Cost-Benefit Analysis Game for Efficient Storage Allocation in Cloud-Centric Internet of Things Systems: A Game Theoretic Perspective

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***Abstract*—The advances in Internet of Everything (IoE) and the market-oriented cloud computing have provided opportunities to resolve the challenges caused by the Internet of Things (IoT) infrastructure virtualization, capacity planning, data storage or complexity. The volume and types of IoT data motivate the need for a data storage framework towards the integration of both structured and unstructured data. In this paper, we propose a novel game theoretic technique for efficient and dynamic storage allocation in cloud-centric IoT systems. The benefit maximization problem is formulated as a cost-benefit analysis game investigating the storage capacity currently used in the cloud. In view of each player's strategy to lease additional storage capacity, the game property is analyzed and we prove that the game always admits a pure strategy Nash equilibrium. Since the player's decision affects the level of benefit maximization, we elaborate on a cost-optimal storage allocation incentive mechanism, which scales effectively once non-linear or linear demand for storage capacity occurs, towards achieving optimal leasing conditions on cloud storage and computing capacity level. The experimental validation tests prove the effectiveness of the proposed game theoretic approach allocating the requests for more storage capacity in a cost-effective manner, which achieves to maximize the benefits.**

Keywords—distributed cloud; Internet of Things; IoT; Internet of Everything; IoE; cloud storage; data storage allocation; game theory; Nash equilibrium

I. INTRODUCTION

The Internet of Things (IoT) architecture entails virtually interconnected physical objects and devices with computing and sensing capabilities [1]. The volume of IoT sensor and communication data requires a data storage framework towards the efficient storage and integration of structured and unstructured data [2]. Such data can be also combined with data from different sources (e.g., cloud-based services and applications [3], mobile big data or localization data), creating applications far richer than those provided by isolated embedded systems. However, the IoT-oriented system requirements are different from other state-of-the-art system requirements in terms of resources consumption or customization of the IoT capabilities due to the high complexity that stems from provisioning large-scale, cloud-oriented IoT systems [4]. On the other hand, the cloud-centric IoT paradigm can be thought as an opportunity for objects and devices to provide sensing services based on cloud-inspired business models [5]. In this direction, the era where data storage and computing capacity are ubiquitously available has commenced, enabling vendors to own multiple data centers in several geographic locations for cloud-hosting purposes, i.e., to safeguard data availability during outages or other data center failures [6]. Since most corporations consider whether to exploit cloud computing or build their own data centers making large capital investments, cloud providers use data centers to house cloud-based services and resources. The business model selection decision affects the level of cost-effectiveness and return on investment (ROI) [7], while the major factors affecting that decision are the data security, privacy and systems' costs. To the best of our knowledge, limited efforts have been devoted examining storage allocation in cloud-centric IoT environments from a cost-benefit analysis viewpoint, focusing primarily on big data-as-a-service (BDaaS) models [8]. Among others, most recent research works study decision procedures for data storage in cloud systems [9], storage allocation issues in mobile social networks [10] or energy-aware resource allocation problems for efficient management of data centers [11]. However, none of them attempt to address the storage upgradation problem exploiting a Nash equilibrium game [12].

In this context, the goal of this paper is to study the storage and resource allocation issue in cloud-centric IoT systems from a non-cooperative game theoretic perspective aiming to achieve higher payoffs and improve the decision making from a strategic viewpoint. The benefit maximization problem is defined as a cost-benefit analysis game, where each company-player requests more storage and computing capacity while the benefits are constantly decreasing, i.e., each player selects the strategy under the necessity of additional storage capacity. A benefit-oriented maximization incentive mechanism is introduced towards the lease of cloud storage and computing capacity at an optimal level, considering the storage currently used by each company among different storage systems or the option of allocating the current data size to another storage system while predicting variations in the demand for storage capacity, which might lead to the minimization of the overall benefits. Once increasing returns to the data size are witnessed, the Nash equilibrium game is applied to allocate the data in different storage systems and, thus, maximize the profits. The outcome of the interaction of multiple companies is associated with the probability of storage upgradation, which automatically leads to service-level agreement (SLA) violations and minimization of the predicted profits. It is finally shown that the cost-benefit analysis game has feasible solutions such that a Nash equilibrium always exists for this game. The rest of this study is organized as follows: section II gives an overview of related research works, while section III presents the cloud-inspired quantitative models from both non-linear and linear perspectives through a data storage framework with a focus on big data-as-a-service models. Section IV proposes the cost-benefit analysis game towards the dynamic storage allocation in cloud-centric IoT systems and section V provides the experimental analysis towards the proof of our theorem. Section VI concludes this research work.

