Coalition Formation and Combinatorial Auctions; Applications to Self-organization and Self-management in Utility Computing

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July 1, 2014

Abstract

We propose a coalition formation protocol based on combinatorial auctions. The protocol consists of two stages. The first one exploits spatial locality for the formation of sub-coalitions of supply agents; the second stage is based on a modified proxy-based clock algorithm and has two phases, a clock phase and a proxy phase. The clock phase supports price discovery; in the second phase a proxy conducts multiple rounds of a combinatorial auction for the package of services requested by each client. The resulting coalition includes all sub-coalitions with winning bids. The protocol strikes a balance between low-cost services for cloud clients and a decent profit for the service providers. We also report the results of an empirical investigation into the protocol.

1 Motivation and Related Work

Motivation. In the past years, large farms of computing and storage servers have been assembled to support several cloud delivery models including Software as a Service (SaaS), Platform as a Service (PaaS), and Infrastructure as a Service (IaaS). In such systems users pay only for computing resources they use, similarly to other utilities such as electricity and water.

A cloud consists of warehouse-scale computers (WSCs) [5]. A WSC connects 50,000 to 100,000 servers and uses a hierarchy of networks. The servers are housed in racks; typically, the 48 servers in a rack are connected by a 48 port Gigabit Ethernet switch. The switch has two to eight up-links which go to higher level switches in the network hierarchy [10].

The communication in a cloud may be supported in the future by interconnection networks which dynamically adapt to the volume of the traffic such as InfiniBand.

Computer clouds raise the question of how far we can push the limits of composability of computing and communication systems, while still being able to support effective policies for resource management and their implementation mechanisms. The software, the glue allowing us to build increasingly more complex systems, consists of more and more layers thus, the challenge of controlling large-scale systems is amplified.

The basic policies for cloud resource management must support: (i) admission control; (ii) capacity allocation; (iii) load balancing; (iv) energy optimization, and (v) quality of service (QoS) [16]. Current mechanisms for the implementation of these policies are not scalable and require detailed models of the system and accurate information about the state of individual servers.

An alternative is to consider market-based solutions. We argue that combinatorial auctions and coalition formation can be successfully exploited by self-organization and self-management of complex systems supporting utility computing [17]. The contribution of this paper is a protocol for coalition formation based on combinatorial auctions in response to reservation requests from a very large population of users.

Algorithms for coalition formation based on combinatorial auctions are at the heart of the cloud ecosys-
Related work. According to the Merriam-Webster dictionary a coalition is “the action or process of joining together with another or others for a common purpose.” Coalition formation is of interest in several areas including electronic commerce, AI, and robotics [14][15][18][20].

Auctions provide a widely used mechanism for resource allocation [7][9][24]. Among the numerous applications of auctions are: the auctioning of airport take-off and landing slots, spectrum licensing by the Federal Communication Commission (FCC), and industrial procurement.

The interest of the economics and the computer science communities in coalition formation and in combinatorial auctions has been amplified by the emergence of large-scale electronic markets, by robotics, and by other AI applications. The availability of powerful computational engines has supported the development of increasingly more complex algorithms for combinatorial auctions and for coalition formation.

A combinatorial coalition formation problem is described in [15]. The paper assumes that a seller has a price schedule for each item. The larger the quantity requested, the lower is the price a buyer has to pay for each item; thus, buyers can take advantage of price discounts by forming coalitions. A similar assumption is adopted by the authors of [14] who investigate systems where the negotiations among deliberate agents are not feasible due to the scale of the system. The paper proposes a macroscopic model and derives a set of differential equations describing the evolution in time of coalitions with a different number of participants. The results show that even a low rate of leaving away participants allows a coalition to achieve a steady state.

A combinatorial auction is one where a buyer requires simultaneous access to a package of goods. The auction allows the seller to obtain the maximum feasible profit for the auctioned goods; it is organized by an auctioneer for every request of a consumer. A proxy is an intermediary who collects individual bids from the buyers participating at an auction, computes the total cost of the package from the bids, and communicates this price to the auctioneer. A vast literature, [1][2][3][8][13][19][23] covers multiple aspects of combinatorial auctions including bidding incentives, stability, equilibrium, algorithm testing, and algorithm optimality.

We discuss briefly the objectives and the challenges of our work in Section 2 then review basic concepts regarding combinatorial auctions in Section 3. Algorithms for the formation of sub-coalitions and for clock-proxy auction are the subjects of Sections 4 and 5 respectively. The results of a simulation experiment and the conclusions of our work are presented in Sections 6 and 7.

2 Objectives and Challenges

The problem we address is to create an environment where a very large user community can access a set of services offered by a cloud infrastructure consisting of a very large number of autonomous servers. The main objectives of our approach, the challenges they pose, and the means to address these challenges are:

1. Support efficient, reliable, and adaptive cloud resource management mechanisms for enforcing global system objectives. The challenge: overcome limitations of existing mechanisms, be scalable, fault-tolerant, and agile. The solution: a reservation system based on self-organization and self-management.

2. Allow individual users to obtain packages of low-cost services and, at the same time guarantee that the service providers make a decent profit. The challenge: balance two conflicting goals. The solution: periodically organize auctions for services.

