Elasticity Debt Analytics Exploitation for Green Mobile Cloud Computing: An Equilibrium Model

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***Abstract*—Mobile cloud computing is the model to ubiquitously access a shared pool of cloud computing resources, data, and services on-demand. This paper introduces the elasticity debt analytics paradigm as a solution concept for the resource provisioning problem in mobile cloud computing environments, guaranteeing the quality of service requirements. A novel green-centric, game theoretic approach to minimizing the elasticity debt on mobile cloud-based service level is proposed, investigating the mobile cloud offloading case. The decision to offload a mobile device user's task on cloud affects the level of elasticity debt minimization for the provided services. The modeling for the computation of the processing time, energy, and overhead in mobile opportunistic offloading is presented. A utility-driven elasticity debt and profit quantification approach is also examined for maximization of resource utilization, exploiting the hidden Markov model. The problem is formulated as an elasticity debt quantification game, elaborating on an incentive mechanism to predict elasticity debt, mitigate the risk of service over-utilization, achieve scalability, and optimize cloud resource provisioning. The experimental results prove the effectiveness of the equilibrium model, which allocates the mobile device user requests to high elasticity debt-level services and facilitates the elasticity debt minimization for green mobile cloud computing environments.**

***Index Terms*—Elasticity debt analytics, game theory, green cloud computing, hidden Markov model, mobile cloud computing, utility computing.**

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I. Introduction

TACKLING the sustainability issues in the communications networks' infrastructure is a major research challenge due to the proliferation of network devices and the increasing demand for network services, which contribute to a dramatic increase in the overall network data traffic and energy consumption [1]–[3]. Among the advantages of cloud computing technology is the reduction of power consumption using virtualized computational resources with auto-scaling mechanisms to dynamically allocate these resources [4]. Numerous research efforts have been devoted examining the mobile cloud computing paradigm as the method for mobile services to overcome issues related to performance [5], energy consumption, storage and bandwidth [6], [7] by offloading on the cloud and augmenting computation capabilities for resource-intensive mobile applications [8]–[10]. In this context, this work introduces the concept of elasticity debt analytics as a methodology to efficiently schedule and provision cloud resources, exploiting a Nash equilibrium approach. A novel definition for *Elasticity Debt Analytics (EDA)* is given as 'the concept that reflects the measurement and interpretation of meaningful patterns in cloud resource data to gain insights for efficient resource scheduling and guarantee quality of service (QoS) requirements'. The elasticity debt analytics paradigm is associated with efficient resource management in the context of green cloud computing and it can be harnessed as a measure to predict and overcome challenges in cloud resource provisioning or optimize the resource utilization on cloud service level. A game theoretic approach [11] is adopted in addition to the elasticity debt analytics paradigm as an optimal technique to study the interactions among multiple mobile device users, considering that each end-user might act in his/her own interest. The user's decision devises incentive compatible elasticity debt mechanisms such that no player has the incentive to deviate unilaterally.

A. Research Motivation

To the best of our knowledge, limited research efforts have been devoted investigating the elasticity debt issues on cloud service level both from the service providers or infrastructure suppliers perspective [12]–[14]. An open challenge in elasticity debt research on cloud level is to translate the elasticity debt

threats into economic opportunities from a resource provisioning perspective by paying off the elasticity debt and increasing the elasticity wealth (EW). A comprehensive elasticity debt theory is therefore imperative to formalize and consolidate relationships between the costs of the elasticity debt and the benefits of the elasticity wealth. In this work, we indicate the novelty that the elasticity debt analytics paradigm can bring when solving the cloud resource provisioning problem. We introduce a novel green-driven game theoretic approach, motivating the need to deal with the research questions on elasticity debt minimization for green mobile cloud computing environments. A utility-driven elasticity debt optimization approach for cloud resource allocation is also proposed based on the Hidden Markov Model.

B. Scientific Contributions

This work introduces the elasticity debt analytics paradigm as a novel concept to solve the scheduling and provisioning issues of resources in mobile cloud computing environments. Initially, this article contributes to two linear and non-linear elasticity debt quantitative metrics in mobile cloud offloading. We also present the modeling for the computation of the processing time, energy and overhead in mobile opportunistic offloading. Finally, a utility-driven elasticity debt and profit optimization perspective is adopted for efficient cloud resource allocation based on the Hidden Markov Model. The scientific problem of the elasticity debt minimization is defined as a Nash equilibrium game, parameterizing the current pool of mobile device users per service and considering that each new user-player's strategy is to select one of the cloud-supported mobile services. It is proved that the game has feasible solutions since a Nash equilibrium always exist. The reduction of elasticity debt units on mobile cloud-based service level is examined from a green-oriented, game theoretic viewpoint to achieve: (a) increased elasticity wealth for the service providers or infrastructure suppliers, (b) efficient resource scheduling and provisioning, (c) maximization of resource utilization, and (d) greener mobile cloud computing environments. The rest of this paper is organized as follows: Section II gives a background of the current state-of-the-art in cloud resource provisioning and Section III presents the elasticity debt quantitative metrics in mobile cloud offloading. Section IV presents the elasticity debt and profit optimization modeling for cloud resource scheduling, exploiting the Hidden Markov Model. Section V presents the quantification game, while Section VI provides an evaluation analysis towards the proof of our theorem. Section VII concludes this work.

II. State-of-the-Art in Cloud Resource Provisioning

The resource provisioning problem in distributed cloud computing environments has been a challenge for academia and industry in recent years. Cloud elasticity enables the dynamic acquisition and release of shared computational resources on demand and one of the major advantages is the adaptation decisions taken to adjust the resource provisioning constrained by QoS and operating costs. Efficient allocation of resources is critical, because the user demands in the cloud are diverse and fluctuate dynamically [15], [16]. The Nash equilibrium has been exploited to analyze resource allocation-related problems in cloud and mobile cloud computing [17]. Cloud resource provisioning problems are classified into optimization of resource utilization – especially in the data centers of cloud infrastructure [18] – and maximization of profits [19], which can be either the overall profit or the profits of the infrastructure suppliers. In this context, the service provisioning problem has been attempted to be solved as a Nash game [20], improving the overall efficiency of the evaluated cloud system. Other research works dealt with the application of Nash equilibrium in mobile cloud computing systems and architectures [21], examining the creation of a resource pool to support mobile applications coupled with a game model for the adoption of optimal strategies on capacity expansion. The energy minimization problem has been examined as a congestion game [22] where each player selects one of the servers to offload the computation – and, therefore, minimize the overall energy consumption – while in [23] the computation offloading decision making problem in mobile cloud computing environments has been formulated as a decentralized computation offloading game. Misra *et al.* [24] attempted to address the problem of QoS-guaranteed bandwidth shifting and redistribution as a utility maximization problem, whereas a green cloudlet network architecture has been introduced in [25] to provide low end-to-end delay between a user equipment and its avatar in the cloudlets and facilitate the workload offloading process. The resource allocation problem in cloud has been also researched in [26], focusing on the usage of resources across a cloud-based environment. This work examines a model based on a Stackelberg game to increase the profits of both resource suppliers and applicants. Decisions for economically optimal scaling at cloud infrastructure level has been explored in [27]. The scaling decisions consider the cost of infrastructure, the revenue from service delivery and the profit of the service provider. An adaptive elastic scaling perspective has been discussed in [28] using cost-aware criteria to detect and analyze the bottlenecks within multi-tier cloud-based applications. The algorithm achieves to reduce the costs incurred by users of cloud infrastructure services, allowing them to scale the applications at the bottleneck tiers.

