GreenCloudTax: A flexible IaaS Tax Approach as Stimulus for Green Cloud Computing

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***Abstract*—Cloud computing is underpinned by huge datacenters which are considered as significant consumers of energy. Under the umbrella term GreenCloud the scientific community developed different architectures, algorithms and methods to improve energy efficiency of these datacenters. However, approaches which try to modify existing or applying new economical concepts to improve energy efficiency of datacenters are rare. In this paper we propose the GreenCloudTax model which is a flexible IaaS tax system for calculating taxes of virtual machines by using the energy efficiency of the underlying server infrastructure. Thereby, providers relying on energy efficient servers can sell their virtual machines with lower taxes than those with energy inefficient servers. This results in a competitive advantage and consequently leads to reduced energy consumption in total too. We analyzed the effects of our GreenCloudTax model on Cloud markets by a simulation environment which is based on CloudSim's Bazaar-Extension.**

***Keywords*-Cloud Computing; SLA Negotiation; Bazaar Market;**

I. Introduction

In the last decade Cloud computing emerged as the dominating computing paradigm in industry as well as in science [1]. For running Clouds huge datacenters are required which are significant energy consumers [2]. For example, in the US the datacenters call for 2% of the total energy consumption [3]. Recently, in the United States Data Center Energy Usage Report [4] a forecast for the energy consumption of Cloud datacenters in 2020 was presented. With the energy efficiency of 2010 the energy consumption of datacenters will approximately triple until 2020. This accentuates the need for new approaches in order to boost energy efficiency in the Cloud domain.

Under the umbrella term *GreenCloud* the scientific community developed different algorithms, architectures and concepts fostering energy efficiency. According to [2] the research trends towards GreenCloud can be classified along the following categories: Networks, Servers, Cloud Management System and Appliance. All these research trends have a strong focus on technology - economical approaches fostering energy efficiency are neglected in [2]. An example of an economical approach for reducing the energy consumption was recently introduced in [5]. Thereby the authors consider processing power used in virtual machines as a significant energy consumer. Hence, they advise Cloud providers to develop pricing models reflecting the usage of processing power. A similar approach was presented in [6] where the energy costs for running servers were identified as a main cost driver and therefore considered as significant influence factor for adequate pricing.

In this paper we propose the GreenCloudTax model. Contrary to technical approaches we use flexible taxes for improving energy efficiency. The widely used value added tax is a proportional tax calculated on basis of the price which does not create incentives. The GreenCloudTax model is the proposal of a governmental instrument with the aim to create incentives for market participants to switch to Clouds which run energy efficient servers. Hereby we define the term server broadly: it encompasses the procesing units, the RAM modules and the hard discs. To the best of our knowledge no similar approach exists. We build our approach on [7] where we introduced a pure economic driven descriptive analysis of classical tax systems for Clouds neither introducing a flexible tax system nor considering any ecological aspects.

Currently, there is a shift from static supermarket based markets on which Cloud providers offer their products at fixed prices to more dynamic markets such as Amazons EC2 spot market [8]. The scientific community proposed different visions of how these dynamic Cloud markets can be realized ranging from centralized auctions [9] over decentralized auctions [10] to bilateral multi-round negotiations [11], [12]. We analysed the GreenCloudTax assuming a marked based on bilateral multi-round negotiations which is also known as Bazaar-based market. This Bazaar-based market is characterized by an alternating exchange of offers between consumers and providers resulting into negotiaton trees. Thereby, negotiation stops if either all offers are rejected or an agreement is formed.

We extended our CloudSim *Bazaar-Component* [13] for the simulation of the effects of the GreenCloudTax model. With this simulation environment researchers are able to create a market, add market participants to the market, assign negotiation strategies to them, define tax systems and analyse the resulting resource allocation. In the paper at hand we focus on Infrastructure as a Service (IaaS) markets where virtual machines (VM) are traded as an example of a Cloud market. The main contributions of the paper are the following: (i) Development of the GreenCloudTax model (ii) Implementation of the GreenCloudTax simulation environment by extending the Bazaar-Extention based on CloudSim (iii) Analysis of the effects of the proposed approach on Cloud markets.

The remainder of the paper is structured as follows: In section II we analyze existing approaches fostering energy efficiency of the Cloud. In section III - after a short discussion of tax systems for the Cloud - we introduce the GreenCloudTax model followed an analysis of the effects of taxes on Cloud markets. In section IV the simulation environment is introduced and the GreenCloudTax model is evaluated. The paper closes with a conclusion in section V.

II. Related Work

We structure the related work section into two parts: First, we introduce approaches which increase energy efficiency in the Cloud by applying new technology. Second, we describe approaches which try to reduce energy consumption by applying new or modifying existing economical concepts.

