direction, cost analysis and benefits comparisons are performed between the two different business models in a 5-year period of time (l = 5) (i.e., investigation prior to the business model selection decision), analyzing three different case scenarios under the prediction that the demand curves for cloud storage are increasing linearly. The variations in the demand for storage capacity and the total cost variations for leasing additional cloud storage for the three case scenarios are presented in Table 2. The values presented in Table 3 are applied to the formulas (1), (2) and (3) accordingly. The choice of the specific case scenarios motivates the comparison of the two different business models. The obtained evaluation results are shown in Tables 4 to 6, while the cost analysis and benefits flows over the 5-year period of time are witnessed in Fig. 1 to 6, respectively.

Table 2. VARIATIONS IN THE DEMAND FOR STORAGE AND THE TOTAL COST FOR THE THREE CASE SCENARIOS.

	Predicted Linear Increase in the Demand for Storage Capacity (per year)	**Total Cost Variation for Leasing Additional Cloud Storage (for the *l*-year period of time)**
Case Scenario 1	$\beta_1\% = 18\%$	$\Delta_1\% = 10\%$
Case Scenario 2	$\beta_2\% = 36\%$	$\Delta_2\% = 18\%$
Case Scenario 3	$\beta_3\% = 48\%$	$\Delta_3\% = 24\%$

Table 3. VALUES TO BE APPLIED TO EQUATIONS (1) TO (3).

Variable Definition	**Values**
Maximum storage capacity (in terabytes)	$S_{max} = 7$
Storage currently used (in terabytes)	$S_{curr} = 3$
Initial monthly cost for leasing cloud storage (in USD)	$Cs_{/m} = 400$

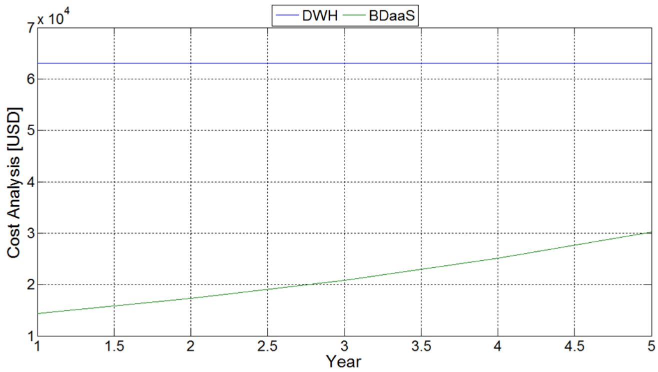

Fig. 1. Case scenario 1: Cost analysis flow.

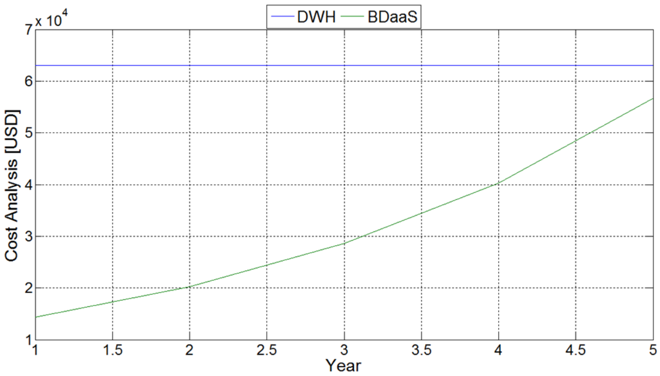

Fig. 2. Case scenario 2: Cost analysis flow.

Towards the analysis of the evaluation results, the first case scenario points out the cost-effectiveness of the big data-as-a-service business models as the cost analysis calculations hold the least positive values over the 5-year period of time. The benefits numerical results are also positive strengthening the aforementioned argument; the decline in the numbers is subject to the predicted linear demand curves for storage capacity. It is worthy of mention that the cost analysis and benefits numerical results in conventional data warehouse appliances remain the same throughout the period as there is charging for the full storage capacity that is not based on actual use.

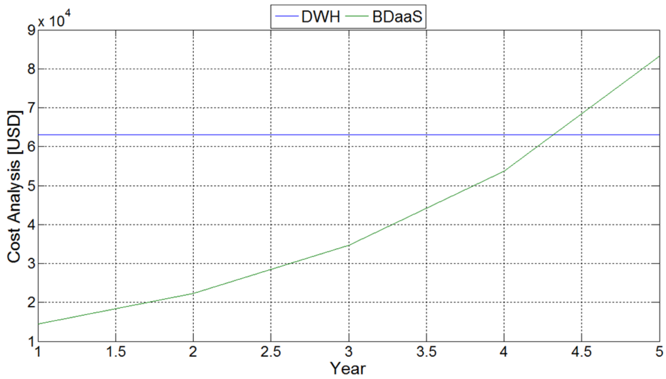

Fig. 3. Case scenario 3: Cost analysis flow.