III. Elasticity Debt Modeling in Mobile Cloud Offloading

A. Problem Definition and Parameter Setting

We introduce the elasticity debt quantification models on mobile cloud-based service level when a task is offloaded, scheduled and executed on the cloud. A set of collocated mobile device users $N = \{1, 2, \ldots, N\}$ is considered on cloud-supported, always-on mobile services, which are leased off. The end-users are also classified into segments, e.g., corporate, premium and basic users. Service subscription, resource selection and allocation are subject to: (a) quality of service (QoS) and quality of experience (QoE) restrictions in terms of delay-sensitivity, network bandwidth, latency and throughput [29], (b) predicted number of active end-users,

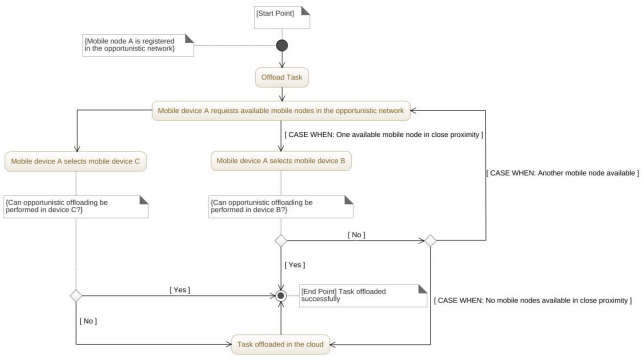

Fig. 1. UML activity diagram: Mobile opportunistic offloading.

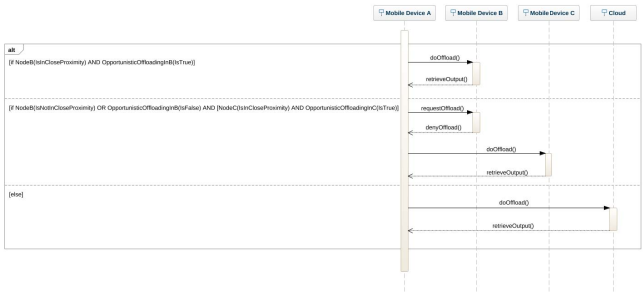

Fig. 2. UML sequence diagram: Mobile opportunistic offloading.

and (c) fluctuations in demand that might lead to service-level agreement (SLA) violations and accumulated elasticity debt. In the view of this assumption, adaptation decisions are taken to adjust the resource provisioning when new user requests occur, requiring a standard level of QoS even during mobility. The set of users N remains unchanged during a computational offloading period, while it might change across different periods due to fluctuations in the number of mobile device users. We illustrate the model formulation in Fig. 1 and 2 from an analytical framework viewpoint, using two UML (Unified Modeling Language) activity and sequence diagrams, respectively. The numerical results are classified into two classes–i.e., positive and negative values as monetary units–while the elasticity debt metrics on mobile cloud-based service level are proposed in [30] and [31] from non-linear and linear perspectives. The descriptions for the variables used to develop these metrics are presented in Table I.

1) Non-Linear Mathematical Modeling: We compute the elasticity debt (*ED*) from a non-linear quantitative viewpoint [30] for year 1 as in (1) and from year 2 and onwards as in (2), i.e.,

$$\begin{aligned} ED_1 &= 12 * \Big[ppm * (U_{max} - U_{curr}) - Cu_{/m} \\ &\quad * (U_{max} - U_{curr}) \Big] \\ &= 12 * (U_{max} - U_{curr}) * \left(ppm - Cu_{/m} \right) \end{aligned} \tag{1}$$

$$\begin{aligned} ED_i &= 12 * \{ K_{i-2} * [U_{max} - L_{i-2}] - M_{i-2} \\ &\quad * [U_{max} - L_{i-2}] \} \\ &= 12 * (U_{max} - L_{i-2}) * (K_{i-2} - M_{i-2}), i > 1 \end{aligned} \tag{2}$$

$$\text{s.t. } K_0 = (1 + \Delta_1\%) * ppm$$

TABLE I
ABBREVIATIONS AND VARIABLE DEFINITIONS FOR ELASTICITY DEBT QUANTITATIVE MODELS

Symbol	Variable Definition
ED	The elasticity debt computations.
i	The λ-year index.
λ	The examined period of time in years.
U_{max}	The maximum number of mobile device users that can be supported.
K_0	The forming of the new subscription price during the second year, once the variation is applied.
$\Delta_1\%$	The variation in the subscription price during the second year.
ppm	The initial monthly subscription price.
K_i	The forming of the new subscription price from the third year and onwards, once the variation in the subscription price is applied.
$\Delta_i\%$	The variation in the subscription price from the third year and onwards.
L_0	The forming of the number of mobile device users during the second year, once the variation in the demand is applied.
$\beta_1\%$	The variation in the number of mobile device users during the second year.
U_{curr}	The initial number of mobile device users.
L_i	The forming of the number of users from the third year and onwards, once the variation in the demand is applied.
$\beta_i\%$	The variation in the number of mobile device users from the third year and onwards.
M_0	The forming of the cost for servicing an end-user in the cloud during the second year, once the monthly cost variation is applied.
$VoC_1\%$	The cost variation for servicing an end-user in the cloud during the second year.
$Cu_{/m}$	The monthly cost for servicing a mobile device user in the cloud.
M_i	The forming of the cost for servicing an end-user in the cloud from the third year and onwards, once the monthly cost variation is applied.
$VoC_i\%$	The total cost variation for servicing a mobile device user in the cloud from the third year and onwards.
$a_i\%$	The variation in the document storage cost.
$\gamma_i\%$	The variation in the data storage cost.
$\theta_i\%$	The variation in the technical support cost.
$\mu_i\%$	The variation in the maintenance service cost.
$\sigma_i\%$	The variation in the network bandwidth cost.
$\eta_i\%$	The variation in the server cost.

$$\begin{aligned} K_i &= K_{i-1} * (1 + \Delta_{i+1}\%), i > 0 \\ L_0 &= (1 + \beta_1\%) * U_{curr} \\ L_i &= L_{i-1} * (1 + \beta_{i+1}\%), i > 0 \\ M_0 &= (1 + VoC_1\%) * Cu_{/m} \\ M_i &= M_{i-1} * (1 + VoC_{i+1}\%), i > 0 \\ VoC_i\% &= a_i\% + \gamma_i\% + \theta_i\% + \mu_i\% + \sigma_i\% + \eta_i\%, i > 0. \end{aligned}$$