Technology approaches can be categorized along four research areas [2]: (i) Networks: Network traffic is increasing exponentially so that computer networks become a significant energy consumer [14]. This research field encompasses all efforts in reducing the cosumed energy of datacenters networks, networks connecting datacenters as well as end user networks. The scientific community tries to reduce network energy consumption for example by redesigning the hardware devices or by optimizing the network architecture. (ii) Servers: This research field tries to investigate how to reduce energy consumption of enclosures (cooling systems), racks and components which do not belong to the network domain. The scientific community tries to reduce energy consumption in this domain by reducing the heat load of components like the CPU or by optimizing cache strategies. (iii) Cloud Management System: According to [2] this field is currently the most emerging research domain coping with virtual machine reconfiguration, virtual machine placement and virtual machine migration and consolidation. It encompasses all virtual machine scheduling algorithms as well as virtualization software and monitoring systems. Researches try to reduce energy consumption by migrating virtual machines to other hosts [15], shutting down idle hosts [16] or by developing lightweight cloud management systems [17]. (iv) Appliance: In a perfect cloud system only running applications consume energy [2]. However, usually also the runtime environments and operating systems are significant energy consumers. So there are three different types of applications: the application itself, the runtime environment and the operating system. Efficient processing paradigms like MapReduce [18] are an example for reducing energy consumption on the application level.

The scientific community focused on developing technology approaches instead of economical approaches for improving energy efficiency. Such an economical approach was e.g. introduced in [6], [19] were the authors developed a comprehensive cost model for cloud providers. Thereby it was shown that expensive servers usually have a lower energy consumption which may lead to an amortisation of the higher acquisition costs. Hence, the usage of the cost model reveals that investing in energy efficient servers is not necessarily contradicting to the goal of profit optimization. In [20] the authors describe that finding an optimal location for datacenters is non-trivial as a huge number of parameters has to be considered. To minimize carbon footprint as well as energy consumption the authors developed an objective function which is solved via (non-linear) programming approaches. Thereby the authors forsee a carbon tax for data centers which is currently only transferred by plants in the US [20]. The authors do not describe how a carbon tax can be used for datacenters. In [21] an auction based approach was introduced which considers energy consumption of providers. Thereby, virtual machines are sold in the form of time slots. Slots get cheaper for non-business hours where providers have a lot of free capacities which gives consumers an incentive to use virtual machine in non-business hours. This leads to a more constant utilization of the datacenters and so energy consumption can be reduced. In [22] it was shown that datacenters which are able to mixture *clean* and *dirty* energy sources can significantly improve their profit. Economical principles were also applied in the demand response domain. For example in [23] the authors introduced a demand response approach to save energy via workload shifting and local generation. Similarly, in [24] a demand response approach was introduced leveraging an auction mechanism.

III. The GreenCloudTax Model

In basic economic literature [25] taxes are characterized by the taxable base and the tax rate. In the course of our research we analyzed these two dimensions in the context of IaaS where virtual machines are taxed.

Today, value added tax is used for the taxation of virtual machines and is calculated based on the price which represents the taxable base. For using Amazon's windows m4.16xlarge virtual machine (64 vCPU, 256GB RAM, 3TB Storage (HDD), region USA east) for one month approximately 4751$ have to be paid whereby 792$ are taxes - assuming a tax rate of 20%. Contrary to other goods, Cloud services are metered services - a key characteristic of Cloud computing [26] - so that the usage of alternative taxable bases is feasible. For virtual machines it is possible to use the VM characteristic processing power, RAM or storage

Table I: Cloud Taxable Bases and Tax Rates

Taxable Base	**Lump Sum**	**Progressive**	**Regressive**	**Proportional**
Price	Fee	Price Tax	Price Tax	Price Tax
Storage	Fee	Incentive Tax	Incentive Tax	Incentive Tax
RAM	Fee	Incentive Tax	Incentive Tax	Incentive Tax
Processing Power	Fee	Incentive Tax	Incentive Tax	Incentive Tax
Server Energy Eff.	Fee	GreenCloudT.	GreenCloudT.	GreenCloudT.

as described in [7] as taxable base. The purpose of using alternative taxable bases is to foster incentives - so we call them incentive taxes. Processing power can be seen as significant energy consumer [5] which can be used as taxable base. Thereby, we tax each MIPS (abstract measurement of processing power [27]) of a virtual machine with a certain amount of money. Hence, virtual machines with a lot of processing power would get more expensive while VMs with less processing power would get cheaper as their tax is reduced. Consequently, some consumers may switch to VMs with less processing power leading to a total reduction of the consumed processing power. Similarly, each GB of RAM cloud be taxed as well as each GB of storage. In table I we summarize the most important taxable bases of virtual machines.

The following equation shows the tax rate calculated by the tax and the price of the virtual machine.

$$\text{tax rate} = \frac{\text{tax}}{\text{price of virtual machine}} \tag{1}$$

Typically it is distinguished between a proportional tax rate, a progressive tax rate, a regressive tax rate as well as a lump sum tax rate [25]. The widely used value added tax is an example of a proportional tax rate. So the tax of a virtual machine is directly proportional to the price of the virtual machine. Progressive tax rates are usually used for taxing payrolls. Thereby, persons with a high payroll face a higher tax rate than persons with low payrolls. A progressive tax rate for virtual machines using the price as taxable base is exemplified by the following: A virtual machine with a price of 100$ is taxed with 10$ resulting to a tax rate of 10%. A virtual machine with a price of 200$ which is taxed with 30$ leads to a tax rate of 15%. Contrary, regressive tax rates decrease with an increasing taxable base. A lump sum tax rate can be considered as a fee which represents a special form of a regressive tax. Thereby each virtual machine is taxed with the same amount.