On the contrary, the second and third case scenarios point out the cost-effectiveness and the benefits gained by adopting big data-as-a-service business models during the first two years. However, the benefits calculations become negative during the third year regarding the second case scenario, motivating the need for upgradation to meet the market needs and requirements. Storage upgradation is also observed to be necessary when examining the third case scenario (i.e., negative benefits numerical results are also witnessed during the third year) due to the increased costs that the big data-as-a-service model selection decision brings in comparison with the ones associated with the conventional data warehouse adoption viewpoint. In this context, the proposed methodology proves that the earnings gained due to the selection of the big data-as-a-service business model should be capitalized on the reinvestment of the additional storage needs in the long run, achieving to maximize the return on investment.

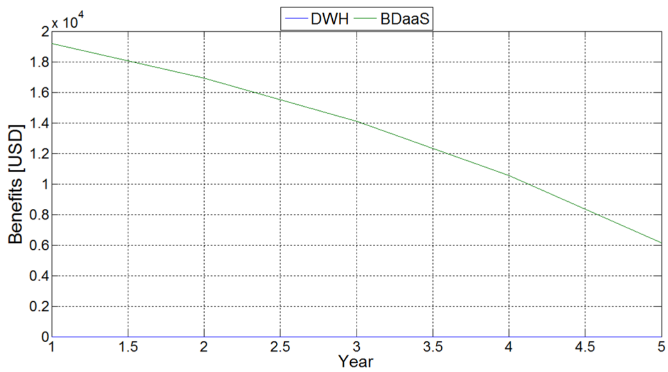

Fig. 4. Case scenario 1: Benefits analysis flow.

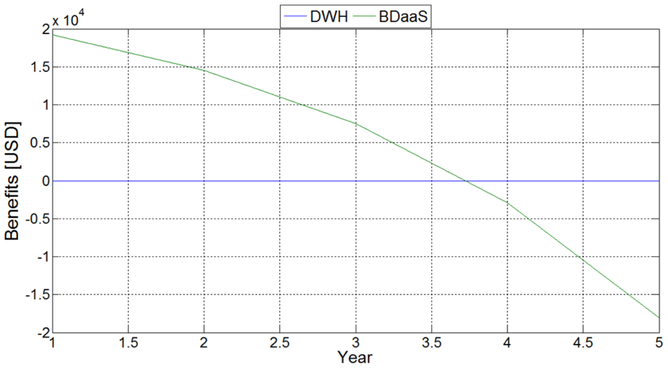

Fig. 5. Case scenario 2: Benefits analysis flow.

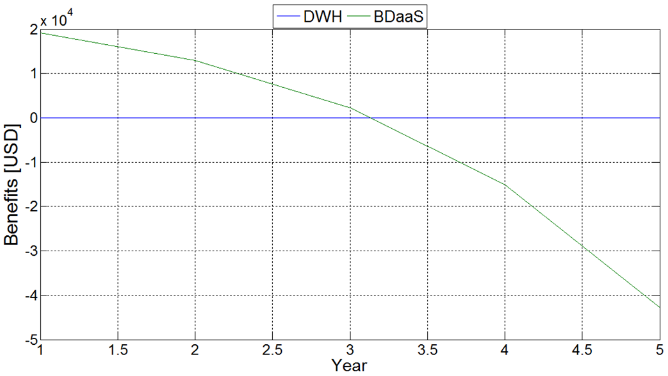

Fig. 6. Case scenario 3: Benefits analysis flow.

Table 4. THE COST AND BENEFITS ANALYSIS CALCULATIONS REGARDING BIG DATA-AS-A-SERVICE FOR CASE SCENARIO 1.

	Year 1	**Year 2**	**Year 3**	**Year 4**	**Year 5**
CA	14400	17331.84	20860.6	25107.82	30219.77
B	19200	16940.16	14096.84	10548.77	6149.95

Table 5. THE COST AND BENEFITS ANALYSIS CALCULATIONS REGARDING BIG DATA-AS-A-SERVICE FOR CASE SCENARIO 2.

	Year 1	**Year 2**	**Year 3**	**Year 4**	**Year 5**
CA	14400	20289.02	28586.42	40277.13	56748.86
B	19200	14520.58	7476.32	-2916.12	-18042.86

Table 6. THE COST AND BENEFITS ANALYSIS CALCULATIONS REGARDING BIG DATA-AS-A-SERVICE FOR CASE SCENARIO 3.

	Year 1	**Year 2**	**Year 3**	**Year 4**	**Year 5**
CA	14400	22334.98	34642.44	53731.81	83340.19
B	19200	12877.82	2260.57	-15057.45	-42809.46

V. Conclusion

In this research work, a novel methodology for capitalizing earnings on cloud storage level through a big data-as-a-service framework is proposed, initiating the reinvestment of these earnings on the additional storage needs in the long run. The cloud-inspired quantitative models enable the evaluation and comparison of big data-as-a-service models against the conventional high-performance data warehouse appliances (DWH) under the assumption that a predicted linear and symmetric increase in the demand for storage capacity occurs.

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