2) Linear Mathematical Modeling: The mathematical modeling of the elasticity debt from a linear quantitative perspective [31] is given as in (3), i.e.,

$$\begin{aligned} ED_i &= 12 * \Big[U_{max} - (1 + \beta\%)^{i-1} * U_{curr} \Big] \\ &\quad * \Bigg[\left(1 + \frac{\Delta\%}{\lambda} \right)^{i-1} * ppm \\ &\quad - \left(1 + \frac{VoC\%}{\lambda} \right)^{i-1} * Cu_{/m} \Bigg], 1 \le i \le \lambda. \end{aligned} \tag{3}$$

3) Mobile Opportunistic Offloading: We propose a mobile opportunistic offloading perspective for virtualized and on-demand service provisioning where a task K_n is finally offloaded to the cloud after denial by two mobile device nodes in close proximity due to resource restrictions. The elasticity debt optimization model can be used to dynamically adapt the loads on different subsystems of the mobile opportunistic system. We compute the computation processing time ($T^{mc}_{n,proc}$) and energy ($E^{mc}_{n,proc}$) of mobile device user *n* for offloading the input data of size B_n as,

$$T^{mc}_{n,proc} = \frac{B_n}{R^{mc}_n(a)} + \frac{D_n}{F^{mc}_n} + \frac{L_n}{R^{mc}_n(a)} + T^{l}_{n,waitA\rightarrow B} + T^{l}_{n,waitB\rightarrow C} + T^{mc}_{n,wait} + \left(P^c_n + T^c_{n,switch}\right) \tag{4}$$

$$E^{mc}_{n,proc} = \frac{P_n * B_n}{R^{mc}_n(a)} + v_n * D_n + \frac{A_n * L_n}{R^{mc}_n(a)} + E^{l}_{n,waitA\rightarrow B} + E^{l}_{n,waitB\rightarrow C} + E^{mc}_{n,wait} + E^{mc}_{n,switch} \tag{5}$$

where R^{mc}_n is the uplink data transfer for transmission, D_n the total number of CPU cycles required (i.e., CPU usage) to accomplish the computation task K_n, F^{mc}_n the computation capability (i.e., CPU cores per second), L_n the data output, $T^{l}_{n,wait}$ the tolerable waiting time for queue in order to receive response, P^c_n the sudden shutdown, $T^c_{n,switch}$ the intermediate switches and routers in the cloud that fluctuate the network delay, A_n the transmission power from the cloud, v_n the cloud coefficient denoting the consumed energy per CPU cycle, and $E^{mc}_{n,\ wait}$ the mobile device user requests based on localization.

According to (4) and (5), the overhead of cloud computing approach (Z^{mc}_n) in terms of processing time and energy is computed as follows, i.e.,

$$Z^{mc}_n(a) = \gamma^T_n * T^{mc}_{n,proc} + \gamma^E_n * E^{mc}_{n,proc} + \gamma^M_n * M^{mc}_{n,proc} \tag{6}$$

where $0 \leq \gamma^T_n, \gamma^E_n, \gamma^M_n \leq 1$ denote the weighting factors of processing time, energy and memory usage for mobile device user *n*'s decision making, respectively.

B. Description of Elasticity Debt Minimization Mechanism

The proposed elasticity debt minimization incentive mechanism uses the algorithm shown in Table II to achieve the following: (a) accurate predictions on the elasticity debt and mitigation of the risk of service over-utilization, (b) scalability as the number of mobile device user requests for cloud resources increases or decreases accordingly, (c) optimization of cloud resources and consumption rates considering the current state of elasticity debt, (d) effective elasticity debt monitoring when parallelization of requests for cloud resources occurs, (e) leasing optimization of cloud-supported mobile services, and (f) allocation of new mobile device user requests to high elasticity debt-level services.

TABLE II
ALGORITHM USED IN ELASTICITY DEBT MINIMIZATION MECHANISM

Algorithm 1. Pseudocode Implementation of Elasticity Debt Quantification (EDQ)

```
// This algorithm monitors and provides an analysis of the current state of
// the elasticity debt and predicts the accumulated state in case of
// parallelization of requests for cloud resources.

procedure EDQ (i, U_max, U_curr, ppm, Cu/m, n, λ, Δ%, β%, VoC%)
  sequential input (i, U_max, U_curr, ppm, Cu/m, n, λ, Δ%, β%, VoC%)
  if (i = 1) then
    ED[i] ⟵ 12 * (U_max − U_curr) * (ppm − Cu/m)
  end if
  for (i = 2, ..., λ) do  // increasing the index of year to provide EDA
    if (n = 1) then
      K[0] ⟵ (1 + Δ_1%) * ppm
      L[0] ⟵ (1 + β_1%) * U_curr
      M[0] ⟵ (1 + VoC_1%) * Cu/m
      ED[i] ⟵ 12 * (U_max − L[0]) * (K[0] − M[0])
    else if (n > 1) then
      K[n − 1] ⟵ K[n − 2] * (1 + Δ_n%)
      L[n − 1] ⟵ L[n − 2] * (1 + β_n%)
      M[n − 1] ⟵ M[n − 2] * (1 + VoC_n%)
      ED[i] ⟵ 12 * (U_max − L[n − 2]) * (K[n − 2] − M[n − 2])
    end if
  end for
  return ED[i]
end procedure
```

IV. HIDDEN MARKOV MODEL EXPLOITATION FOR CLOUD RESOURCE SCHEDULING BASED ON ELASTICITY DEBT

In this section, we examine the resource allocation strategy from the infrastructure suppliers and service providers viewpoint. We propose a utility-driven elasticity debt quantification approach for cloud resource scheduling and maximization of resource utilization based on the Hidden Markov Model (HMM). In this context, the cloud resource scheduling model is formulated as a four-tuple of $H = <A,B,N,S>$, where A is the set of N services providers. $A = <a1, a2, \ldots, at>$ and $B = <b1, b2, \ldots, bt>$ is the price set of the service providers. For $\forall b_i, b_i =< \lambda^{CPU}_i, \lambda^{MEM}_i, \lambda^{BW}_i, \lambda^{SR}_i, \lambda^{TP}_i, \lambda^{IOP}_i >$ specifies the service provider *i*'s bid of CPU, memory, bandwidth, storage, throughput and I/O processor, respectively. $N = <n1, n2, \ldots, nt>$ indicates the combinatorial demand of all types of resources requested by the service providers. For $\forall n_i, n_i =< k^{CPU}_i, k^{MEM}_i, k^{BW}_i, k^{SR}_i, k^{TP}_i, k^{IOP}_i >$ presents the service provider *i*'s demand for all types of resources. $S = (s^{CPU}, s^{MEM}, s^{BW}, s^{SR}, s^{TP}, s^{IOP})$ shows the resources of CPU, memory, bandwidth, storage, throughput and I/O processor managed by the infrastructure providers. The modeling of elasticity debt optimization (*EDO*) and profit optimization (*PRO*) for cloud resource scheduling is given as follows in (7) and (8) respectively, i.e.,

$$EDO = \max \sum_{i=1}^{N} \left[s^{CPU} - (1+\beta_i\%) * \delta_i * k^{CPU}_i \right] + \left[s^{MEM} - (1+\beta_i\%) * \delta_i * k^{MEM}_i \right] + \left[s^{BW} - (1+\beta_i\%) * \delta_i * k^{BW}_i \right]$$