3. Encourage autonomous servers to form limited lifetime sub-coalitions offering services which demand resources above and beyond those available from individual members. The challenge: the sub-coalition members must reach consensus on policies, service conditions, and service pricing. The solution: devise a process based on consensus algorithms.

4. Reduce computing and communication costs and satisfy QoS requirements. The challenge: guarantee spatial and temporal locality. The solution: exploit hierarchical organization of the cloud infrastructure to guarantee spatial locality during sub-coalition formation and ensure that auctions favor service demands for larger number of time slots.

These objectives are correlated with one another and aim to address critical problems for the cloud ecosystem of the future. The solution discussed in this paper involves concepts, policies, and algorithms from several well-established areas of economics and computer science: (1) self-organization and self-management of complex systems; (2) auction theory and practice; (3) consensus policies and mechanisms; and (4) system organization and computer architecture. We review basic concepts in these areas using domain-specific terminology in Sections 3 and 4. We have to map related concepts to one another; for example, buyers and sellers in auction theory become clients and servers in the context of system organization and management.

Self-organization and self-management. Informally, self-organization means synergetic activities of elements when no single element acts as a coordinator and the global patterns of behavior are distributed. Self-management means that individuals can effectively set
their own goals, make decisions on how to achieve those goals, plan and schedule their activities independently, and evaluate the progress towards these goals. In the context of our discussion, self-management is in fact a limit case of distributed control; it allows autonomous servers to decide their own fate, and do this effectively. Self-management can in principle lead to faster and more accurate resource management decisions. Scalability is another strong argument for self-management.

Control theory tells us that accurate state information and a tight feedback loop are the critical elements for effective control of a system. In the case of a hierarchical organization, the quality of state information degrades as we move up in the hierarchy; only local information about the state of a platform is by definition accurate. Moreover, this information is volatile, it must be used promptly because the state changes rather rapidly. This line of reasoning shows that only a distributed management scheme, when most decisions are made locally, has a chance of working well.

Self-management as a result of auctions eliminates the need for a system model and requires only local thus, more accurate information about the state of individual components [17]. This approach has the potential of optimizing the use of resources and allow Cloud Service Providers (CSPs) to offer services at a lower cost for the consumers.

**Challenges of self-management.** Though the virtues of self-management have long been recognized, there is, to our knowledge, no cloud computing infrastructure, or large-scale computing or communication system based on self-organizing principles or self-management. This is in itself proof of the difficulties to apply these concepts in practice. Indeed, self-management has to be coupled with some mechanisms for coalition formation allowing autonomous agents, the servers, to act in concert. Autonomous systems have to cooperate to guarantee QoS by distributing and balancing the workload, replicate services to increase reliability, and implement other global system policies. Cooperation means that individual systems have to partially surrender their autonomy.

Tensions between local and global objectives exist. These tensions manifest themselves in questions such as: How to balance the individual cost of autonomous servers with global goals e.g., maximizing the CSP payoff? How to adapt the price for services to the actual demand? How to find an equilibrium between system reconfiguration and continuous system availability?

Moreover, cooperation must reflect the particular characteristics of the physical organization. Locality is important; indeed, communication across multiple layers of the networking infrastructure is less desirable as the latency increases and the bandwidth decreases.

Self-organization cannot occur instantaneously in an adaptive system. It is critical to give the autonomous cloud platforms interconnected by a hierarchy of networks the time to form coalitions in response to services requests thus, self-management requires an effective reservation system. Reservations are ubiquitous for systems offering services to a large customer population, e.g., airline ticketing, chains of hotels, and so on. Existing clouds, e.g., the Amazon Web Services, offer both reservations and spot access, with spot access rates lower than those for reservations.

**PC²P - a proxy-based combinatorial auction and coalition formation protocol.** This protocol is designed for large farms of heterogenous systems supporting utility computing. The auction we propose adapts ideas from the coalition formation discussed in [15] and the clock-proxy-auction [3].

In the auction and agent coalition literature the bidders are the buyers and there is one seller; the items auctioned are distinct. In our case the items to be sold are cloud resources packaged as services. There is also a time dimension, each service can be offered for one or more time slots and the service providers, assumed to be autonomous, have to form coalitions subject to locality constraints when assembling the resources required by reservation requests. These elements make a direct application of traditional auctions infeasible.

Combinatorial auctions are organized periodically in response to service reservation requests for a wide range of services and for very large user populations. A reservation request specifies the type of services, the amount of resources needed, and the time slots. The process encourages the formation of sub-coalitions of servers that can act as a group based on their physical proximity and past history of successful collaborations.

Auctions consist of two stages. In the first stage, a consensus algorithm is used to assemble sub-coalitions of servers and to determine the price per unit of service, vCPU, agreeable to the members of sub-coalition. The second stage resembles a clock-proxy auction with two phases, a clock phase and a multiple round proxy phase.

The PC²P protocol is scalable and enjoys all the other advantages of self-organization and self-management strategies. The PC²P protocol supports the creation of packages tailored to the actual needs of a user. In contrast, existing systems, e.g., the EC2 (Elastic Compute Cloud) service provided by AWS (Amazon Web Services), present a client with a limited menu of resource combinations.

We believe that autonomous and rational supplier agents motivated by self-interest can collaborate to respond to the demands of clients which request packages of resources. We expect the process to reach a Nash equilibrium, as each supplier agent chooses the best group to join and the optimal price to ask for its services based on the information about the actions of other agents.