II. Related Works and Research Gap

In game theory, the Nash equilibrium is a game involving a group of rational decision makers in which each decision maker knows the equilibrium strategies of the other decision makers and the outcome depends on the decisions of the others [12]. However, authors in [13] proved the absence of an efficient algorithm for computing Nash equilibria. Since Nash equilibrium has been exploited to analyze various problems in computer science, one of the applications of this solution concept is in cloud computing. Authors in [14] attempted to solve the service provisioning problem as a Nash game, achieving to improve the efficiency of the cloud system evaluated in terms of Price of Anarchy. The resource allocation problem has been examined in [15], [16] exploiting game theory. The usage of resources across a cloud-based network is investigated and the cost depends on the amount of computation. An evolutionary mechanism is used to solve the problem, which achieves to change the multiplexed strategies of the initial optimal solutions and minimize their efficiency losses. Game theoretic channel access strategies are adopted in [17] by estimating equilibrium points to achieve balance between conserving energy and completing the data dissemination.

On the contrary, the cloud storage service selection strategy has been investigated in [18] from a game theoretic point of view towards the promotion of truth-telling among different service providers. Another study [19] deals with the cooperative behavior of multiple cloud providers divided into groups from a resource and revenue sharing perspective of a resource pool. The authors attempt to develop a stochastic linear programming game which considers the uncertainty of internal users. Since trust evaluation is critical for the IoT, an energy-aware trust derivation scheme is presented in [20] to reduce overhead while maintaining adequate security of wireless sensor networks (WSNs). Finally, a performance evaluation of the Bayesian coalition game among objects and devices in the IoT environment is performed in [21], exploiting game theoretic techniques. In this work, the players have variable learning rates in the coalition game, opposed to the constant learning rates provided in the majority of other solutions, based on a utility function. To the best of our knowledge, limited research works focus on the investigation of cost and benefit issues [22]–[25] of different data storage frameworks in cloud-centric IoT level. In this research work, a novel game theoretic approach is introduced, motivating the need to deal with the benefit maximization problem in cloud-centric IoT environments.

III. Mathematical Modelling in Cloud-Oriented Environments

The cost-benefit cloud-inspired models are introduced in this section from a big data-as-a-service perspective, considering a set of collocated companies $N = \{1, 2, \dots, N\}$ with respect to the storage capacity currently leased off by each one. Each company selects the storage and capacity to lease off on the subject of the quality of service and the predicted fluctuations in the demand, which might result in service-level agreement violations. The set of players N is assumed to remain unchanged during a capacity planning period of time, while it might change across different periods due to possible fluctuations in the demand for storage and computing capacity. Since companies succeed in the big data era, the yearly cost (CA) is initially calculated from the conventional high-performance data warehouse appliance point of view as [26]

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

where the storage currently used (S_{curr}) is encountered only in big data-as-a-service models (i.e., cloud scalability). The variable descriptions for the presented quantitative models are witnessed in Table 1. In data warehouse appliances, the profits are always zero ($B = 0$) over the period of l-years, while in case of such an increase in the demand for storage and computing capacity that $S_{curr} > S_{max}$, then incremental capacity should be added to the storage systems with overhead and downtime.