$$+\left[s^{SR}-(1+\beta_i\%)*\delta_i*k_i^{SR}\right]$$
$$+\left[s^{TP}-(1+\beta_i\%)*\delta_i*k_i^{TP}\right]$$
$$+\left[s^{IOP}-(1+\beta_i\%)*\delta_i*k_i^{IOP}\right] \quad (7)$$

$$PRO=\max\sum_{i=1}^{N}\Big[\delta_i*\Big(\lambda_i^{CPU}+\lambda_i^{MEM}+\lambda_i^{BW}+\lambda_i^{SR}+\lambda_i^{TP}+\lambda_i^{IOP}\Big)\Big]$$

$$\text{s.t.}\ \sum_{i=1}^{N}\delta_i k_i^{CPU}\le s^{CPU},\sum_{i=1}^{N}\delta_i k_i^{MEM}\le s^{MEM},\ \sum_{i=1}^{N}\delta_i k_i^{BW}\le s^{BW},\sum_{i=1}^{N}\delta_i k_i^{SR}\le s^{SR},\sum_{i=1}^{N}\delta_i k_i^{TP}\le s^{TP},\sum_{i=1}^{N}\delta_i k_i^{IOP}\le s^{IOP}. \quad (8)$$

V. Elasticity Debt Quantification Game

The concept of elasticity debt is examined as a methodological model to reason about elasticity decisions in cloud from a utility-driven viewpoint. The rationale is based on the fact that the mobile devices are owned by different individuals and the decision to offload a user's task to the cloud has a significant impact on the level of the elasticity debt minimization for the provided cloud-based mobile services. Let the number of active users for a service be satisfactory enough such that the elasticity debt is minimized holding the least positive values. In such a case, under-utilization of this service is guaranteed, avoiding the incurrence of accumulated elasticity debt. The new mobile device user requests are encountered as adaptation decisions to adjust the resource provisioning for the remaining services. The level of adaptation of the new user requests, which imply additional cloud resources, is based on the elasticity debt results obtained for each service. The elasticity debt minimization mechanism is triggered for the remaining services in accordance to the different interests of each individual-user. The subscription and charging policies are also subject to the lease decision. The adaptation decision making problem is examined based on the number of active mobile device users for each SaaS-centric mobile service within an elasticity debt prediction period of time. In this direction, let $a_{-n}=(a_1,\ldots,a_{n-1},a_{n+1},\ldots,a_N)$ be the adaptation decisions by all other mobile device users except new device user *n*. Given the other user's decisions a_{-n}, user *n* selects a proper decision $a_n\in\{0,1\}$ to minimize the elasticity debt, i.e.,

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

The elasticity debt minimization problem is resolved in a different manner between the SaaS-based mobile services due to the distinction between the number of active end-users each one can host [32], which is witnessed on the different elasticity debt numerical results. The elasticity debt function is formed with respect to the new mobile device user *n* as follows,

$$ED_n(a_n,a_{-n})=\begin{cases}ED_1, & if\ a_n=0\\ ED_2, & if\ a_n=1\end{cases} \quad (9)$$

where ED_1 is the elasticity debt quantification formula to be triggered when the basic service is selected according to the new user *n*'s request for resources, while ED_2 refers to the elasticity debt equation that is triggered when the premium service is selected.

Towards the proof of the theorem, we construct, for a game *G*, a function *ED* over the set of strategy profiles such that the optimal behavior of *ED* yields a Nash equilibrium in strategies of *G*. The adaptation decision making problem is formulated as a game $G=(N,\{A_n\}_{n\in N},\{ED_n\}_{n\in N})$, where *N* is the set of mobile device users, $A_n\triangleq\{0,1\}$ is the set of strategies for the new user *n*'s request and the elasticity debt function $ED_n(a_n,a_{-n})$ of each new user *n* is the cost-oriented function to be minimized by user *n*. The game *G* is the elasticity debt quantification game and we now proceed to the concept of Nash equilibrium [33].

Definition 1: A strategy profile $a^*=(a_1^*,\ldots,a_N^*)$ is a Nash equilibrium of the elasticity debt quantification game if at the equilibrium a^*, no new player can be allocated to a cloud-based mobile service to further minimize the elasticity debt by unilaterally changing its strategy, i.e.,

$$ED_n\big(a_n^*,a_{-n}^*\big)\le ED_n\big(a_n,a_{-n}^*\big),\forall a_n\in A_n,n\in N \quad (10)$$

The Nash equilibrium achieves to minimize the elasticity debt by organizing the mobile device users into a mutually satisfactory condition and no user is motivated to deviate unilaterally. The adaptation decisions associated with each service's elasticity debt quantitative result is leveraged towards the optimization of resource provisioning. The number of active users per service or the option of allocating current device users are considered due to the non-linear demand as a result of the new resource requests. The game property investigates the existence of Nash equilibrium in the elasticity debt game, introducing the concept of best response [33].

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

$$ED_n(a_n^*,a_{-n})\le ED_n(a_n,a_{-n}),\forall a_n\in A_n \quad (11)$$

According to (10) and (11), we observe that all users play the best response strategies towards each other at the Nash equilibrium, concluding with the following lemma.

Lemma 1: Given the strategies a_{-n} of the other mobile device users in the elasticity debt game, the best response of a new user *n* is given as the following elasticity debt status strategy, i.e.,

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

The elasticity debt status of a cloud-based mobile service is significant both before and after the adaptation decision of a new user *n*'s request for additional resources. Lemma 1 indicates that in the event of elasticity debt results greater than zero, the service remains under-utilized and the new user *n*'s

TABLE III
USE CASE SCENARIOS: NON-LINEAR DEMAND VARIATIONS

	Variation in Demand		
Term	**Case Scenario A**	**Case Scenario B**	**Case Scenario C**
Year 1 to 2	$\beta_1\% = 5\%$	$\beta_1\% = 18\%$	$\beta_1\% = 28\%$
Year 2 to 3	$\beta_2\% = 5\%$	$\beta_2\% = 22\%$	$\beta_2\% = 25\%$
Year 3 to 4	$\beta_3\% = 32\%$	$\beta_3\% = 35\%$	$\beta_3\% = 30\%$
Year 4 to 5	$\beta_4\% = 40\%$	$\beta_4\% = 25\%$	$\beta_4\% = 10\%$

requests are satisfied. In addition, the elasticity debt is further minimized without risking to enter into an accumulated elasticity debt in the long run. However, in case that the elasticity debt results are less than or equal to zero, the service is over-utilized and no resource capabilities are available to satisfy new requests. In this case, we achieve to avoid accumulated elasticity debt by adapting the requests to those services where the elasticity debt could be further minimized. This theory enables the prediction and auto-scaling of the elasticity debt in mobile cloud computing environments when multiple adaptation decisions for resource provisioning are taken.

