Networking-Computing resource allocation for Hard Real-Time Green Cloud applications

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Wireless Days '14 - November 12-14, 2014 - Rio de Janeiro, Brazil

Abstract

Performing real-time applications on top of virtualized cloud systems requires that the overall per-job delay due to the in-cloud processing is upper bounded in a hard way. This opens the question about the optimal dynamic joint allocation of both computing and networking resources hosted in the Cloud. This is the focus of this contribution, where we develop in closed-form *the optimal* fully scalable *energy-saving scheduler for the joint allocation of the task sizes, communication rates and processing rates in delay-constrained Clouds composed by multiple frequency-scalable parallel Virtual Machines (VMs).*

Introduction and Cloud Architecture

The goal of the Green Cloud Computing is to develop models and techniques for the integrated management of computing-communication virtualized platforms, so as to provide QoS, robustness and energy efficiency. The resulting challenge is to minimize the energy usage and still meet the QoS requirements of the supported applications. About the QoS support, an energy-saving *joint* allocation of both networking and computing resources hosted in the Cloud is needed. This is the focus of this paper, where the contrasting objectives of minimizing *both* networking and computing energies in *real-time* applications running on top of virtualized Clouds are cast in the form of a suitable *constrained* optimization problem.

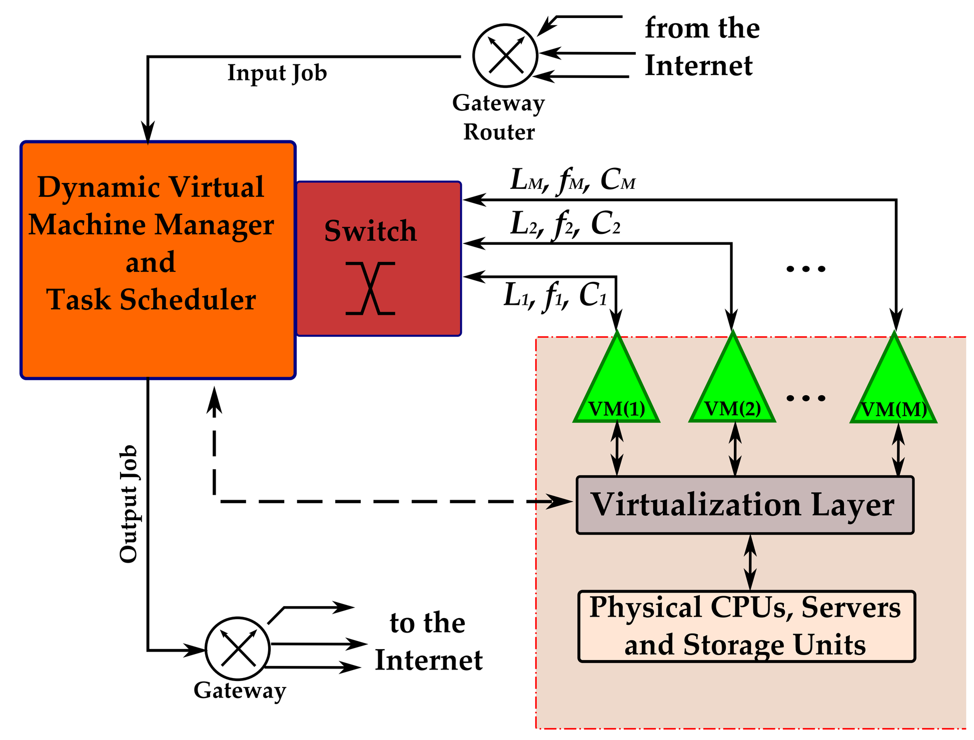

Fig. 1: The Considered NetDC architcture.

Problem setup and optimal resource allocation

Task sizes: $\{L_i, i = 1, \ldots, M\}$ communication rates $\{C_i, i = 1, \ldots, M\}$ and computing rates $\{f_i, i = 1, \ldots, M\}$, of the DVFS-enabled VMs, so as to minimize the overall computing-plus-networking energy:

$$\mathcal{E}_{tot} \triangleq \sum_{i=1}^{M} \mathcal{E}_c(i) + \sum_{i=1}^{M} \mathcal{E}^{net}(i) \ \ (Joule), \tag{1}$$

On the worst case of sequential activation, the corresponding delay-constraint becomes:

$$\left[\sum_{i=1}^{M} 2D(i)\right] + \max_{i=1,\ldots,M}\{\Delta(i)\} \leq T_t. \tag{2}$$