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2 vCPU like the ECU (Elastic Compute Unit) is a measure of computing capacity. Recently Amazon Web Services changed from ECU to vCPU and it is yet to define the specification for the new measure; one ECU used to represent the equivalent CPU capacity of a 1.0-1.2 GHz 2007 Opteron or 2007 Xeon processor.
Combinatorial Auctions

The protocol we present in Section 5 borrows ideas from several combinatorial auctions supporting package bidding [8]. Package bidding assumes that a seller offers \( N \) different types of items. A buyer bids for packages of items. A package is a vector of integers \( Z = \{z_1, z_2, \ldots, z_N\} \) which indicates the quantity of each item in the package; the price of items is given by \( M = \{m_1, m_2, \ldots, m_N\} \).

Package bidding can be traced back to generalized Vickerey auctions based on the Vickerey-Clarke-Groves mechanisms [7] [9] [24]. In Vickerey auctions a bidder reports its entire demand schedule. The auctioneer then selects the allocation which maximizes the total value of the package and requires a bidder to pay the lowest bid it would have made to win its portion of the final allocation, considering all other bids.

In a Vickerey auction the bidder’s interest is best served when bids based on her actual demand schedule regardless of other bids. It turns out that this type of auction has fundamental flaws [1]: even when the items auctioned are of a high value the revenues it generates can be very low or even zero. Vulnerability to fake-name bids and collusion and high costs for determining valuations are other problems of this type of auction and have motivated the search for other auctioning protocols.

Simultaneous ascending auctions have multiple rounds and provide feedback to the bidders. The identity of the standing high-bidders and the amounts of the standing high bids for each item are disclosed after each round. The bidding starts out high and declines because the rise in prices discourages bidders. Large bidders can withhold their true demand to reduce prices; this undesirable behavior has been observed in FCC auctions.

In an ascending package auction (APA) there are \( K \) participants identified by an index, \( k = 0 \) is the seller and \( k = 1, 2, \ldots, K \) are the buyers [1]. Each buyer has a valuation vector \( v_t = (v_t(z), z \in [0, M]) \); \( v_k(z) \) represents the value of package \( z \) to the bidder \( k \). Some of the rules for this type of auction are: all bids are firm, a bid cannot be reduced or withdrawn; the auctioneer identifies after each round the set of the bids that maximize the total price, the so-called provisional winning bids. The auction ends when a new round fails to elicit new bids; the provisional winning bids become the winners of the auction.

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In an ascending package auction the bidder can be deterred from bidding for the package she really desires by the threat that competitors could drive prices up; this would threaten the equilibrium. This problem does not exist in ascending proxy auctions when each bidder instructs a proxy agent to bid on her behalf [1]. The proxy accepts as input the bidder’s valuation profile and bids following a “sincere strategy.” Nash equilibrium can be reached when the bid increments are negligibly small [1].

In a clock auction the auctioneer announces prices and the bidders indicate the quantities they wish to buy at the current price. When the demand for an item increases, so does its price until the there is no excess demand. On the other hand, when the offering exceeds the demand, the price decreases [1]. In a clock auction the bidding agents see only aggregate information, the price at a given time, and this eliminates collusive strategies and interactions among bidding agents. The auction is monotonic, the amounts auctioned decrease continually and this guarantees that the auction eventually terminates. When the price of a package can be computed as the sum of products of prices and quantities it is said that auction benefits from linear pricing.

A common activity rule for clock auctions is monotonicity in quantity - as prices rise, quantities cannot increase. This activity rule dictates that bids should be consistent with a downward slopping demand function. In the ascending proxy auction the bidders report to the proxy the types of items in the package they bid on, the quantities and the price; then the proxies submit bids for the package to the auctioneer.

The clock-proxy-auction is a hybrid auction based on an iterative process with two phases [3]. A clock phase is followed by a proxy round. During the proxy round the bidders report the values they have submitted to the proxy which in turn submit bids for the package to the auctioneer. A bidder has a single opportunity to report the quantity and the price to the proxy, bid withdrawals are not allowed, and the bids are mutually exclusive. The auctioneer then selects the winning bids that maximize the seller’s profit.

The revealed preference activity rule [3] relates the price vectors, \( p^t \) and \( p^s \), and the quantities \( q^t \) and \( q^s \) proposed by a sincere bidder at times \( t \) and \( s \), respectively,

\[
(p^t - p^s) \cdot (q^t - q^s) \leq 0. \tag{2}
\]

Indeed, if \( v(q) \) is the value of package \( q \) for the bidder, the bidder prefers \( q^t \) to \( q^s \) when

\[
v(q^t) - p^t q^t \geq v(q^s) - p^t q^s
\]

and the bidder prefers \( q^s \) to \( q^t \) when

\[
v(q^s) - p^s q^s \geq v(q^t) - p^s q^t
\]

Adding inequalities 3 and 4 we obtain the activity rule in Equation 2.
4 Sub-coalition Formation and Consensus Algorithms

In a clustered organization the cluster leader manages the formation of the sub-coalition offering services in each auction. A sub-coalition consists of servers willing to provide a set of services. The members of a sub-coalition are located in “proximity” to one another and thus benefit from lower latency and higher bandwidth. A consensus algorithm allows the members of a sub-coalition to elect a leader who can negotiate on their behalf; they also agree on the price for the services and resources its members are willing to offer during the auction. We now justify the need for sub-coalitions, present a consensus algorithm, and introduce the agreement regarding the price for services provided by a sub-coalition.