Since the benefit numerical results can be classified into two classes (i.e., positive and negative values as monetary units), the cost-benefit modelling in cloud environments from the storage perspective has been introduced by Skourletopoulos et al. in both non-linear [26] and linear [27] manners. The cost (CA) and benefits (B) are computed from an asymmetric quantitative perspective within a big data-as-a-service framework in year 1 (i.e., Equations (2) and (4)) and from year 2 and onwards (i.e., Eq. (3) and (5)) as [26]

$$CA_1 = 12 * \left(Cs_{/m} * S_{curr}\right) \quad (2)$$

$$CA_i = 12 * (\Delta_{i-2} * K_{i-2}),\, i \geq 2 \quad (3)$$

$$B_1 = 12 * \left[Cs_{/m} * (S_{max} - S_{curr})\right] \quad (4)$$

$$B_i = 12 * [\Delta_{i-2} * (S_{max} - K_{i-2})],\, i \geq 2 \quad (5)$$

where, $$Cs_{/m} = Cs_{/m(curr)}$$

$$\Delta_0 = (1 + \delta_1\%) * Cs_{/m}$$

$$\Delta_i = (1 + \delta_{i+1}\%) * \Delta_{i-1},\, i \geq 1$$

$$\delta_i\% = a_i\% + \gamma_i\% + \eta_i\% + \theta_i\% + \kappa_i\% + \lambda_i\% + \mu_i\% + \sigma_i\%,\, i \geq 1$$

$$K_0 = (1 + \beta_1\%) * S_{curr}$$

$$K_i = (1 + \beta_{i+1}\%) * K_{i-1},\, i \geq 1$$

We then calculate the cost and benefits from a symmetric perspective (i.e., Eq. (6) and (7)), which is given as [27]

$$CA_i = 12 * \left[\left(1 + \frac{\Delta\%}{l}\right)^{i-1} * Cs_{/m} * (1 + \beta\%)^{i-1} * S_{curr}\right] \quad (6)$$

$$B_i = 12 * \left\{\left(1 + \frac{\Delta\%}{l}\right)^{i-1} * Cs_{/m} * [S_{max} - (1 + \beta\%)^{i-1} * S_{curr}]\right\} \quad (7)$$

with $1 \leq i \leq l$.

Table 1. ABBREVIATIONS AND VARIABLE DEFINITIONS FOR QUANTITATIVE MODELS.

Symbol	Variable Description
CA	The cost analysis computations.
B	The benefit computations.
i	The l-year index.
l	The period of time in years.
$Cs_{/m}$	The initial monthly cost for leasing cloud storage.
S_{max}	The maximum storage capacity.
S_{curr}	The storage currently used.
Δ_0	The forming of the cost for leasing cloud storage in the second year, once the monthly cost variation is applied.
$\delta_1\%$	The variation in the cost for leasing cloud storage during the second year.
Δ_i	The forming of the cost for leasing cloud storage from the third year and onwards, once the monthly cost variation is applied.
$\delta_i\%$	The variation in the cost for leasing cloud storage from the third year and onwards.
$\Delta\%$	The variation in the cost for leasing cloud storage for the l-year period of time.
K_0	The storage used during the second year, once the variation in the demand is applied.
$\beta_1\%$	The variation in the demand for storage capacity in the second year.
K_i	The storage used from the third year and onwards, once the variation in the demand is applied.
$\beta_i\%$	The yearly variation in the demand for storage capacity from the third year and onwards.
$\beta\%$	The predicted yearly variation in the demand for storage capacity.
$\alpha_i\%$	The variation in the monthly data storage cost.
$\gamma_i\%$	The variation in the monthly document storage cost.
$\eta_i\%$	The variation in the monthly maintenance services cost.
$\theta_i\%$	The variation in the monthly network cost.
$\kappa_i\%$	The variation in the monthly on-demand I/O cost.
$\lambda_i\%$	The variation in the monthly operations cost.
$\mu_i\%$	The variation in the monthly server cost.
$\sigma_i\%$	The variation in the monthly technical support cost.