VI. EVALUATION OF THEOREM AND SCHEME

A. Numerical Results and Analysis

We validate the proposed theorem focusing on the resource scheduling and optimization problem for each service on mobile cloud-based service level. The formulae and algorithms were implemented in a MATLAB-based testbed to quantify the elasticity debt and take proper adaptation decisions for resource provisioning where necessary. The adaptation strategy to adjust resource provisioning triggers a game theoretic, cost-optimal and control mechanism when new user requests occur. The Nash equilibrium game tends towards elasticity debt optimization with threshold for auto-scaling be $ED_i = 0$ (included). Three cloud-supported mobile services are studied in three different use case scenarios, considering non-linear demand curves (see Table III) in a 5-year elasticity debt period ($\lambda = 5$) and the group composition to minimize the elasticity debt. The key attributes of each service are presented in Table IV, which constitute the input data for the elasticity debt formulae. The variations in the monthly subscription price and service cost are presented in Table V. Our tests aim at identifying whether accumulated elasticity debt occurs during the examined period due to fluctuations in the number of mobile device users. The research findings are summarized in the quantification results obtained before the elasticity debt control mechanism is triggered (see Table VI) and those obtained after the mechanism is triggered (see Table VII). Likewise, the plots of the elasticity debt flow for the three case scenarios are presented in Fig. 3 to 8 both before and after the mechanism is triggered. In case scenario A, the results we obtain for the basic service demonstrate over-utilization of the service during year 5. Towards the elasticity debt optimization as an effect of the equilibrium model, the estimated increase in the demand during year 5 should have been up to 37.4 per cent, i.e.,

$$6,000 - (1 + x) * 4,365.9 = 0 \Rightarrow x = 0.37428$$
$$\approx 37.4\% \approx 1,634.1 \; new \; mobile \; device \; users$$

TABLE IV
KEY SERVICE ATTRIBUTES

Variable Definition	**Corporate (C)**	**Premium (P)**	**Basic (B)**
Maximum number of mobile device users	$U_{max} = 14,000$	$U_{max} = 9,000$	$U_{max} = 6,000$
Initial number of device users	$U_{curr} = 6,000$	$U_{curr} = 4,000$	$U_{curr} = 3,000$
Initial subscription price per month	$ppm = 8$	$ppm = 5$	$ppm = 2$
Initial cost per month for servicing a mobile device user in the cloud	$Cu_{/m} = 4$	$Cu_{/m} = 3$	$Cu_{/m} = 1$

TABLE V
VARIATIONS IN THE MONTHLY SUBSCRIPTION PRICE AND COST FOR SERVICING A MOBILE DEVICE USER IN THE CLOUD

	Corporate (C)	**Premium (P)**	**Basic (B)**
Variable Definition	**Case Scenario A**		
Variations in subscription price	$\Delta_1\% = 0.3\%$	$\Delta_1\% = 0.4\%$	$\Delta_1\% = 0.5\%$
	$\Delta_2\% = 0.4\%$	$\Delta_2\% = 0.4\%$	$\Delta_2\% = 0.6\%$
	$\Delta_3\% = 1.6\%$	$\Delta_3\% = 1.7\%$	$\Delta_3\% = 2\%$
	$\Delta_4\% = 1.9\%$	$\Delta_4\% = 2.1\%$	$\Delta_4\% = 2.2\%$
Variation in the cost	$VoC_1\% = 0.8\%$	$VoC_1\% = 0.9\%$	$VoC_1\% = 1.2\%$
	$VoC_2\% = 0.9\%$	$VoC_2\% = 1\%$	$VoC_2\% = 1.4\%$
	$VoC_3\% = 2\%$	$VoC_3\% = 2.2\%$	$VoC_3\% = 2.8\%$
	$VoC_4\% = 2.5\%$	$VoC_4\% = 2.8\%$	$VoC_4\% = 3.2\%$
	Case Scenario B		
Variations in subscription price	$\Delta_1\% = 0.7\%$	$\Delta_1\% = 0.8\%$	$\Delta_1\% = 1\%$
	$\Delta_2\% = 0.8\%$	$\Delta_2\% = 0.9\%$	$\Delta_2\% = 1.2\%$
	$\Delta_3\% = 0.9\%$	$\Delta_3\% = 1.1\%$	$\Delta_3\% = 1.3\%$
	$\Delta_4\% = 0.7\%$	$\Delta_4\% = 1\%$	$\Delta_4\% = 1.1\%$
Variation in the cost	$VoC_1\% = 0.9\%$	$VoC_1\% = 1.1\%$	$VoC_1\% = 1.6\%$
	$VoC_2\% = 1\%$	$VoC_2\% = 1.2\%$	$VoC_2\% = 1.7\%$
	$VoC_3\% = 1\%$	$VoC_3\% = 1.3\%$	$VoC_3\% = 1.9\%$
	$VoC_4\% = 1.2\%$	$VoC_4\% = 1.5\%$	$VoC_4\% = 1.6\%$
	Case Scenario C		
Variations in subscription price	$\Delta_1\% = 0.5\%$	$\Delta_1\% = 0.8\%$	$\Delta_1\% = 1.2\%$
	$\Delta_2\% = 0.4\%$	$\Delta_2\% = 0.7\%$	$\Delta_2\% = 1.1\%$
	$\Delta_3\% = 0.8\%$	$\Delta_3\% = 1\%$	$\Delta_3\% = 1.5\%$
	$\Delta_4\% = 0.2\%$	$\Delta_4\% = 0.3\%$	$\Delta_4\% = 0.5\%$
Variation in the cost	$VoC_1\% = 0.8\%$	$VoC_1\% = 1.1\%$	$VoC_1\% = 1.7\%$
	$VoC_2\% = 0.7\%$	$VoC_2\% = 1\%$	$VoC_2\% = 1.6\%$
	$VoC_3\% = 1\%$	$VoC_3\% = 1.3\%$	$VoC_3\% = 2\%$
	$VoC_4\% = 0.4\%$	$VoC_4\% = 0.5\%$	$VoC_4\% = 0.8\%$

The actual 40 per cent increase in the demand that was adopted in our initial scenario corresponds to approximately 1,746.36 new users. The elasticity debt control mechanism achieves to automatically allocate the remaining 112.26 new users to the premium service, helping towards the elasticity debt minimization. The pool of users for the premium service during year 5 is approximately 8,149.68 + 112.26 = 8,261.94. The increase in the demand for the premium service is now restructured to approximately 41.9 per cent estimated as follows

$$(1 + y) * 5,821.2 = 8,261.94 \Rightarrow y = 0.41928 \approx 41.9\%$$

TABLE VI
ELASTICITY DEBT QUANTIFICATION RESULTS BEFORE THE CONTROL MECHANISM IS TRIGGERED

	Year 1	Year 2	Year 3	Year 4	Year 5
	Case Scenario A				
C	384,000	368,860.80	353,399.55	255,107.72	87,079.06
P	120,000	114,796.80	109,213.18	76,338.17	20,625.90
B	36,000	34,131.60	32,177.27	19,758.24	-1,373.01
	Case Scenario B				
C	384,000	333,820.80	260,232.21	114,428.37	-28,228.63
P	120,000	103,079.52	78,419.39	29,898.70	-17,531.74
B	36,000	29,638.08	20,395.67	2,071.90	-15,824.22
	Case Scenario C				
C	384,000	303,966.72	211,830.22	73,615.02	13,172.79
P	120,000	93,445.92	62,772.84	16,506.70	-3,689.48
B	36,000	26,101.44	14,587.08	-2,946.30	-10,626.93