Why form sub-coalitions? Sub-coalitions support aggregation of resources and of services. Resource aggregation is necessary because a single platform may not be able to provide the resources demanded by a cloud client. Service aggregation is necessary to reduce the number of agents involved in an auction thus, the time and space requirements of the auctioning algorithms.

A third motivation is to reduce the computing and communication costs. This requires resource management mechanisms that exploit the organization of the cloud infrastructure. Spatial and temporal locality are critical requirements for the functionality of the protocol being proposed here.

Spatial locality means that an auction should favor packages which involve servers in the same sub-coalition; spatial locality reduces the communication costs. Temporal locality means that an auction should favor reservations consisting of a run of consecutive slots. This reduces the overhead involved in saving partial results and then reloading them at a later time. The auctions provide incentives for packages that use services offered by one sub-coalition over a run of consecutive slots.

A consensus algorithm. A cluster leader uses a Paxos-type algorithm [11, 12] to determine the price range the sub-coalition can agree on. The basic Paxos considers several types of entities: (a) client, an agent that issues a request and waits for a response; (b) proposer, an agent with the mission to advocate a request from a client, convince the acceptors to agree on the value proposed by a client, and to act as a coordinator moving the protocol forward in case of conflicts; (c) acceptor, an agent acting as the fault-tolerant “memory” of the protocol; (d) learner, an agent acting as the replication factor of the protocol and taking action once a request has been agreed upon; and finally (e) the leader, a distinguished proposer. A quorum is a subset of all acceptors.

The flow of messages can be described as follows [12]: “clients send messages to a leader; during normal operations the leader receives the client’s command, assigns it a new command number i, and then begins the i-th instance of the consensus algorithm by sending messages to a set of acceptor processes.” A proposal consists of a pair, (pn, v), with pn a unique proposal number and v a proposed value; multiple proposals may propose the same value v. A value v is chosen if a simple majority of acceptors have accepted it. We need to guarantee that at most one value can be chosen, otherwise there is no consensus. The phases of the algorithm are:

1. Proposal preparation: a proposer (the leader) sends a proposal (pn = j, v). The proposer chooses a proposal number pn = j and sends a prepare message to a majority of acceptors requesting: (a) that a proposal with pn < j should not be accepted; (b) the pn < j of the highest number proposal already accepted by each acceptor.

2. Proposal promise: An acceptor must remember the proposal number of the highest proposal number it has ever accepted as well as the highest proposal number it has ever responded to. The acceptor can accept a proposal with pn = j if and only if it has not responded to a prepare request with pn > j; if it has already replied to a prepare request for a proposal with pn > j then it should not reply. Since they are indistinguishable, lost messages are treated as an acceptor that chooses not to respond.

3. Accept request: if the majority of acceptors respond, then the proposer chooses the value v of the proposal as follows: (a) the value v of the highest proposal number selected from all the responses; (b) an arbitrary value if no proposal was issued by any of the proposers. The proposer sends an accept request message to a quorum of acceptors including (pn = j, v).

4. Accept: If an acceptor receives an accept message for a proposal with the proposal number pn = j it must accept it, if and only if, it has not already promised to consider proposals with a pn > j. If it accepts the proposal it should register the value v and send an accept message to the proposer and to every learner; if it does not accept the proposal it should ignore the request.

Figure [17] illustrates the flow of messages for the consensus protocol. By merging the three roles, proposer, acceptor, and learner, the protocol “collapses” into an efficient client-master-replica style protocol.

Reaching agreement regarding the price for services. In our case, the suppliers, the autonomous servers able and willing to respond to a request for service reservations, play the role of both clients and acceptors. They propose a price per unit of service and, eventually, agree on one of the proposals. The cluster leader coordinates the consensus procedure.

Now we provide more detail on the sub-coalition formation process. A supply agent, Ck,i, wishing to join
sub-coalition $C_k$ provides the leader with two parameters, $q_{k,i}$ the quantity and $c_{k,i}$ the supplier’s internal cost per unit of service. We assume that the members of sub-coalition $C_k$, \{C_{k,1}, C_{k,2}, \ldots, C_{k,n_k}\}, are listed in the order of their internal costs per unit of service

$$c_{k,1} \leq c_{k,2} \ldots \leq c_{k,n_k-1} \leq c_{k,n_k}$$

The price for the unit of service the coalition chooses should satisfy the condition:

$$p_k \geq c_{k,n_k}$$

Then the value, $V_k$, of sub-coalition $C_k$ is defined as the difference between the price of the package auctioned by $C_k$ and the internal costs of the individual members

$$V_k = p_k \sum_{i=1}^{n_k} q_{k,i} - \sum_{i=1}^{n_k} q_{k,i} c_{k,i}$$

The value per unit of service of sub-coalition $C_k$ and the reward or the individual payoff of the agent $C_{k,i}$ are, respectively,

$$v_k = \frac{V_k}{\sum_{i=1}^{n_k} q_{k,i}}$$

and

$$r_{k,i} = q_{k,i}(p_k - c_{k,i})$$

A payoff division is a vector reflecting the financial gains of individual members of $C_k$

$$\mathcal{R}_k = \{r_{k,1}, r_{k,2}, \ldots, r_{k,n_k}\}$$

The core of a sub-coalition is the collection of all payoff divisions such that $r_{k,i} > 0$ $\forall i \in \{1, n_k\}$.