As shown in [6] all virtual machine resources (processing power, storage and RAM) are significant energy consumers. With the currently introduced taxable bases we are able to set incentives to reduce the consumption of processing power, RAM or storage. Therefore, energy consumption can be reduced indirectly by taxing these characteristics. However, providers running different servers usually vary in energy efficiency. The proposed incentive taxes do not consider the efficiency of servers. So virtual machines running on an energy efficient server infrastructure are taxed with the same amount as the identical virtual machine running on an energy inefficient server. The incentive taxes do not set stimuli for consumers to buy virtual machines from providers which run energy efficiency servers. Hence, we propose the GreenCloudTax model (last row in table I). It uses the energy efficiency of servers as taxable base. Virtual machines which run on energy efficient servers are lower taxed than virtual machines running on energy inefficient servers. This gives consumers an incentive to switch to providers which host VMs on energy efficient servers as their prices get more attractive. The usage of energy efficient servers is an essential step towards GreenCloud [28].

This form of the GreenCloudTax model implies that neither the price nor the consumption of resources of the virtual machines are used for calculating the tax. So a resource intensive virtual machine used for e.g. database applications running on the same server as a small virtual machine used as working station would be taxed with the same amount. Alternatively, combined taxable bases can be used instead of the strict GreenCloudTax. For example, the taxable bases price and server energy efficiency can be combined as shown in the following equation:

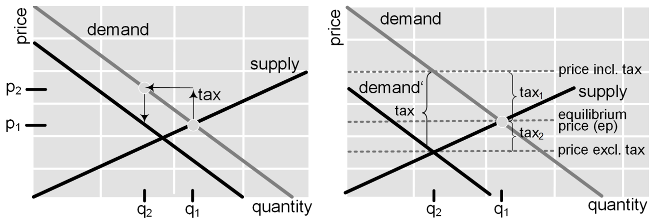
$$\text{tax} = \text{price} \cdot \text{tax rate} \cdot \text{server energy efficiency factor} \tag{2}$$

Thereby, the tax is calculated based on the price as well as on a server energy efficiency factor reflecting the energy efficiency of the sever hosting the VM.

The main challenge using the GreenCloudTax model is to profile the energy efficiency of the servers which run the virtual machines. Further, live migration of VMs from energy-efficient servers to non-energy efficient servers and vice versa makes the calculation difficult. The limited knowledge of the used servers is also a challenging problem for governments which apply the GreenCloudTax. In our use cases we follow a pragmatic approach by using the energy efficiency metric ssj_ops[1] of the SPEC benchmark [29] as taxable base for the GreenCloudTax.

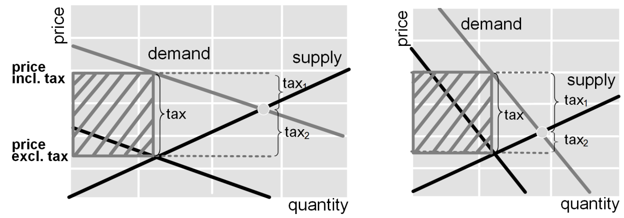
Usually either the consumers or the providers - called tax entities - have to transfer the tax which is determined by the tax authority. The so called flypaper theory [25] implies that the entity which transfers the tax has to pay the tax (receives the tax burden). However, as shown in [25] this theory is not in line with reality as described in the following paragraphs. The impact of taxes is visualized in figure 1a. It shows a typical market with demand and supply curve. Virtual machines can be seen as virtual goods which are supplied by providers and demanded by consumers. Therefore, fundamental market mechanisms can be applied to VMs. The initial demand curve is the gray one. The

[1]The more ssj_ops the system under test can produce with one watt of power, the better is the efficiency of the system under study - see https://www.spec.org/power/docs/SPECpower_ssj2008-User_Guide.pdf



(a) Shift of demand curve (b) Tax incidence

Figure 1: Impact of taxes on demand and supply



(a) Elastic demand (b) Inelastic demand

Figure 2: Tax burden examples

price p_1 of the good traded on the market is determined by the intersection of the demand curve and the supply curve. At this price the consumers demand quantity q_1. Assume that the consumer has to transfer the tax - a fixed amount of money in addition to price p_1. Hence, the consumer demands as much as p_1 plus the tax. So the demand curve shifts inwards (black curve) representing the demand curve including taxes.

According to the tax incidence theory the entity which transfers taxes does not necessarily pay the taxes - it does not receive the total tax burden [25]. This is illustrated in figure 1b. Again this figure shows two demand curves: the gray demand curve shows the demand curve before the introduction of the tax while the black demand curve is the demand curve after the introduction of the tax. The intersection of the demand and the supply curve forms the so called equilibrium price. After introducing the tax the demand curve shifts inwards leading to a new equilibrium price (price excl. tax) as well as to a new quantity (q_2). Even if the consumer has to transfer the tax, both the consumer and the provider have to pay a tax as described in the following:

- Before the tax is introduced the consumer pays the equilibrium price to the provider. After, the consumer pays the lower price excluding tax and additionally the tax. So finally, the consumer pays the price including the tax for the good traded on the market. The difference between the initial equilibrium price and the price including tax is represented by tax_1.
- The provider gets the equilibrium price before the tax is introduced. After, the equilibrium price drops and the provider receives only the price, termed price excluding tax in figure 1b. The difference between the initial price and the price excluding tax is represented by tax_2.