TABLE VII
ELASTICITY DEBT QUANTIFICATION RESULTS AFTER THE CONTROL MECHANISM IS TRIGGERED

	Year 1	Year 2	Year 3	Year 4	Year 5
	Case Scenario A				
C	384,000	368,860.80	353,399.55	255,107.72	87,079.06
P	120,000	114,796.80	109,213.18	76,338.17	17,960.81
B	36,000	34,131.60	32,177.27	19,758.24	15.31
	Case Scenario B				
C	384,000	333,820.80	260,232.21	114,428.37	347.05
P	120,000	103,079.52	78,419.39	29,898.70	138.37
B	36,000	29,638.08	20,395.67	2,071.90	6.58
	Case Scenario C				
C	384,000	303,966.72	211,830.22	73,615.02	480.90
P	120,000	93,445.92	62,772.84	10,769.18	165.13
B	36,000	26,101.44	14,587.08	0.00	0.00

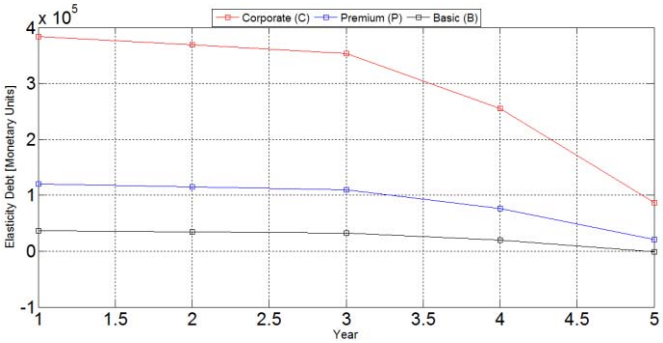

Fig. 3. Plot for case scenario A: The flow of the elasticity debt before the elasticity debt control mechanism is triggered.

The variations in the subscription price per month and cost for servicing an end-user in the cloud for the premium service are restructured to $\Delta_4\% = 2.2\%$ and $VoC_4\% = 2.9\%$, respectively. The elasticity debt quantification result for the premium service during year 5 is finally formed to approximately $ED_5 \approx 17,960.81$ monetary units, contributing to a further minimization of the elasticity debt. Likewise, the variations in the subscription price and cloud service cost for the basic service are now restructured to $\Delta_4\% = 2.1\%$ and $VoC_4\% = 3.1\%$. The elasticity debt calculation during year 5 is now formed to approximately $ED_5 \approx 15.31$ monetary units, tending towards optimality in terms of minimizing the elasticity debt. In case scenario B, the results for

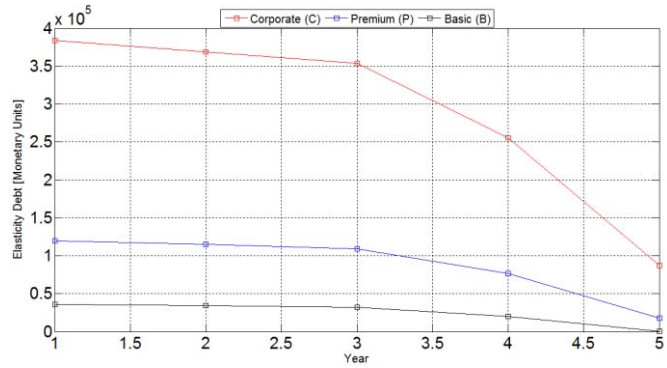

Fig. 4. Plot for case scenario A: The flow of the elasticity debt after the elasticity debt control mechanism is triggered.

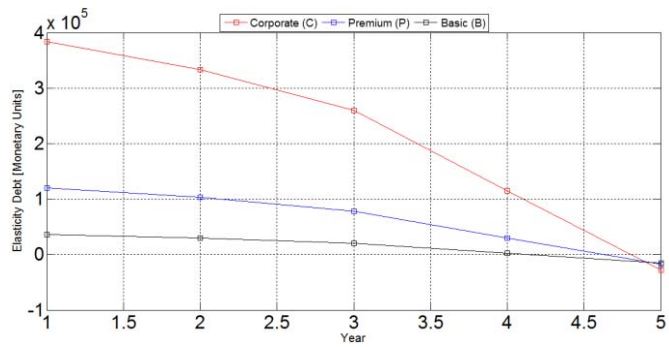

Fig. 5. Plot for case scenario B: The flow of the elasticity debt before the elasticity debt control mechanism is triggered.

all services indicate over-utilization during year 5. The estimated increase in the demand should have been as follows for the three different services in order to achieve elasticity debt optimization, i.e.,

$$\boldsymbol{Corporate}: 14,000 - (1+x) * 11,660.76 = 0 \Rightarrow$$
$$x = 0.20060 \approx 20\% \approx 2,339.24 \ new \ device \ users$$
$$\boldsymbol{Premium}: 9,000 - (1+x) * 7,773.84 = 0 \Rightarrow$$
$$x = 0.15772 \approx 15.7\% \approx 1,226.16 \ new \ device \ users$$
$$\boldsymbol{Basic}: 6,000 - (1+x) * 5,830.38 = 0 \Rightarrow x = 0.02909$$
$$\approx 2.9\% \approx 169.62 \ new \ device \ users$$

In case scenario C, the results we obtain for the basic service demonstrate over-utilization of the service during year 4. To achieve optimization of the elasticity debt, the estimated increase in the demand during year 4 should have been up to 25 per cent, i.e.,

$$6,000 - (1+x) * 4,800 = 0 \Rightarrow x = 0.25 = 25\% \Rightarrow 1,200$$
$$new \ mobile \ device \ users$$

The actual 30 per cent increase in the demand in our initial scenario corresponds to approximately 1,440 new users. The elasticity debt control mechanism achieves to automatically allocate the remaining 240 new users to the premium service, when triggered. The pool of users for the premium service during year 4 is approximately 8,320 + 240 = 8,560. The increase in the demand for the premium service is now

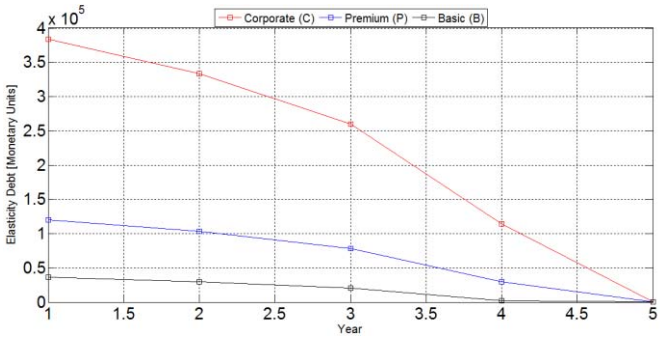

Fig. 6. Plot for case scenario B: The flow of the elasticity debt after the elasticity debt control mechanism is triggered.