The sub-coalition $C_k$ is said to be stable in the core if the corresponding payoff vector $\mathcal{R}_k$ is in the core. The condition given by Equation 6 guaranties stability in the core. The leader communicates $c_{k,n_k}$ to the members of the sub-coalition and requests proposals for the sub-coalition target value. The agreed target value determines the price for the particular service. The total number of messages exchanged to establish the consensus in a sub-coalition with $n_k$ members, including the leader, is $N_k^{msg} \leq 8 \times (n_k - 1)$.
A Reservation System Based on a Combinatorial Auction Protocol

The protocol introduced in this section assumes a clustered organization of the cloud infrastructure and targets primarily the IaaS cloud delivery model represented by Amazon Web Services (AWS). Reservation systems are used by CSPs. For example, AWS supports reservations as well as spot allocation and offers a limited number of instance families, including M3 (general purpose), C3 (compute optimized), R3 (memory optimized), I2 (storage optimized), G2 (GPU) and so on. An instance is a package of system resources; for example, the c3.8xlarge instance provides 32 vCPU, 60 GiB of memory, and $2 \times 320$ GB of SSD storage.

The combinatorial auction protocol is inspired by the clock-proxy auction [3]. The clock-proxy auction has a clock phase, where the price discovery takes place, and a proxy phase, when bids for packages are entertained. In the original clock-proxy auction there is one seller and multiple buyers who bid for packages of goods. For example, the airways spectrum in the US is auctioned by the FCC and communication companies bid for licenses. A service is characterized by sub-coalitions of autonomous servers and the bidders pay the prices they committed to during the clock phase. Our protocol supports auctioning service packages; a package consists of combinations of services in one or more time slots. The items sold are services advertised by sub-coalitions of autonomous servers and the bidders are the cloud users. Each service is characterized by

1. A type describing the resources offered and the conditions for service,
2. The time slots when the service is available.

Protocol specification. The terms used to describe the protocol are discussed next. An allocation slot (AS) is a period of fixed duration, e.g., one hour, that can be auctioned. An auction, $A^t$, is organized at time $t$ if there are pending reservation requests which require immediate attention. Figure 2 shows two consecutive auctions at times $t$ and $s$; during the first slot of auction $A^t$ new reservation requests are received and the allocation slot $AS^t$ is not fully covered; this slot becomes $AS^s$ for $A^s$.

A service $A$ is described by a relatively small number of attributes, $\{a_1, a_2, \ldots\}$. Each attribute $a_i$ can take a number of distinct values, $v_i = \{v_{i,1}, v_{i,2}, \ldots\}$. For example, an attribute could be “architecture” with two values “32-bit” and “64-bit”; another attribute could be “organization” with values “vN” (von Neumann), “DF” (data-flow), or “GPU” (graphics co-processor).

Call $S^t$ the set of services the clients want to reserve during auction $A^t$

$$S^t = \{S^t_1, S^t_2, \ldots, S^t_{\nu^t}\} \quad \text{with} \quad S^t_i = [sId, (a_j, v_{j,k})] \quad (10)$$

A reservation bundle, $\alpha^t_{i,j} \subset S^t$, is the set of services requested by client $i$ in slot $j$ of auction $A^t$

$$\alpha^t_{i,j} = \{(S^t_{i,j,1}, r^t_{i,j,1}), (S^t_{i,j,2}, r^t_{i,j,2}), \ldots\} \quad (11)$$

with $r^t_{i,j,l}$ a measure of the quantity; for example, if the attribute is “CPU cycles” the quantity is the number of ECUs.

An advertised bundle, $\beta^t_{k,l} \subset S^t$, is the set of services advertised by sub-coalition $k$ in slot $j$ of auction $A^t$

$$\beta^t_{k,l} = \{(S^t_{k,j,1}, q^t_{k,j,1}, p^t_{k,1}), (S^t_{k,j,2}, q^t_{k,j,2}, p^k,2)\ldots\} \quad (12)$$

with $q^t_{k,j,l}$ a measure of the quantity of service $l$ and $p^t_{k,1}$ the price per ECU of service $S^t_l$ determined by sub-coalition $k$. A package, $P^t_i$ is a set of reservations for services requested by client $i$ for slots $j_1, j_2, \ldots$ during auction $A^t$.

$$P^t_i = \{\alpha^t_{i,j_1}, \alpha^t_{i,j_2}, \ldots\} \quad (13)$$

The clock phase. Figure 3 illustrates the basic idea of a clock phase: the auctioneer announces prices and the bidders indicate the quantities they wish to buy at the current price. When the demand for an item increases, so does its price until there is no excess demand; on the other hand, when the offering exceeds the demand, the price decreases.