IV. NON-COOPERATIVE COST-BENEFIT ANALYSIS GAME

The proposed game theoretic approach is introduced in this section towards the maximization of the profits evoked by the storage allocation in cloud systems, taking into account that specific storage capacity is assigned to each company-player. We therefore construct, for a given game *G*, a potential function *B* over the set of strategy profiles in such a way that the optimal behavior of *B* yields a Nash equilibrium in pure strategies of *G*. Leveraging the storage allocation options with respect to the benefit numerical results delivered by each storage system, we achieve to organize the companies into a mutually satisfactory condition while maximizing the profits. For example, we assume two storage systems, i.e., storage system 1 and storage system 2. The number of companies currently accommodated in storage system 1 is satisfactory enough such that the profits are maximized, holding the least positive values. In this case, the additional storage capacity requests should be allocated in storage system 2. This optimal allocation strategy is based on the benefit results delivered by the system's storage capacity and guarantees that storage upgradation will not occur in the long run, avoiding the minimization of the profits. Hence, we constantly work towards the benefits maximization in system 2 always in compliance with the different interests of each company. In this direction, the charging policy is restructured according to the additional storage capacity requests and the overall resources to be leased off.

As per the *game formulation*, the storage allocation problem is examined with respect to the companies-players and data size within a benefit prediction period of time. Let $a_{-n} = (a_1, \dots, a_{n-1}, a_{n+1}, \dots, a_N)$ be the storage allocation selection decisions by all other companies except new company n. Given the other company's decisions a_{-n}, company n selects a proper decision $a_n \in \{0, 1\}$ (i.e., storage system 1 or 2) towards the maximization of the profits and overall benefits, i.e.,

$$\min_{a_n \in \{0,1\}} B_n(a_n, a_{-n}), \forall\, n \in N$$

The benefit experimental results are being proved to differ between the storage systems due to the different pool of companies and data size that each one can accommodate. Therefore, the benefit maximization problem is not resolved in the same manner for all systems. According to (4), (5) and (7), the benefit function is formed (i.e., either non-linear or linear viewpoint) with respect to the new company n as

$$B_n(a_n, a_{-n}) = \begin{cases} B_1, & \text{if } a_n = 0 \\ B_2, & \text{if } a_n = 1 \end{cases} \tag{8}$$

where B_1 refers to the benefits equation for system 1 when selected by the new company n, and B_2 indicates the benefits mathematical formula for system 2.

The storage allocation selection decision problem is formulated as a game $G = (N, \{A_n\}_{n \in N}, \{B_n\}_{n \in N})$, where N is the set of companies-players, $A_n \triangleq \{0, 1\}$ is the set of strategies for the new company n and the benefit function $B_n(a_n, a_{-n})$ of each new company n is the cost-oriented function to be minimized by player n. The game G constitutes the cost-benefit analysis game and we now proceed to the concept of Nash equilibrium [12].

Definition 1. A strategy profile $a^* = (a_1^*, \dots, a_N^*)$ is a Nash equilibrium of the cost-benefit analysis game if at the equilibrium a^*, no new player can be allocated to a storage system to further maximize the benefits by unilaterally changing its strategy, i.e.,

$$B_n(a_n^*, a_{-n}^*) \le B_n(a_n, a_{-n}^*), \forall\, a_n \in A_n, n \in N \tag{9}$$

The Nash equilibrium achieves to organize the increasing requests for storage capacity into a mutually satisfactory condition while maximizing the benefits and no company-player is motivated to deviate unilaterally. Henceforth, the lease of cloud storage and computing capabilities occurs at an optimal level, considering the current pool of companies per storage system, the option of allocating a current company to another system and estimating the non-linear demand by new requests. In the sequel, the *game property* analysis investigates the existence of Nash equilibrium in the cost-benefit analysis game, introducing the concept of best response [12].

Definition 2. Given the strategies a_{-n} of the other companies, company n's strategy $a_n^* \in A_n$ is a best response if

$$B_n(a_n^*, a_{-n}) \le B_n(a_n, a_{-n}), \forall\, a_n \in A_n \tag{10}$$

According to (9) and (10), we observe that all companies play the best response strategies towards each other at the Nash equilibrium. Given that statement, we may conclude to the following lemma.