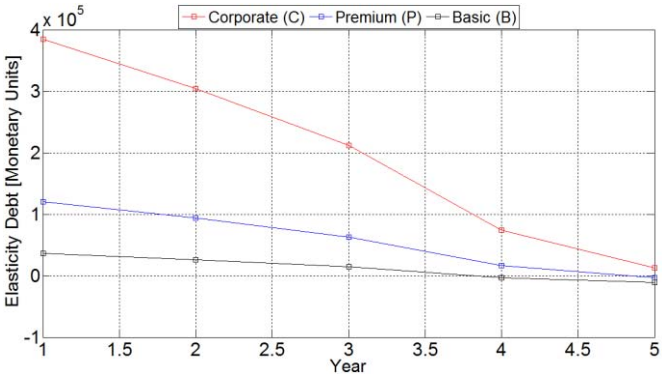

Fig. 7. Plot for case scenario C: The flow of the elasticity debt before the elasticity debt control mechanism is triggered.

restructured to approximately 33.7 per cent estimated as,

$$(1 + y) * 6,400 = 8,560 \Rightarrow y = 0.3375 \approx 33.7\%$$

Once the restructured variations in the subscription price and the cost for servicing an end-user in the cloud are applied, the elasticity debt result for the premium service during year 4 is formed to $ED_4 \approx 10,769.18$, while complete optimization is achieved for the basic service with $ED_4 = 0$. Likewise, the estimated increase in the demand during year 5 for the premium service should have been up to 5.1 per cent, i.e.,

$$9,000 - (1 + x) * 8,556.8 = 0 \Rightarrow x = 0.0517 \approx 5.1\% \\ \Rightarrow 443 \; new \; mobile \; device \; users$$

Furthermore, the estimated increase for the corporate service during year 5 is 12.1 per cent, i.e.,

$$14,000 - (1 + x) * 12,480 = 0 \Rightarrow x = 0.1217 \approx 12.1\%$$

Once the re-estimated variations in the subscription price and service cost are applied, the elasticity debt result for the premium service is formed to $ED_5 \approx 165.13$ during year 5, while for the corporate service is $ED_5 = 480.90$. These results hold the least positive values, minimizing the elasticity debt to the lowest level. Based on the elasticity debt incentive mechanism, the corporate service will satisfy 272 new user requests allocated from the premium and basic services, while the remaining 740 will be automatically allocated to other cloud-based mobile services.

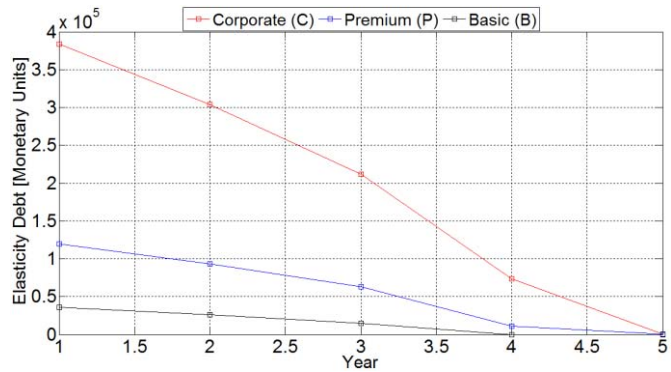

Fig. 8. Plot for case scenario C: The flow of the elasticity debt after the elasticity debt control mechanism is triggered.

B. Comparison With Existing Schemes

Different from previous research works [14], [27], we are the first to introduce the elasticity debt analytics paradigm to support the adaptation decisions when tasks are offloaded, scheduled and executed on highly dynamic mobile cloud computing environments. To date, most existing state-of-the-art techniques in the literature, which are related to dynamic trade-offs for resource provisioning, rarely take into account this scientific problem, because they tend to examine the applications' quality of service without addressing adequately issues relating to minimizing the costs of using cloud-based mobile services. Our theorem and scheme use the necessary metrics to overcome these challenges and automate the resource allocation process based on the elasticity debt quantitative results. Additionally, the equilibrium model ensures the consideration of the non-cooperative behavior of users, service providers and infrastructure suppliers towards the minimization of the elasticity debt and maximization of overall profits of both the resource supply and the resource on demand. The obtained results prove the effectiveness of this theorem in terms of: (a) allocation of multiple resources simultaneously by applying resource allocation metrics based on elasticity debt, and (b) high efficiency when the number of users is large and the number of service providers in cloud environments varies.

VII. Conclusion and Future Work

This research work proposes the concept of elasticity debt analytics as a method for optimal resource scheduling, provisioning and management in mobile cloud computing. We exploit a Nash equilibrium approach to deal with the interactions between different mobile device users and auto-allocate incoming resource requests to high-level elasticity debt services towards the optimal utilization and auto-scaling of cloud resources. The experimental results prove the effectiveness of the equilibrium model by: (a) taking proper adaptation decisions that enable the auto-allocation of new users to high elasticity debt-level services, (b) delivering elasticity debt results close to the threshold value (i.e., elasticity debt minimization) and avoiding accumulated elasticity debt, and (c) increasing the elasticity wealth for service providers and infrastructure

suppliers. In the future, we will examine the applicability of this technique for more complex scenarios with dynamic QoS and QoE analysis, and resource allocation in a second scale (i.e., short-term predictions).

REFERENCES

[1] X. Wang, A. V. Vasilakos, M. Chen, Y. Liu, and T. T. Kwon, "A survey of green mobile networks: Opportunities and challenges," *Mobile Netw. Appl.*, vol. 17, no. 1, pp. 4–20, 2012.

[2] J. M. Batalla, A. Vasilakos, and M. Gajewski, "Secure smart homes: Opportunities and challenges," *ACM Comput. Surveys*, vol. 50, no. 5, p. 75, 2017.

[3] M. Gajewski, J. M. Batalla, G. Mastorakis, and C. X. Mavromoustakis, "A distributed IDS architecture model for smart home systems," *Clust. Comput.*, pp. 1–11, 2017, doi: 10.1007/s10586-017-1105-z.

[4] K. Gai, M. Qiu, H. Zhao, L. Tao, and Z. Zong, "Dynamic energy-aware cloudlet-based mobile cloud computing model for green computing," *J. Netw. Comput. Appl.*, vol. 59, pp. 46–54, Jan. 2016.

[5] V. W. Wong, R. Schober, D. W. K. Ng, and L.-C. Wang, *Key Technologies for 5G Wireless Systems*. Cambridge, U.K.: Cambridge Univ. Press, 2017.

[6] R. Zhou, Z. Li, and C. Wu, "A truthful online mechanism for location-aware tasks in mobile crowd sensing," *IEEE Trans. Mobile Comput.*, vol. 17, no. 8, pp. 1737–1749, Aug. 2018.

[7] C. You, K. Huang, H. Chae, and B.-H. Kim, "Energy-efficient resource allocation for mobile-edge computation offloading," *IEEE Trans. Wireless Commun.*, vol. 16, no. 3, pp. 1397–1411, Mar. 2017.