tax_1 and tax_2 form together the total tax prescribed by the tax authority. Again, the example illustrates that the entity which transfers the tax does not necessarily pay it. Instead, the price elasticity of the demand and supply curve determines the amount of the tax an entity has to pay as defined by the following equation:

$$\text{price elasticity} = \left| \frac{dQ/Q}{dP/P} \right| \tag{3}$$

The higher the price elasticity of the demand or supply curve the lower is the tax the consumer or provider has to pay. A high price elasticity represents a high price sensibility. Such a price sensible consumer leaves the market because of price increments and chooses alternative goods. Contrary, a consumer with a low price elasticity buys the good even if its price is increased. This is because the consumer has no alternatives and therefore it has to accept the higher price. In both examples shown in figure 2 the tax is transferred by the consumer and its amount is identical. In figure 2a the demand is elastic so that the provider has to pay a larger part of the tax than the consumer. In figure 2b the demand is inelastic so that the consumer pays most of the tax. In both examples the quantity sold is lower than in the situation without taxes. The tax revenue is represented by the dashed areas in the figures. It is calculated by multiplying the quantity with the tax amount as shown in equation:

$$\text{tax revenue} = \text{quantity} \cdot \text{tax size} \tag{4}$$

Increasing taxes make goods more expensive leading to a reduced quantity of traded goods. The resulting two effects are described in the following: (i) *Effect 1:* By increasing the size of the tax the tax revenue increases by each sold item. (ii) *Effect 2:* Increasing the size of the tax leads to reduced quantity because goods get more expensive. Consumers having lower willingness to pay than the price do not purchase the good any more. So some goods will not be sold and consequently no tax revenue is earned.

The Laffer Curve [25] visualizes these two effects. If the tax size is low then an increment of the tax size leads to an increment of the tax revenue. Thereby, Effect 1 dominates Effect 2. However, if the tax size is already very high, an increment of the tax size leads to a reduction of the tax revenue. Due to the high tax market participants leave the market leading to a reduced number of transactions. So Effect 2 dominates Effect 1.

IV. Evaluation by Simulation

A. Simulation Environment

CloudSim and the Bazaar-Extension [13] allow to simulate Bazaar-based Cloud markets. Now, we extended the Bazaar-Extension with the GreenCloudTax component. This simulation environment allows to create market participants,

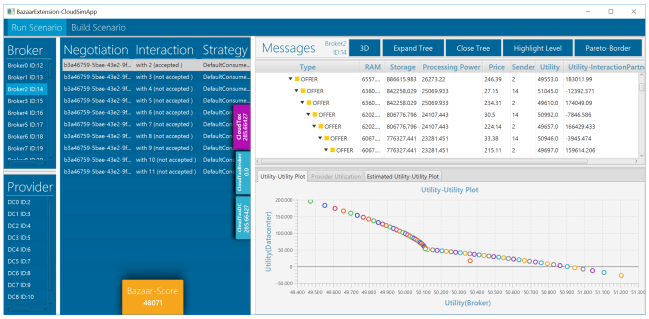


Figure 3: Simulation environment for simulating taxes including the GreenCloudTax

add a negotiation strategy to them, add an *GreenCloudTax system* to the market and analyze the resulting market outcomes. A screenshot of our simulation environment is shown in figure 3. The left side shows the market participants attending the market. There are consumers (brokers) and providers. By selecting a market participant you see all its negotiations in the second column. By selecting a negotiation all offers exchanged during negotiation can be seen on the right side which are exchanged. They are shown as tree list and utility-utility plot. Utility functions are used by market participants for ranking offers - for more information about utility function see [30]. The plot shows on the ordinate the utility of the provider (datacenter) and on the abscissa the utility of the consumer. The government's tax revenue of the executed scenario is shown in the violate box.

B. *GreenCloudTax Use Case*

To show how the GreenCloudTax model affects the Cloud market we present as use case a market scenario with 50 brokers and 10 providers (datacenters). For fostering comparability of the different tax systems which we will analyse within this use case we create providers which have the identical capacity - each server is able to host 10 brokers (consumers). Further, we assume some typical configurations such as a homogeneous server infrastructure of providers. The first provider runs only ASUSTek servers as described in the first row in table III, the second provider runs only the Acer Incorported server as described in the second row and so on. In table III the servers and consequently the providers show different energy efficiency (ssj_ops metric). We simulated Bazaar-based markets. Thereby we used the well know consumer and provider strategy introduced in [12].

C. *Consumer Strategy*

According to [12] consumers have a maximum as well as a minimum value for each characteristic of the traded good. Thus, in case of virtual machines consumers have maximum and minimum values for processing power, storage, RAM and price. Bilateral negotiation strategies have to describe (i) which offers are accepted, and (ii) if the offers are not accepted, how are counteroffers created.