Lemma 1. Given the strategies a_{-n} of the other companies in the cost-benefit analysis game, the best response of a new company n is given as the following benefits status strategy, i.e.,

$$a_n^* = \begin{cases} 1, & \text{if } B_i > 0 \\ 0, & \text{if } B_i \le 0 \end{cases}$$

Since the current benefits status of a storage system is of primary importance as well as the status after the adoption of the request by the new company n, Lemma 1 points out that in case of benefits result greater than zero for a specific system, the potential selected system has storage capacity left and the new company n's request can be satisfied always in compliance with the current pool of companies and data size. In this context, the benefits and profits are further maximized without risking to enter in a storage upgradation status in the long run. Otherwise, once the benefits result is less than or equal to zero, there is no storage capacity left in the selected system to accommodate new requests (i.e., the current pool of companies and data size are satisfactory enough to maximize the return on investment). In the latter case, we avoid accumulated costs by allocating the company's request to other available systems in the data center where the benefits can be further maximized through the adopted strategy. The proposed technique enables the benefits prediction in the cloud from the storage perspective when multiple companies are making decisions simultaneously and the outcome depends on the current or past decisions of the other companies-players.

V. Experimental Validation Tests and Numerical Results

In this section, we prove the effectiveness of our theorem for achieving optimality regarding the benefits outcome when examining different storage systems. We particularly elaborate on a cost-optimal storage allocation incentive mechanism, achieving optimal leasing conditions in the cloud storage and computing capacity level, parameterizing the storage currently used per company and scaling efficiently as non-linear or linear demand for storage capacity occurs. Our experimental analysis considers two storage systems in the cloud-oriented IoT environment, where non-linear demand curves are predicted in a 4-year benefits prediction period ($l = 4$) as shown in Table 2. We prove that our theorem is sufficient for achieving benefits and return on investment maximization through an optimal storage allocation and control mechanism. It is important to mention that achieving optimality in the benefits level is almost illusionary as debts and interests always occur (i.e., optimal condition is achieved when $B_i = 0$); however, the Nash equilibrium game tends towards storage allocation optimality while maximizing the benefits. Each storage system's characteristics are shown in Table 3, whereas the variations in the total cost for leasing additional storage capacity on cloud service level is witnessed in Table 4 as a consequence of the constantly increasing demand. Throughout the evaluation analysis, an effort was made to identify whether storage upgradation will be necessary during the 4-year period of time. The obtained experimental numerical results indicate that the necessity for storage upgradation in system 1 will not occur due to the positive values, while the benefits are constantly maximizing (see Table 5).

Table 2. CASE SCENARIO: NON-LINEAR DEMAND VARIATIONS FOR CLOUD STORAGE.

Term	Variation in the Demand
Year 1 to 2	$\beta_1\% = 5\%$
Year 2 to 3	$\beta_2\% = 25\%$
Year 3 to 4	$\beta_3\% = 30\%$

Table 3. STORAGE SYSTEM CHARACTERISTICS.

Variable Definition	Storage System 1	Storage System 2
Maximum storage capacity (in terabytes)	$S_{max} = 8$	$S_{max} = 5$
Storage currently used	$S_{curr} = 4$	$S_{curr} = 3$
Initial monthly cost for leasing cloud storage	$Cs_{/m} = 420$	$Cs_{/m} = 400$

Table 4. VARIATIONS IN THE COST FOR LEASING ADDITIONAL CLOUD STORAGE.

Variable Definition	Storage System 1	Storage System 2
Total cost variation for leasing additional storage	$\delta_1\% = 2\%$ $\delta_2\% = 8\%$ $\delta_3\% = 9\%$	$\delta_1\% = 3\%$ $\delta_2\% = 10\%$ $\delta_3\% = 12\%$

Table 5. BENEFITS NUMERICAL RESULTS UNDER THE BIG DATA-AS-A-SERVICE FRAMEWORK.