[8] K. Kumar, J. Liu, Y.-H. Lu, and B. Bhargava, "A survey of computation offloading for mobile systems," *Mobile Netw. Appl.*, vol. 18, no. 1, pp. 129–140, 2013.

[9] R. Vilalta *et al.*, "TelcoFog: A unified flexible fog and cloud computing architecture for 5G networks," *IEEE Commun. Mag.*, vol. 55, no. 8, pp. 36–43, Aug. 2017.

[10] R. Munoz *et al.*, "The CTTC 5G end-to-end experimental platform: Integrating heterogeneous wireless/optical networks, distributed cloud, and IoT devices," *IEEE Veh. Technol. Mag.*, vol. 11, no. 1, pp. 50–63, Mar. 2016.

[11] R. B. Myerson, *Game Theory: Analysis of Conflict*. Cambridge, U.K.: Harvard Univ. Press, 1991.

[12] C. Mera-Gómez, F. Ramírez, R. Bahsoon, and R. Buyya, "A debt-aware learning approach for resource adaptations in cloud elasticity management," in *Proc. Int. Conf. Service Orient. Comput.*, 2017, pp. 367–382.

[13] P. Jamshidi, C. Pahl, and N. C. Mendonça, "Managing uncertainty in autonomic cloud elasticity controllers," *IEEE Cloud Comput.*, vol. 3, no. 3, pp. 50–60, May/Jun. 2016.

[14] C. Mera-Gómez, R. Bahsoon, and R. Buyya, "Elasticity debt: A debt-aware approach to reason about elasticity decisions in the cloud," in *Proc. IEEE/ACM 9th Int. Conf. Utility Cloud Comput. (UCC)*, Shanghai, China, 2016, pp. 79–88.

[15] R. N. Calheiros, R. Ranjan, A. Beloglazov, C. A. De Rose, and R. Buyya, "CloudSim: A toolkit for modeling and simulation of cloud computing environments and evaluation of resource provisioning algorithms," *Softw. Pract. Exp.*, vol. 41, no. 1, pp. 23–50, 2011.

[16] G. Skourletopoulos *et al.*, "Cost-benefit analysis game for efficient storage allocation in cloud-centric Internet of Things systems: A game theoretic perspective," in *Proc. 15th IFIP/IEEE Int. Symp. Integr. Netw. Manag. (IM)*, Lisbon, Portugal, 2017, pp. 1149–1154.

[17] X. Chen, L. Jiao, W. Li, and X. Fu, "Efficient multi-user computation offloading for mobile-edge cloud computing," *IEEE/ACM Trans. Netw.*, vol. 24, no. 5, pp. 2795–2808, Oct. 2016.

[18] A. Beloglazov, J. Abawajy, and R. Buyya, "Energy-aware resource allocation heuristics for efficient management of data centers for cloud computing," *Future Gener. Comput. Syst.*, vol. 28, no. 5, pp. 755–768, 2012.

[19] G. Skourletopoulos, C. X. Mavromoustakis, G. Mastorakis, J. M. Batalla, and J. N. Sahalos, "An evaluation of cloud-based mobile services with limited capacity: A linear approach," *Soft Comput. J.*, vol. 21, no. 16, pp. 4523–4530, Aug. 2017.

[20] D. Ardagna, B. Panicucci, and M. Passacantando, "Generalized Nash equilibria for the service provisioning problem in cloud systems," *IEEE Trans. Services Comput.*, vol. 6, no. 4, pp. 429–442, Oct./Dec. 2013.

[21] D. Niyato, P. Wang, E. Hossain, W. Saad, and Z. Han, "Game theoretic modeling of cooperation among service providers in mobile cloud computing environments," in *Proc. IEEE Wireless Commun. Netw. Conf. (WCNC)*, Shanghai, China, 2012, pp. 3128–3133.

[22] Y. Ge, Y. Zhang, Q. Qiu, and Y.-H. Lu, "A game theoretic resource allocation for overall energy minimization in mobile cloud computing system," in *Proc. ACM/IEEE Int. Symp. Low Power Electron. Design*, Redondo Beach, CA, USA, 2012, pp. 279–284.

[23] X. Chen, "Decentralized computation offloading game for mobile cloud computing," *IEEE Trans. Parallel Distrib. Syst.*, vol. 26, no. 4, pp. 974–983, Apr. 2015.

[24] S. Misra, S. Das, M. Khatua, and M. S. Obaidat, "QoS-guaranteed bandwidth shifting and redistribution in mobile cloud environment," *IEEE Trans. Cloud Comput.*, vol. 2, no. 2, pp. 181–193, Apr./Jun. 2014.

[25] X. Sun and N. Ansari, "Green cloudlet network: A distributed green mobile cloud network," *IEEE Netw.*, vol. 31, no. 1, pp. 64–70, Jan./Feb. 2017.

[26] W. Wei, X. Fan, H. Song, X. Fan, and J. Yang, "Imperfect information dynamic stackelberg game based resource allocation using hidden Markov for cloud computing," *IEEE Trans. Services Comput.*, vol. 11, no. 1, pp. 78–89, Jan./Feb. 2018.

[27] M. Fokaefs, C. Barna, and M. Litoiu, "Economics-driven resource scalability on the cloud," in *Proc. 11th Int. Symp. Softw. Eng. Adapt. Self Manag. Syst. (SEAMS)*, Austin, TX, USA, 2016, pp. 129–139.

[28] R. Han, M. M. Ghanem, L. Guo, Y. Guo, and M. Osmond, "Enabling cost-aware and adaptive elasticity of multi-tier cloud applications," *Future Gener. Comput. Syst.*, vol. 32, pp. 82–98, Mar. 2014.

[29] X. Sun, N. Ansari, and R. Wang, "Optimizing resource utilization of a data center," *IEEE Commun. Surveys Tuts.*, vol. 18, no. 4, pp. 2822–2846, 4th Quart., 2016.

[30] G. Skourletopoulos *et al.*, "A fluctuation-based modelling approach to quantification of the technical debt on mobile cloud-based service level," in *Proc. IEEE Glob. Commun. Conf. (GLOBECOM)*, San Diego, CA, USA, 2015, pp. 1–6.

[31] G. Skourletopoulos *et al.*, "Quantifying and evaluating the technical debt on mobile cloud-based service level," in *Proc. IEEE Int. Conf. Commun. (ICC)*, Kuala Lumpur, Malaysia, 2016, pp. 1–7.

[32] G. Skourletopoulos *et al.*, "A game theoretic formulation of the technical debt management problem in cloud systems," in *Proc. 14th IEEE Int. Conf. Telecommun. (ConTEL)*, Zagreb, Croatia, 2017, pp. 7–12.

[33] M. J. Osborne and A. Rubinstein, *A Course in Game Theory*. Cambridge, MA, USA: MIT Press, 1994.

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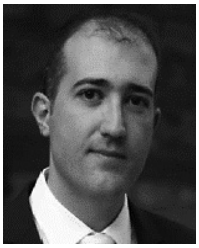

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