Creation of counteroffers: Counteroffers are denoted with $O^t_{a\to b}$ whereby a is the sender and b is the receiver of the offer. In [12] the following strategy is suggested for creating counteroffers:

$$O^t_{a\to b}[i] = \begin{cases} min^a_i + \alpha^a_i(t)\cdot(max^a_i - min^a_i) \\ \text{if } V^a_i \text{ decreasing} \\ min^a_i + (1-\alpha^a_i(t))\cdot(max^a_i - min^a_i) \\ \text{if } V^a_i \text{ increasing} \end{cases} \tag{5}$$

i is a characteristic of the virtual machine, V^a_i is the value of characteristic i for sender a, max_i and min_i are the minimum and the maximum values for characteristic i and $\alpha^a_i(t)$ is a time dependent variable which has values between 0 and 1. The basic idea behind this strategy is that the consumers starts with offers which maximize their utility. In cases of virtual machines the initial offer will contain the following values: $max^a_{RAM}, max^a_{Storage}, max^a_{ProcessingPower}, min^a_{price}$. Over time the characteristics are modified until the deadline is reached. So the last offer of the consumer (if a binding agreement is not formed before) is: $min^a_{RAM}, min^a_{Storage}, min^a_{ProcessingPower}$ and max^a_{price}. $\alpha^a_i(t)$ determines how fast the initial max/min values are decreased/increased to final min/max values. Therefore [12] suggested to use polynomial or exponential functions. We used the polynomial function as shown in the following equation:

$$\alpha^a_i(t) = k^a_i + (1-k^a_i)\cdot\left(\frac{min(t,t_{max})}{{t_{max}}^{1/\beta}}\right) \tag{6}$$

t_{max} represents the deadline. We used the following setup: $\beta = 2$ and $k = 0$.

Offer acceptance conditions: Inspired by the offer acceptance conditions described in [12] consumers accept offers if the following condition is fulfilled: $UV_{O^t_{b\to a}} > UV_{O^{t+\epsilon}_{a\to b}}$. So a received offer $UV_{O^t_{b\to a}}$ is accepted by consumer a if the utility of the received offer exceeds the utility of the counteroffer, which would be created in response to the received offer according to equation 5. Precondition for applying this decision rule is the definition of a consumer utility function for calculating the utility. As [31] do not introduce a consumer utility function we used the following one inspired by [30] which considers basic economical principles:

$$\begin{aligned} UV_{con.} =& log(storage\cdot w_{storage}) + log(processingp.\cdot \\ & w_{\text{processing p.}}) + log(RAM\cdot w_{RAM}) + \\ & log(max_{price} - price)\cdot w_{price} \end{aligned} \tag{7}$$

D. *Provider Strategy*

The provider strategy for the creation of counteroffers is similar to the consumers strategy. In [12] the provider

Table II: Simulation parameters

Consumer			
Parameter	Value	Parameter	Value
w_{RAM}	0.01	$w_{\text{processing p.}}$	0.01
$w_{storage}$	0.01	w_{price}	0.97
min_{RAM}	3072 MB	max_{RAM}	7168 MB
$min_{\text{processing p.}}$	5000 MIPS	$max_{\text{processing p.}}$	30000 MIPS
$min_{Storage}$	102400 MB	$max_{Storage}$	1024000 MB
min_{price}	10\$-20\$	max_{price}	35\$-100\$
t_{max} (simulation clock)			7200
Provider			
Parameter	Value	Parameter	Value
A_{RAM}	0.8	$A_{\text{processing p.}}$	0.8
$A_{storage}$	0.8	w_{RAM}	0.5
$w_{storage}$	0.25	$w_{\text{processing p.}}$	0.25
MinRP$_{storage}$	0.000002\$-0.0000022\$	MaxRP$_{storage}$	0.00001\$-0.000011\$
MinRP$_{RAM}$	0.002\$-0.0022\$	MaxRP$_{RAM}$	0.03\$-0,033\$
MinRP$_{\text{processing p.}}$	0.0002\$-0.00022\$	MaxRP$_{\text{processing p.}}$	0.001\$-0.0011\$
t_{max} (simulation clock)			7200

strategy is responsible for suggesting a price for received offers. Therefore the provider calculates so called resource prices RP_{jt} for each resource characteristic j of the virtual machine (RAM, storage, processing power) at time t. The resource prices are time dependent as shown in the following. The provider has for each resource characteristic a maximum resource price ($MaxRP$) as well as a minimum resource price ($MinRP$). The structure of this equation is similar to the one in equation 5.

$$RP_{jt} = MinRP_j + \alpha RP_j(t)(MaxRP_j - MinRP_j) \quad (8)$$

$\alpha RP_j(t)$ is a time dependent factor taking values between 0 and 1. The authors of [12] suggest to use a polynomial function for calculating this factor as defined in the following:

$$\alpha RP_{jt} = IRP_j + (1 - IRP_j)\Big(\frac{min(t, t_{max})}{t_{max}}\Big)^{1/\beta_j} \quad (9)$$

IRP is an acronym for initial resource price. We used the $MaxRP$ as IRP. β can be calculated in two ways: The first one is called resource aware β while the second one is called priority oriented β. For the resource aware β we first calculate the share of the available resource A_j for the resource characteristic j so that we can calculate the average share of available resources: $\bar{A} = \frac{\sum_{j=1}^{m} A_j}{m}$. The resource aware β is then calculated as $\beta_j = e^{A_j - \bar{A}}$. For our simulation we assumed an equal utilization of all resources. The preference based β is calculated as $\beta_j = e^{1/n - w_j}$. n is the number of resources and w_j is the importance factor so that $\sum_{j=1}^{m} w_j = 1$.