During the clock phase of auction $A^t$ the price discovery is done for each time slot and for each type of service; a clock runs for each one of the $\nu^t$ slots and for each one of the $\nu^t$ services. Next we describe the clock phase for service $S^t_j$ in slot $j$. Assume that there are $n$ sub-coalitions $C = \{C_1, C_2, \ldots, C_n\}$ offering the service and $m$ requests for reservations from clients $D = \{D_1, D_2, \ldots, D_m\}$.

A clock auction starts at clock time $t = 0$ and at price per unit of service for $S^t_j$

$$p^0_{l,k} = \min_{c_k} \{p_{k,l}\} \quad (14)$$

Call $C_0$ the available capacity at this price and $D_0$ the demand for service $S^t_j$ offered at price $p^0_{l,k}$ in slot $j$

$$C_0 = \sum_{k=1}^{n} q^t_{k,j,l} \quad \text{and} \quad D_0 = \sum_{i=1}^{m} r^t_{i,j,l}. \quad (15)$$

If $C_0 < D_0$ the clock $c$ advances and the next price per unit of service is

$$p^1_{l,k} = p^0_{l,k} + I \quad (16)$$

with $I$ the price increment decided at the beginning of auction. There is an ample discussion in the literature regarding the size of the price increment; if too small, the duration of the clock phase increases, if too large, it introduces incentives for gaming [3].
The process is repeated at the next clock value starting with the new price. The clock phase for service $S_j^t$ and slot $j$ terminates when there is no more demand.

**The proxy phase.** In a traditional clock-proxy auction the bidders do not bid directly, they report to a proxy the price and the quantity of each item in the package they desire. The proxy then bids in an ascending package auction.

In our application, the proxy phase of the auction consists of multiple rounds. The auction favors bids for long runs of consecutive slots when the service is provided by the same sub-coalition. This strategy is designed to exploit temporal and spatial locality.

The auction starts with the longest runs and the lowest price per slot and proceeds with increasingly shorter runs and diminished incentives. Once a run of consecutive slots is the subject of a provisional winning bid, all shorter runs of slots for that particular service are removed from the sub-coalition offerings.

During the first round only the longest run of consecutive slots for each one of the services offered by the participating sub-coalitions is auctioned and only bidders that have committed to any of the slots of the run are allowed to bid. The price per slot for the entire run is the lowest price for any slot of the run the bidder has committed to during the clock phase of the auction. If there are multiple bids for service $S_j^t$ the **provisional winner** is the one providing the largest revenue for the sub-coalition offering the service.

If $\kappa_j^t$ is the longest run of consecutive slots for service
Figure 3: The clock phase for service $S^t_i$ and slot $j$. The starting price is $p_i^0$ given by Equation 14. The clock advances and the price increases from $p_c$ to $p_c + I$ when the available capacity at that price given by Equation 15 is exhausted; the demand is given by Equation 15.

$S^t_i$ auctioned in the first round then, in the second round, a shorter run of $\kappa_i - 1$ slots is auctioned. The price for the entire run equals the second lowest price for any slot of the run the bidder has committed to during the clock phase of the auction times the number of the time slots in the run.

The length of the consecutive slot runs auctioned decreases and the incentives diminish after each round. The preliminary rounds end with the auction of a single slot for each service. At the end of the preliminary round each bidder is required to offer the price for the slot committed to during the clock phase. Figure 4 depicts a plausible snapshot at the end of the preliminary rounds of the proxy phase when four services $S_1, S_2, S_3$ and $S_4$, are offered and shows the provisional winners for service $S_4$.

During the final round the bidders reveal the packages they want to reserve; these packages include only the provisional winners from the preliminary slots. Once all provisional winning bids for services in a reservation request are known, the auctioneer chooses the package that best matches the consumer’s needs and, at the same time maximizes the profit for the cloud service provider. The coalition for a reservation request consists of the set of sub-coalitions that provide the services in the winning package.

In this auction all bids are firm, they cannot be withdrawn. The auction is monotonic, the length of runs of consecutive slots auctioned decreases continually; this guarantees that the auction eventually terminates. Linear pricing guarantees that the price of any package can be computed with ease.

The **effectiveness of the protocol** is captured by several metrics including:

- The *customer satisfaction index* - percentage of reservation requests fully or partially satisfied in each reservation slot given the total number of requests.
- The *service mismatch index* - percentage of services requested but not offered in each reservation slot given the total number of services in that slot.
- The *service success index* - percentage of services used in each reservation slot given all services offered in that slot.
- The *capacity allocation index* - percentage of the capacity offered but not auctioned in each reservation slot given the capacity offered in that slot.
- The *overbidding factor* - percentage of slots with a provisional winner that have not been included in any package given all slots offered at the beginning of the auction.
- The *temporal fragmentation index* - percentage of services successfully auctioned in non-consecutive slots given all services successfully auctioned.
- The *additional profit index* - percentage of additional profit of sub-coalitions involved in the auction (the difference of the actual price obtained at the auction and the price demanded by the sub-coalition) relative to the price demanded by the sub-coalition.

**Limitations and vulnerabilities.** The protocol is fairly complex and has at least one vulnerability. A bidder may be the provisional winner of services in slots not included in its winning package; such services will remain unassigned during the current auction. A solution is to penalize excess bidding activity and charge the bidder a percentage of the costs for these services. Another alternative is to include, in a reservation request, a set of “substitute services” for a service $S_i$. Then, during the last round of the proxy phase, the auctioneer could try to match services having provisional winners with unsatisfied requests for services.

