Adaptive Control for Cloud Systems

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***Abstract*—Energy efficiency has triggered significant interests in ICT areas. Maintaining best possible QoS services as well as reducing energy consumptions is new research area in cloud systems. Cognitive Packet Network (CPN) has been used in many applications with respect to cloud system in previous researches. It also shows its ability to tackle the energy saving problems since it can explore a network and take on-line measurements of those nodes that smart packets travelled. Hence, two aspects can be studied. Firstly, it is to find optimal paths for transmitting packets regarding to energy consumption and declared QoS. Secondly, it is worth to focus on adaptively task dispatching schemes on energy efficiency for cloud systems.**

I. Introduction

Cloud computing is a style of computing in which dynamically scalable and often provided as a service over the Internet to clients who do not have knowledge of the technology infrastructure in the "could". Could computing enables techniques, such as hardware virtualisation, distributed and parallelised computing, web services thanks to characteristics of scalability, elasticity. Scalability indicates ability to either handle increasing amount of works in a graceful manner or to be enlarged. Elasticity also indicates ability to apply a quantifiable methodology that allows for the basis of an adaptive introspection within a real time infrastructure. In order to achieve certain a Quality of Service (QoS) with respect to customer care evaluations and technological evaluations, cloud systems have to be controlled and monitored, such that system is capable of self-management to overcome growing complexity of computing system [1]. Therefore, the cloud system should built up a highly performance and optimised environment to deliver services to clients. The goals can be achieved by means of parallel computing, load balancing and job scheduling.

The Cognitive Packet Network (CPN) is a QoS-deriven routing protocol invented by professor E. Gelenbe. Users or applications are able to declare QoS requirements that CPN provides best possible QoS by adaptively routing traffic with online sensing and measurement [2], [3], [4], [5], [6]. Intelligence is constructed in smart packets (SPs), rather than at nodes or in the protocols. Dumb packets (DPs) carry payloads and conduct measurements. Acknowledgements (ACKs) fetch back the information discovered by SPs. Specified QoS which is declared by users, such as *Jitter, Response Time, Energy Consumption*, or a combinations with a goal function are used in CPN algorithm in which SPs explore the best possible route with respect to specified QoS, by means of reinforcement learning random neural network (RL-RNN) [7], [8]. At each node, an installed RNN corresponds to a QoS, and each neuron of a RNN represents the choice to forward a given packet to a outgoing link. The weights of the corresponding RNN are updated by Reinforcement Learning by taking measurements stored in the node's mailbox. The most excited neutron is chosen, such that the given packet is forwarded to corresponding output link [4]. CPN and CPN-based algorithm have been widely used in many applications such as load balancing, job scheduling [9], [10], [11], [12].

Nowadays, energy efficiency have been more and more important issue in ICT, especially due to economic cost of electricity in data centres, servers and network routers [13], [14], [15], [16], [17], [18]. Therefore, maintaining the best possible services while reducing energy consumption for cloud system has triggering significant interests to researchers. An allocated scheme that minimising the average response time as well as reducing energy consumption has been proposed with probabilistic approach in [19]. The simplest method to reduce energy consumption is to concentrate computation on a certain amount of resources such that under-utilised machine can be turned off or hibernated [20]. However, it contradicts the QoS and Service Level Agreement (SLA) as increasing response time degrades performance. Thus, a goal function

$$C_{job} = aW_{job} + bJ_{job} \tag{1}$$

has to be dynamically optimised. For instance, W_{job} and J_{job} can be response time and energy consumption per job respectively. The a and b are weights representing importance of performance and energy consumption to a given job. Hence, researches can be studied on optimising cloud energy consumption and performance and through the Internet.

II. Random Neural Network

The random neural network (RNN) was first introduced by professor E. Gelenbe in 1989 [21], [22], [23] and has been used in a number of application such as Image Processing [24] and Deep Learning [25].

The RNN is a recurrent model with Poisson external signal arrivals, exponential signal emission intervals, Markovian signal movement between neurons. Furthermore, it has "product form" solution that provides analytical expressions for the system states.