The resource prices are calculated twice: one time using the resource aware β and one time using the preference based β. The two prices are combined for each resource using a weighted average:

$$RP_{jt} = RP_{jt}^{\text{resource aware } \beta} \cdot 0.5 + RP_{jt}^{\text{preference } \beta} \cdot 0.5 \quad (10)$$

At end, the resource prices are summarized to a final price $P_t = \sum_{j=1}^{m} RP_{jt} \cdot j$. Consumers can accept the price suggested by the provider and form a binding agreement, or respond with counteroffers. A decision rule for the provider which determines if an offer is accepted is not foreseen. Hence, only the consumer can create an agreement.

The rest of the used parameters are summarized in table II.

E. Simulation Setup

We simulated an idealized market as shown in figure 2 where the demand curve represents consumers with a different willingness to pay and the supply curve represents providers with different costs. This is reflected by the resource prices (provider) and the minimum and maximum prices (consumer) shown in table II. For the providers we created the resource prices proportional to their efficiency. So the provider running the most inefficient servers (i.e. ASUSTeK servers) - the first provider called P1 - has the lowest resource price while the provider which runs the most efficiency servers (i.e. Quanta servers) - the 10^{th} provider called P10 - has the highest resource price. Thereby, we assumed that acquisition costs of efficient servers are higher than the acquisition costs of inefficient servers leading to higher prices - the reduced energy costs of efficient servers can not compensate the higher acquisition costs.

For the evaluation we used three different tax systems:

(i) *Value added tax.* The value added tax uses a 10% tax rate which is calculated on the basis of the price.

(ii) *GreenCloudTax 1.* By using this tax system we combined the GreenCloudTax with the value added tax using equation 2. Thereby we calculated the energy efficient factor as following:

$$\begin{aligned}\text{server energy efficient factor} &= \\ (1 - \text{interpolation factor}) &\cdot \text{ecoMarkup}\end{aligned} \quad (11)$$

The interpolation factor is a number between 0 and 1 and reflects the energy efficiency of the underlying server infrastructure. We calculated it by normalizing the ssj_ops of server i as shown in the following. Thereby $ssj\_ops_{minimum}$ represents the ssj_ops most inefficient server. In our case this is the first server shown in table III. $ssj\_ops_{maximum}$ represents the ssj_ops of the most efficient server. This is the last server shown in table III.

$$\text{interpolation factor}_i = \frac{ssj\_ops_i - ssj\_ops_{\text{minimum}}}{ssj\_ops_{\text{maximum}} - ssj\_ops_{\text{minimum}}} \quad (12)$$

So the interpolation factor is 1 for the most efficient server and 0 for the most energy inefficient server. It can be used as a weight for the ecoMarkup, which controls how much the taxes are increased/decreased for the servers. We used a ecoMarkup of 1.3 of the GreenCloudTax 1.

(iii) *GreenCloudTax 2.* This tax system is identical to the previous tax system. However, we used an increased ecoMarkup of 2.1.

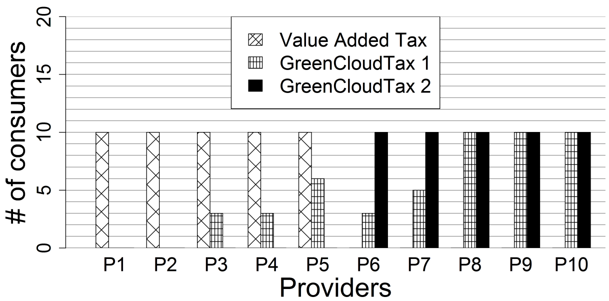


Figure 4: Simulation results - number of consumers hosted by the providers using different tax systems (10 is the capacity limit)

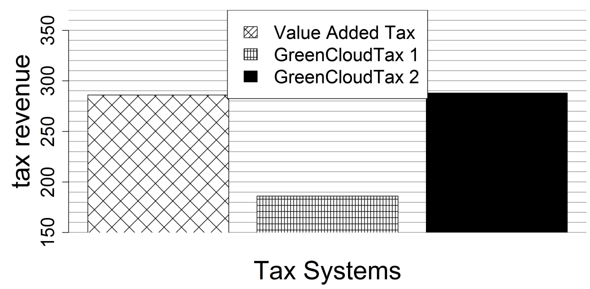


Figure 5: Tax revenues of different tax systems (zoom)

Table III: Server characteristics from SPEC benchmark [29]

Provider	System	ssj_ops/watt
P1	ASUS RS100-E5 (Xeon X3360, 2.83 GHz)	905
P2	Gateway GW1000-GW170 F1	1588
P3	1253Ra Datacenter Server	2106
P4	PRIMERGY TX150 S7 (Intel Xeon X3480)	2513
P5	Gateway GT150 F1(Intel Xeon X5670, 2.93 GHz)	2716
P6	B8228Y190X2-045V4H	3293
P7	Acer AC100	3741
P8	I IBM System x iDataPlex	5043
P9	PowerEdge C5220 (Intel Xeon E3-1265LV2)	6000
P10	QuantaGrid D51B-2U	11568

F. Simulation Results

We simulated the Cloud market with the three different tax systems. The simulation results are depicted in figure 4. Using the value added tax the providers which run the the most inefficient servers host all virtual machines. This is because they have lower prices (see simulation setup). The value added tax system does not give an incentive to consumers to switch to providers running energy efficient servers. Contrary, the GreenCloudTax 1 gives consumers an incentive to switch to more energy efficient providers: As figure 4 shows, consumer move from providers running inefficient servers to providers running efficient servers. This is because providers which have servers with a high energy efficiency are lower taxed than providers which have servers which are inefficient. GreenCloudTax 2 has a greater ecoMarkup than the GreenCloudTax 1. Hence, in the scenario the most energy efficient providers host all consumers while the energy inefficient servers are idle. This is because providers with inefficient servers are highly taxed resulting into high brutto prices.