The capacity offered, but not auctioned in each slot is available for *spot allocation* thus, it has the potential to be used, rather than being wasted. The capacity of a sub-coalition left uncommitted at the end of the auction $A^t_i$ for $AS^t_i$, the first slot of the auction, is then available for *spot allocation* at a price equal to $p_{K,t}$, while the free capacity in slots starting with $AS^t_2$ can be offered at the next auction if this auction takes place before the beginning of the slot. This capacity is measured by the *spot allocation opportunity index*. 


6 Protocol Analysis and Evaluation

We report on the results of our simulation experiments to gain some insight into the proxy phase of the clock-proxy auction of the PC²P protocol. The system we wish to evaluate requires the description of the environment in which the auction takes place, the reservation requests, and the services offered.

(a) The environment description includes:

- \( n \) - the number of sub-coalitions offering services in this round.
- \( m \) - the number of clients.
- \( \kappa \) - the number of slots auctioned.

(b) The description of the package \( j \) requested by client \( i \) includes:

1. \( \alpha_i^n \) - the number of services in the package.
2. For each service \( S_k \) the slots desired, ordered by the length of consecutive slots.
3. \( r_{k,j} \) - the quantity of service \( S_k \) in slot \( j \).
4. \( p_{k,j} \) - the price per unit of service for slot \( j \) if client \( i \) was a provisional winner of that slot during the clock phase.

(c) The description of the service \( S_k \) provided by sub-coalition \( C_k \) includes:

1. \( \gamma_k \) - the largest run of consecutive slots for each offered service \( S_k \).
2. The profile of the service \( S_k \) - the slots offered ordered by the length of consecutive slots, when it is available.
3. \( q_{k,j} \) - the quantity of service \( S_k \) offered in slot \( j \).
4. \( p_k \) - the price per unit of service offered by sub-coalition \( C_k \).

For simplicity, we assume that a sub-coalition offers one service only and the number of services is \( \nu < n \). We also assume that all platforms have a maximum capacity of 100 vCPUs and that \( q_{k,j} \), the quantity of service \( S_k \) offered for auction, and \( r_{k,j} \), the quantity of \( S_k \) requested in slot \( j \) are the same for all the slots of an offered/requested run. The number of slots auctioned is fixed, \( \kappa = 50 \).

The range and the distribution of parameters for the protocol evaluation are chosen to represent typical cases. The parameters of the simulation are random variables with a uniform distribution:

- The number of sub-coalitions and clients requesting reservations, \( n \) and \( m \), respectively; the interval is \([200 – 250]\).
- The number of services offered and requested \( \nu \); the interval is \([10 – 20]\).
- The number of clients bidding for each service in a given slot; the interval is \([0 – 4]\).
- The capacity offered for auction for a service in a given slot; the interval is \([60 – 90]\) ECUs.
- The services offered by a coalition; the interval is \([1 – \nu]\).
- The number of consecutive slots a service is offered in; the interval is \([1 – \kappa]\).
- The number of services in the package requested by a client; the interval is \([1 – 3]\).
- The number of consecutive slots of the services in the package requested by a client; the interval is \([1 – \kappa]\).

We also randomly choose the slots when the client is the provisional winner. The evaluation process consists of the following steps:

A. Initialization.

B. Preliminary rounds. Carry out \( \gamma \) preliminary rounds with \( \gamma = \max_k \gamma_k \).

1. In the first preliminary round auction auction \( \kappa_1 \) slots of service \( S_1 \), \( \kappa_2 \) slots of service \( S_2 \), and so on.
2. Identify the first slot of each run and the reservation request that best matches the offer.
3. Identify the provisional winners if such matches exist and remove the corresponding runs from the set of available runs. A match exists if the run consists of the same number of slots or is one slot longer than requested and if the capacity offered is at least the one required by the reservation request. For services without a match, remove the last slot, add both the shorter run and the last slot to the list of available runs.
4. Continue this process until only single slots are available.

C. Final round. In this round we:

1. Identify the packages for each client and if multiple packages exist determine the one which best matches the request.
2. Compute the cost for the winning package for each client.

Figures 5(a)-(e) show several performance metrics including the customer satisfaction index, the service mismatch index, the auction success ratio, the spot opportunity index, the temporal fragmentation index, and the
Figure 5: Proxy phase of an auction with 50 time slots. Indices of: (a) Customer satisfaction; (b) Service mismatch; (c) Auction success; (d) Spot allocation opportunity; (e) Temporal fragmentation; (f) Capacity allocation.
capacity allocation index. The simulation covers 50 time slots. A time slot could be a fraction of an hour or one or more hours; for example, an AWS time slot is one hour.

The 5% confidence intervals for the mean of all performance metrics are computed for 25 batches each one of 200 realization of each random variable. The simulation times are 6.4 seconds for 2,000 runs and 11.7 seconds for 5,000 runs. The confidence intervals are rather tight; this indicates that the performance of the protocol is relatively stable for the range of parameters explored in this evaluation.

The auction success rate is high, typically above 80%. The initial low auction success rate is an artifact of the manner we conducted the simulation; we picked up randomly the service start up time. The spot allocation opportunity index is in turn correlated with the auction success rate and shows that a significant fraction of the capacity is available for spot allocation. This result is correlated with the one in Figure 5(f) which shows that on average some 50% of the server capacity is not allocated by the reservation system and so is available for spot contention.