In a open random network, it exists n interconnected neurons where *positive* and *negative* signals circulate. The state of the network at time t is a vector $\mathbf{k}(t) = [k_1(t), k_2(t), \ldots, k_n(t)]$ where $k_i(t)$ is a non-negative integer random variable representing *potential* of i-th neuron at time t. The potential is added by 1 when a positive signal arrives whereas it is reduced by 1 when a negative signal arrives or no effect if potential is zero. A i-th neuron is excited if its potential is greater than zero and it fires with exponentially distributed random variable with rate r_i.

It may fire positive signal to j-th neuron with probability of p_{ij}^+ or negative signal to j-th neuron with probability of p_{ij}^-. Moreover, signal fired by excited i-th neuron can also leave network with probability d_i. Hence, one has

$$\sum_{j=1}^{n} p_{ij}^+ + p_{ij}^- + d_i = 1 \quad \text{for} \quad i = 1, \ldots, n \tag{2}$$

The positive and negative signals arriving i-th neuron can also be external arrivals with Poisson process rate Λ_i and λ_i respectively. Let weight $\omega_{ij}^+ = r_i p_{ij}^+ \geq 0$ and $\omega_{ij}^- = r_i p_{ij}^- \geq 0$ denote fire rate of positive and negative signal from i-th to j-th neuron respectively. Let q_i denotes the quantity

$$q_i = \frac{\lambda_i^+}{r_i + \lambda_i^-} \quad \text{for} \quad i = 1, \ldots, n \tag{3}$$

where

$$\lambda_i^+ = \sum_{j=1}^{n} q_j \omega_{ji}^+ + \Lambda_i, \quad \lambda_i^- = \sum_{j=1}^{n} q_j \omega_{ji}^- + \lambda_i \tag{4}$$

Let $\mathbf{k} = [k_1, \ldots, k_n]$ be a particular vector and $p(k)$ denote the stationary probability distribution, such that

$$p(k) = \lim_{t \to \infty} Prob[\mathbf{k}(t) = \mathbf{k}] \tag{5}$$

It has been proved in [21] that if a non-negative solution $\{\lambda_i^+, \lambda_i^-\}$ exits for equation 3 and 4 such that $q_i \in [0, 1]$, one has product form solution:

$$p(k) = \prod_{i=1}^{n} (1 - q_i) q_i^{k_i} \tag{6}$$

Thanks to convergence property, non-liner equation 3 can be solved numerically by means of fixed-point iteration that

$$q_i^{m+1} \leftarrow \min \left\{ 1, \frac{\sum_j q_j^m \omega_{ji}^+ + \Lambda_i}{r_i + \sum_j q_j^m \omega_{ji}^- + \lambda_i} \right\} \tag{7}$$

with initial condition $q_i^0 = 0.5$ for $i = 1, \ldots, n$.

III. Cognitive Packet Network

CPN is a adaptive packet routing protocol with enhanced monitoring and self-improvement capabilities that address QoS by using adaptive techniques based on on-line measurements [2], [3], [4], [5], [6]. The CPN consists three types of packets:

- SPs used for discovery and classified for certain QoS requirement;
- DPs carrying the payload;
- ACKs bringing back information discovery by SPs.

SPs are generated to explore best possible QoS routes to some CPN node according to assigned goal functions or to discover parts of the networks state such as location of certain fixed or mobile nodes, power levels at nodes, topology, path and their QoS metrics. Moreover, in order to avoid overloading the system and explore all possible routes, each SP make a random routing decision with small probability, saying 5%, at each hop. Additionally, the mailbox (MB), a short-term memory store in a router, stores received information from SPs. Moreover, there could be more than one MB in a router since a certain class of SPs using one certain MB. SPs read corresponding MBs and execute their code via the node base on information in MBs, update MBs in the node and decided next movement. Furthermore, a SP stores the router it follows as well as "timestamp" regarding the local time at which it visited a node.

An ACK packet that contains measurement information collected by the SP is generated when the SP arrives destination. The ACK travels back to the source with reverse path travelled by the SP. At the source, the route and QoS measurement data stored in ACK are cached in a table, the dumb packet route repository (DPRR). The last path cached in DPRR is the one that DPs follow.