According to [25] the government uses taxes not only to set incentives but also to get tax revenue. Hence the tax revenue gained by applying a certain tax system has to be considered too. The tax revenues of our simulation are illustrated in figure 5. It can be seen that the tax revenue of the value added tax and the GreenCloudTax 2 are approximately identical. The tax revenue of the GreenCloudTax 1 is lower. Using the GreenCloudTax 1 the increased tax on energy inefficient servers can not compensate the loss of taxes granted to providers running energy inefficient server. So by introducing this tax the government will loose money.

The discussed Laffer Curve in section III shows that the tax revenue which the tax authority can gain is limited. This has to be considered during the design of tax systems. For example we executed a simulation scenario using an ecoMarkup of 20 which destroys the market: only the provider running the most efficient servers is able to sell virtual machines as it is not taxed according to the used GreenCloudTax system. All the other providers are unable to sell a virtual machine due to the high taxes leading to high prices. The analysis of the tax revenue is a promising topic for further research.

V. Conclusion and Further Research

Datacenters used for running Clouds are significant consumers of energy. While most of the research focuses on the technical engineering of existing protocols, architectures or algorithms the research in applying or modify economical concepts - especially taxes - to increase energy efficiency is limited. In this paper we designed the GreenCloudTax for virtual machines. This tax system proposes a new tax model for virtual machines based on the energy efficiency of the underlying hosting servers. For analyzing our GreenCloudTax model we developed a novel simulation environment based on CloudSim's Bazaar-Extension. It allows to simulate Bazaar-based markets where different tax systems such as the GreenCloudTax model can be tested. This paper is a first step towards the GreenCloudTax. In our further research we will analyze the tax revenue as well as it effects on ecological variables such as carbon footprint. Moreover, we will investigate more complex tax sytems which take into acount the used type of computing resource. The management of the simulation with models [32] seems to be promising too.

References

[1] W. Mach and E. Schikuta, "A generic negotiation and renegotiation framework for consumer-provider contracting of

web services," in *Proceedings of the 14th International Conference on Information Integration and Web-based Applications & Services*. ACM, 2012, pp. 348–351.

[2] T. Mastelic, A. Oleksiak, H. Claussen, I. Brandic, J. Pierson, and A. V. Vasilakos, "Cloud computing: Survey on energy efficiency," *ACM Comput. Surv.*, vol. 47, no. 2, pp. 33:1–33:36, 2014.

[3] Y. Sverdlik, "Heres How Much Energy All US Data Centers Consume," *DataCenterKnolwedge. com. June*, vol. 27, 2016.

[4] A. Shehabi, S. J. Smith, N. Horner, I. Azevedo, R. Brown, J. Koomey, E. Masanet, D. Sartor, M. Herrlin, and W. Lintner, "United States data center energy usage report," *Lawrence Berkeley National Laboratory, Berkeley, California. LBNL-1005775 Page*, vol. 4, 2016.

[5] M. Hinz, C. C. Miers, M. A. Pillon, and G. P. Koslovski, "A cost model for iaas clouds based on virtual machine energy consumption," in *Proceedings of the XII Brazilian Symposium Information Systems: Information Systems in the Cloud Computing Era*, ser. SBSI 2016. Porto Alegre, Brazil: Brazilian Computer Society, 2016, pp. 19:136–19:143.

[6] W. Mach and E. Schikuta, "A consumer-provider cloud cost model considering variable cost," in *IEEE Ninth International Conference on Dependable, Autonomic and Secure Computing, DASC 2011, 12-14 December 2011, Sydney, Australia*, 2011, pp. 628–635.

[7] B. Pittl, W. Mach, and E. Schikuta, "Cloudtax: A cloudsim-extension for simulating tax systems on cloud markets," in *2016 IEEE International Conference on Cloud Computing Technology and Science, CloudCom 2016, Luxembourg, December 12-15, 2016*, 2016, pp. 35–42.

[8] Amazon, "Amazon EC2-Spot-Instances." [Online]. Available: http://aws.amazon.com/de/ec2/purchasing-options/spot-instances/

[9] P. Samimi, Y. Teimouri, and M. Mukhtar, "A combinatorial double auction resource allocation model in cloud computing," *Information Sciences*, vol. 357, pp. 201–216, 2016.

[10] P. Bonacquisto, G. D. Modica, G. Petralia, and O. Tomarchio, "A strategy to optimize resource allocation in auction-based cloud markets," in *IEEE International Conference on Services Computing, SCC 2014, Anchorage, AK, USA, June 27 - July 2, 2014*, 2014, pp. 339–346.