Gartner Research [22] reports that the average server utilization in large data-centers is 18%, while the utilization of x86 servers is even lower, 12%. These results confirm earlier estimations that the average server utilization is in the 10% – 30% range [4]. A 2010 survey [6] reports that idle or under utilized servers contribute 11 million tones of unnecessary CO2 emissions each year and that the total yearly cost for the idle servers is $19 billion.

A reservation system covering 50% of the server capacity is probably the most significant result; it shows that self-management based on auctions can drastically improve server utilization. We live in a world of limited resources and cloud over-provisioning is not sustainable either economically or environmentally.

The service mismatch index is fairly high, typically in the 50% range and it is above 60% in a few slots. The customer satisfaction is correlated with the service mismatch and typically is in the region of 50%. In a realistic scenario, when sub-coalitions maintain statistics regarding the services offered and avoid offering services unlikely to be demanded by the cloud users, the service mismatch would not affect the performance of the algorithm. Temporal fragmentation, though rather low, is undesirable. The overbidding factor $64 \pm 2.93\%$ is another indication that the protocol needs to be fine tuned.

Self-organization cannot occur instantaneously in an adaptive system and this simple observation has important consequences. It is critical to give autonomous cloud platforms, interconnected by a hierarchy of networks, the time to form coalitions in response to services demanded. Thus, self-management requires an effective reservation system and our results indicate that the reservation protocol is working well.

7 Conclusions

The main reasons for the success of cloud computing are: low service cost, convenience, elimination of the need for a local computing infrastructure, and elasticity. Elasticity is the ability to deliver the resources needed by applications with peak demands considerably larger than the average one.

Elasticity is achieved by means of over-provisioning - assembly of cloud infrastructures with considerably more resources than those necessary to respond to the average service demands. As a result, the average server utilization in a cloud is abysmally low. A reservation system which guarantees a high degree of resource utilization and, at the same time, accommodates spot allocations could lower cloud energy consumption and operating costs and increase the level of customer satisfaction.

Self-organization and self-management offer an appealing alternative to existing cloud resource management policies; they have the potential to significantly alter the cloud computing landscape. The virtues of self-organization, self-management, and self-healing in the design of complex systems have been praised but, to our knowledge, there is no cloud infrastructure implementing them. Self-organization would enable the operation of heterogeneous cloud environments including many-core systems, workflow engines, GPUs and other types of co-processors. Heterogeneous clouds could provide a better environment than existing clouds for applications which require fine-grain parallelism and could also allow “big data” applications to run efficiently.

Self-organization could support cloud interoperability based on a small number of standards/protocols. Indeed, sub-coalitions of platforms from different clouds could participate in auctions organized by one of them, provided that they use a common description of the services offered. Self-management could reduce the operating costs of heterogeneous clouds by optimizing resource utilization and provide a scalable solution to cloud resource management. At the same time, a self-managed cloud will be able to deliver services tailored to the precise needs of the cloud clients, and at lower cost.

So far, pragmatic means for the adoption of self-organization principles for large-scale computing and communication systems have eluded us. A main reason for this state of affairs is that self-management has to be coupled with some mechanisms for cooperation; these mechanisms should allow autonomous servers, to act in concert towards global system goals. Cooperation means that individual systems have to partially surrender their autonomy. Striking a balance between autonomy and cooperation is a challenging task, it requires a fresh look at the mechanics of self-organization and the practical means to achieve it.

Algorithms for coalition formation based on combinatorial auctions are at the heart of the cloud ecosystem we propose. The path we chose seems logical as
auctions have been successfully used for resource management in the past. Auctions do not require a model of the system, while traditional resource management strategies do. The auction-based protocol is scalable, and the computations can be done efficiently, though the computational algorithms involved are often fairly complex.

The challenge is to adapt the well-researched algorithms for auctions to a very different environment. Instead of a single seller and many buyers, we have large sets of sellers and buyers. The sellers are the autonomous service providers which have to form coalitions subject to locality constraints when assembling the resources demanded by the service requests of the buyers. In the combinatorial auctions discussed in the literature, the buyers form coalitions to take advantage of price discounts when buying in large quantities. For us, a service can be offered for one or more discrete time slots whereas traditional auctions assume a continuous time interval; this is the case of auctions for airport landing slots or for airwaves bandwidth.

The results reported in Section 6 indicate that the performance of the protocol is relatively stable for the range of parameters explored in our evaluation. The protocol leads to a higher server utilization and it seems reasonable to expect that a fine-tuned version of the protocol could further improve this critical performance measure.

The future work should address several problems revealed by this investigation. First, the sub-coalition formation should be based on historic data to reduce the service mismatch ratio. At the same time, the protocol has to address the effects of overbidding, the process which allows a client to become a provisional winner of one or more service slots and then, in the final round failing to acquire some of them. This situation is critical for the first slot of an auction as the next auctions could find clients for these slots. A more difficult problem is the temporal fragmentation which does not seem to have an obvious solution.

A successful system must evolve in time, otherwise it will become a victim of its own success. Dynamically formed sub-coalitions coupled with a well-tuned auction could be at the heart of the cloud ecosystems of the future.

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