Reinforcement learning random neural networks [8] and Genetic algorithms [26] are two main algorithms that are used in a node to help SPs to explore path and take measurements. The RL algorithm based on RNN is trigged by SP's arrivals. Each RNN installed in a node represents a class of QoS and a source-destination pair, where each neuron represents a decision to choose a known output like for a SP. Hence the number of neuron N is equal to the number of output links. A output link is chosen if its corresponding neuron is the most excited. The RL-RNN algorithm installed in CPN has been proposed in [27]. The RL algorithm changes the weight ω_{ij}^+ and ω_{ij}^- to reward or penalise the neuron based on the level of goal satisfaction measured on the corresponding output link. Hence it is also related to whether the SP achieves it QoS goal. The RL algorithm can be found in [28], [29].

IV. Recent Researches

A. Lan Wang and Professor Gelenbe's work

In recent researches, Lan Wang and professor Gelenbe studied and designed protocols for real-time traffic [11], intercontinental overlays [10] and job allocation of cloud servers using CPN [9], [30], [31], [32], [33].

In [11], the designed protocol uses QoS goal to match the specified requirements of real-time packet transmission in the presence of background traffic. It presents a series of causes and effects that help researches to design and understand the networks with respect to real-time traffic. In [10], a learning based network overlay improves the QoS experienced by long-haul intercontinental packet communications. The internet-scale experiments using CPN routing and an intercontinental overlay has been done. It uses small monitoring effort and significant QoS to improve the conventional Internet protocol which does not achieve optimal performance.

The rest Lan Wang and professor Gelenbe researches are related to cloud computing. The online QoS aware adaptive task allocation schemes have been proposed. In the scheme, they use reinforcement learning and a sensible allocation algorithm that dispatch arriving workload into sub-systems with respect processing capabilities. Moreover, adaptive job distribution in local and remote clouds are also studied using similar approaches.

In these recent researches, they are forced on specified QoS requirement of *Response time* or end-to-end *Delay*. However, the energy consumption has not been concerned. Therefore, I would like to focus on a specified QoS requirement which is energy consumption. Using CPN based routing, energy consumption can be minimised as well as providing good QoS.

B. Lent and Professor Gelenbe's work

Ricaddo Lent and professor Gelenbe have also done a number of researches on energy-efficient cloud computing [15]. In [19], it proposed a simple and realistic formulae, $\Pi = A + B\rho$ for power consumption relation where A is the power consumption of the processing unit when it is idle and B is the rate at which it increases as a function of the load factor ρ. λ and $E[S]$ are denoted to average arrival rate of jobs and average services time respectively. Hence, energy consumption per job is

$$J_{job} = \frac{A}{\lambda} + BE[S] \tag{8}$$

Assuming Poisson arrivals and exponential services times for jobs in a single server queue, it also posed a simple cost function for energy consumption and QoS (response time),

$$C_{job} = a\frac{E[S]}{1 - \lambda E[S]} + bJ_{job} \tag{9}$$

where b and a are weights regarding to energy consumption and QoS respectively. Analytically and experimentally, a operating point that reduces energy energy and maintains good QoS is found. Moreover, it extends related research on job allocation in N heterogeneous sub-system.

Note in [19], it only studied the case that processor is constantly on. Therefore, in [20], it investigated systems that are on and off since the simplest means for saving energy is to turn off the processor and networks units when they are not being used, provided one can restart them rapidly when requests for computation or communication services do arrive. In a single server queue, it is assumed Poisson arrivals and general services times. It concluded that putting a system intermittently to sleep can reduce overall energy consumption.

In [34], [35], it proposed a mathematical model of energy and QoS at the local cloud and remote cloud to investigate rational selection of best service providers among all possibilities with respect to energy consumption and QoS. It also addressed board area of research directions. There are related problem that I am going to investigate:

1 Investigating optimum operation point of each sub-system in an interconnected network of servers when sub-system can be turn on and off.

2 Investigating optimum operation point for an organisation of servers as a set of specialised facilities with multiple specialised units.