[11] B. Pittl, W. Mach, and E. Schikuta, "A classification of autonomous bilateral cloud SLA negotiation strategies," in *Proceedings of the 18th International Conference on Information Integration and Web-based Applications and Services, iiWAS 2016, Singapore*, 2016, pp. 379–388.

[12] A. V. Dastjerdi and R. Buyya, "An autonomous time-dependent SLA negotiation strategy for cloud computing," *The Computer Journal*, pp. 3202–3216, 2015.

[13] B. Pittl, W. Mach, and E. Schikuta, "Bazaar-extension: A cloudsim extension for simulating negotiation based resource allocations," in *IEEE International Conference on Services Computing, SCC 2016, San Francisco, CA, USA, June 27 - July 2, 2016*, 2016, pp. 427–434.

[14] D. C. Kilper, G. Atkinson, S. K. Korotky, S. Goyal, P. Vetter, D. Suvakovic, and O. Blume, "Power trends in communication networks," *IEEE Journal of Selected Topics in Quantum Electronics*, vol. 17, no. 2, pp. 275–284, 2011.

[15] L. Liu, H. Wang, X. Liu, X. Jin, W. B. He, Q. B. Wang, and Y. Chen, "Greencloud: A new architecture for green data center," in *Proceedings of the 6th International Conference Industry Session on Autonomic Computing and Communications Industry Session*, ser. ICAC-INDST '09. New York, NY, USA: ACM, 2009, pp. 29–38.

[16] D. Borgetto, H. Casanova, G. Da Costa, and J.-M. Pierson, "Energy-aware service allocation," *Future Generation Computer Systems*, vol. 28, no. 5, pp. 769–779, 2012.

[17] K. Ma, R. Sun, and A. Abraham, "Toward a lightweight framework for monitoring public clouds," in *Computational Aspects of Social Networks (CASoN), 2012 Fourth International Conference on*. IEEE, 2012, pp. 361–365.

[18] J. Dean and S. Ghemawat, "MapReduce: simplified data processing on large clusters," *Communications of the ACM*, vol. 51, no. 1, pp. 107–113, 2008.

[19] W. Mach and E. Schikuta, "Toward an economic and energy-aware cloud cost model," *Concurrency and Computation: Practice and Experience*, vol. 25, no. 18, pp. 2471–2487, 2013.

[20] A.-H. Mohsenian-Rad and A. Leon-Garcia, "Energy-information transmission tradeoff in green cloud computing," *Carbon*, vol. 100, no. 2010, p. 2011, 2010.

[21] T. T. Huu and C.-K. Tham, "An auction-based resource allocation model for green cloud computing," in *Cloud Engineering (IC2E), 2013 IEEE International Conference on*. IEEE, 2013, pp. 269–278.

[22] N. Deng, C. Stewart, D. Gmach, M. Arlitt, and J. Kelley, "Adaptive green hosting," in *Proceedings of the 9th international conference on Autonomic computing*. ACM, 2012, pp. 135–144.

[23] Z. Liu, A. Wierman, Y. Chen, B. Razon, and N. Chen, "Data center demand response: Avoiding the coincident peak via workload shifting and local generation," *Performance Evaluation*, vol. 70, no. 10, pp. 770–791, 2013.

[24] Z. Zhou, F. Liu, Z. Li, and H. Jin, "When smart grid meets geo-distributed cloud: An auction approach to datacenter demand response," in *Computer Communications (INFOCOM), 2015 IEEE Conference on*. IEEE, 2015, pp. 2650–2658.

[25] N. G. Mankiw, *Principles of Microeconomics*. Thomson/South-Western, 2004.

[26] P. Mell, T. Grance, and others, "The NIST definition of cloud computing," *NIST*, 2011. [Online]. Available: http://faculty.winthrop.edu/domanm/csci411/Handouts/NIST.pdf

[27] R. Buyya, S. Pandey, and C. Vecchiola, "Cloudbus toolkit for market-oriented cloud computing," in *IEEE International Conference on Cloud Computing*. Springer, 2009, pp. 24–44.

[28] E. M. Elnozahy, M. Kistler, and R. Rajamony, "Energy-efficient server clusters," in *International Workshop on Power-Aware Computer Systems*. Springer, 2002, pp. 179–197.

[29] SPEC, "Server Efficiency Rating Tool (SERT)." [Online]. Available: http://www.spec.org/sert/

[30] B. Pittl, W. Mach, and E. Schikuta, "A negotiation-based resource allocation model in iaas-markets," in *8th IEEE/ACM International Conference on Utility and Cloud Computing, UCC 2015, Limassol, Cyprus, December 7-10, 2015*, 2015, pp. 55–64.

[31] A. V. Dastjerdi and R. Buyya, "An autonomous reliability-aware negotiation strategy for cloud computing environments," in *Cluster, Cloud and Grid Computing (CCGrid), 2012 12th IEEE/ACM International Symposium on*. IEEE, 2012, pp. 284–291.

[32] D. Karagiannis, R. A. Buchmann, P. Burzynski, U. Reimer, and M. Walch, "Fundamental conceptual modeling languages in omilab," in *Domain-Specific Conceptual Modeling*. Springer, 2016, pp. 3–30.