	Year 1	Year 2	Year 3	Year 4
Storage System 1	20,160	19,535.04	15,268.18	7,110.81
Storage System 2	9,600	9,146.4	5,778.3	-723,31

On the other hand, the immediate need for upgradation will be faced in the long run regarding storage system 2. Towards achieving optimality through our game theoretic formulation, the estimated increase in the demand in year 4 should have been up to 26.9 per cent, i.e.,

$$5 - (1 + x) * 3.9375 = 0 \Longrightarrow x = 0.26984 \approx 26.9\% \\ \approx 1.06\ terabytes$$

More specifically, the actual 30 per cent that was adopted in our initial scenario corresponds to approximately 1.18 terabytes (TB). According to our storage allocation control mechanism, the remaining 0.12 TB is allocated automatically in storage system 1, helping towards the benefits maximization for this system. Therefore, since the storage allocation control mechanism is initiated, the storage currently used for system 1 is approximately $6.825 + 0.12 = 6.837$ TB in year 4 and the true increase in the demand is now formed to approximately 30.2 per cent, which is estimated as follows

$$(1 + y) * 5.25 = 6.837 \Longrightarrow y = 0.30229 \approx 30.2\%$$

This true increase in the demand will be considered in the next variation in the demand and not the actual 30 per cent that was initially adopted when investigating this case scenario. Furthermore, the variation in the total cost for leasing additional storage for storage system 1 is now restructured to 9.1 per cent (i.e., $\delta_3\% = 9.1\%$) and, thus, the benefits numerical result for the storage system 1 will be finally formed to approximately 7,053.73 monetary units ($B_4 \approx 7{,}053.73$) in year 4. Likewise, the variation in the total cost for the storage system 2 will be reformed to 11 per cent (i.e., $\delta_3\% = 11\%$) and, therefore, the benefits calculation is now formed to approximately 0.03 monetary units ($B_4 \approx 0.03$) in year 4, tending towards optimality in terms of maximizing the benefits at the highest level. Once the storage allocation mechanism is initiated, the final flow of the benefits for both systems is observed in Fig. 1. In this context, the proposed game theoretic formulation motivates the need to minimize the risk for storage upgradation in the long run, which leads to service-level agreement violations. It is finally important to mention that this is an indicative use case scenario towards the verification and validation of our theorem.

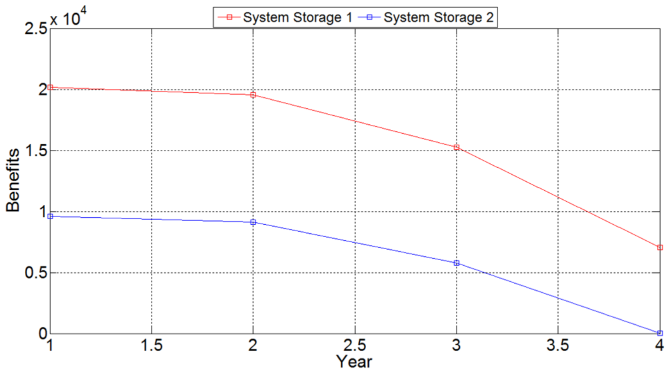

Fig. 1. The flow of the benefits, once the storage allocation control mechanism is initiated.

VI. CONCLUSION

This paper contributes to a novel game theoretic formulation for achieving optimal storage allocation conditions in cloud-centric IoT systems through a data storage framework. The benefit maximization problem is formulated as a cost-benefit analysis game, intending to scale efficiently as the demand for additional cloud storage capacity fluctuates. Towards the proof of our theorem, we construct, for a game G, a function B over the set of strategy profiles such that the optimal behavior of B yields a Nash equilibrium in strategies of G. The outcome of this interaction among multiple players demonstrates the minimization of the risk for storage upgradation in the long run, which leads to service-level agreement violations and minimization of the predicted payoffs. The experimental numerical results prove the sufficiency of the proposed game theoretic methodology, which motivates the benefit maximization and stability in cloud-oriented IoT systems. More complex scenarios with various fluctuations in the demand for storage capacity, interactions between the companies-players or reallocation in the current pool of companies for different storage systems will be further examined in the future.

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