3 Investigating best job allocation scheme for multiple job types.

C. Other Related Researches

In [36], [37], professor Gelenbe and T. Mahmoodi proposed a novel CPN-based Energy Aware Routing Protocol (EARP) that minimises the total consumed power in the network but also remains requested QoS. It derived a total power cost function on the path going from the one node to its destination of a certain flow. With respect to corresponding cost function, reinforcement learning algorithm is triggered to find best routing. In [38], [39], the gradient optimising algorithm was used to improve EARP. From each EARP path we can generate a new path using the gradient algorithm, and it was observed a significant energy saving.

In [40], [41], it developed a new bilateral QoS differentiation between pairs of communicating nodes. Traffic volume asymmetry between the received and sent data is used to trigger changes in QoS and therefore, lower traffic requires short delay QoS, while higher traffic rate requires loss minimisation. The developed scheme that allows a network node A to communicate with another network node B using multiple paths which simultaneously supports different QoS criteria.

V. Objectives for the First Year

In the first year, I would like to focus on energy efficient cloud management. Maintaining the best possible QoS as well as reducing energy consumption can be investigated.

A. Routing Optimisation on Energy Efficiency

Firstly, it is to find a optimal routing with respect to energy consumption and declared QoS. In a source-destination pair, a packet travels through several nodes that may consume different amount of energy to serve a packet. The problem is to find a path that consumes minimum energy without SLA violations. CPN has potential to tackle the problem since route carried by an ACK, along with QoS data are stored in DPRR, such that genetic algorithm is able to modify, filter and combine the paths found by SPs to generate new undiscovered, valid source-destination paths and choose optimal one regarding energy consumption and QoS.

Furthermore, as in a source, its DPRR provides route and QoS measurement discovered by CPN, the discovered network can be considered as a graph containing vertices (nodes) connected by weighted edges (QoS measurement). Then, it is possible to find a non-directed and non-cycle subset of the graph that connects all vertices with minimum total sum of weights. Therefore, a minimum total energy consumptions (weights) without SLA violations can be found for the discovered network. It can be considered as a minimum spanning tree (MST) problem [42].

Suppose the number of vertices is V and the number edges is E, then Kruskal's algorithm for finding minimum spanning tree is introduced:

1. Sort all the edges in non-decreasing order of their weight.
2. Pick the smallest edge. Check if it forms a cycle with the spanning tree formed so far. If cycle is not formed, include this edge. Else, discard it.
3. Repeat step 2 until there are $V - 1$ edges in the spanning tree.

The Kruskal's algorithm is a greedy algorithm with overall time complexity of $O(E \log E)$ or $O(E \log V)$. Time required for sorting edges is $O(E \log E)$. After sorting, find-union algorithm is applied to check if a cycle is formed. It takes at most $O(\log V)$ time. Therefore, the overall time required is $O(E \log E + E \log V)$. However, the E is less than V^2. Hence, the overall time complexity is $O(E \log E)$ or $O(E \log V)$.

B. Tasks Allocation on Energy Efficiency

Secondly, it is to adaptively dispatch tasks to the cloud with respect to energy efficiency. It allows an extension of CPN-based algorithm to adaptively distribute workloads to available servers such that energy consumption is reduced without degrading performance. Some researches [19] proposed workloads in a computer system can be tuned so that an optimum trade-off is achieved between the response time the system provides and the energy cost per job that is being executed. There are still much researches to be done. Consider both execution time and energy saving as parts of goal function stated in equation 1, such that an optimal tasks allocation scheme based on-line measurement could be a research direction.

Moreover, it is worth to study the situations that on-line measurement provides delayed or degraded information for users to make decisions to dispatch tasks. Since it is inevitable that information about loads and subsystems or system characteristics will be delayed or degraded in larger distribution system, such as Gird and Cloud Computing.

VI. Conclusion

In this initial research plan, we discuss the general area of controlling cloud systems with respect to energy efficiency. Two main tools, the RNN and CPN are briefly discussed. They help to explore and measure the states of the network. The objectives for the first year are to seek energy optimal paths to transmit packets without SLA violations and study adaptive job allocation schemes on energy efficiency.

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