Posing $\Delta_{max} \triangleq \max_{i=1,\ldots,M}\{\Delta(i)\}(sec)$, the constrained optimization problem (COP):

$$\min_{\{C_i, f_i, L_i\}} \sum_{i=1}^{M} \Psi_i\left(\frac{f_i}{f_i^{\max}}\right)\mathcal{E}_i^{\max} + k_e\left(f_i - f_i^0\right)^2 + 2P_i^{net}\left(\frac{L_i}{C_i}\right) \tag{3.1}$$

$$\text{s.t.:} \ \ (L_i)/f_i \leq \Delta(i), \ \ i = 1, \ldots, M, \tag{3.2}$$

$$\sum_{i=1}^{M} L_i = L_t, \qquad \sum_{i=1}^{M} 2D(i) + \Delta_{max} \leq T_t, \tag{3.3}$$

$$0 \leq f_i \leq f_i^{max}; L_i \geq 0; 0 \leq C_i \leq C_{max}, \ i = 1, \ldots, M. \tag{3.4}$$

f_i is the variable to be optimized, while f_i^0 describes the "current" state of the VM(i)

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Effects of the networking powers and Hibernation

To evaluate the effect on $\mathcal{E}_{tot}^*$ of the networking powers, we have set: $T_t = 500$ (ms), $C_{max} = 150$ $(Mbit/s)$, $L_t = 10$ $(Mbit)$, $k_e = 0.05 (mJ)/(MHz)^2$, $f_i^{max} = 100$ $(Mbit/s)$, $f_i^0 = 0$ $(Mbit/s)$, $\mathcal{E}_i^{max} = 1$ (mJ), $\Delta(i) = 1$ (s). We have evaluated $\mathcal{E}_{tot}^*$ $(Joule)$ for the following three network scenarios: *i)* $P_i^{net} = 0$ (mW) (i.e., no communication costs); *ii)* $P_i^{net} = 1$ (mW) (i.e., homogeneous communication costs); and, *iii)* $P_i^{net} = 1 + 0.25(i - 1)$ (mW), for $i = 1, \ldots, M$ (i.e., heterogeneous communication costs).

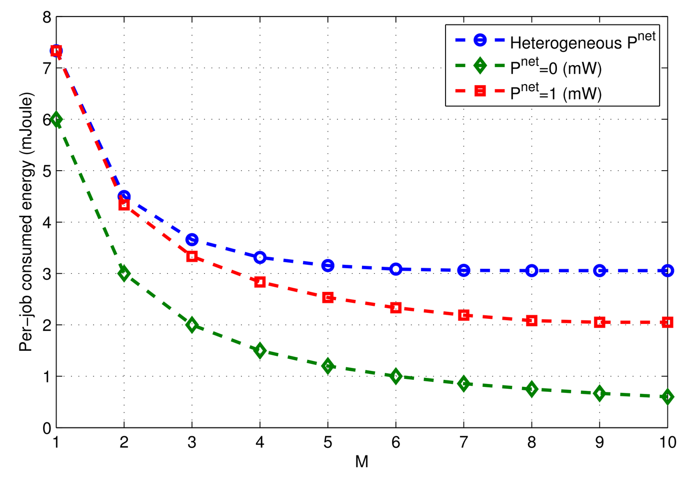

Fig. 6: Effects of the networking power demands on the Cloud performance.

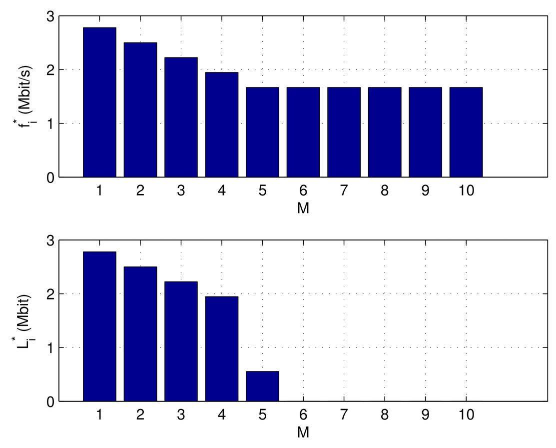

Fig. 7: Optimal processing rates and optimal workloads for the application scenario of Numerical Results.

Feasibility issues and optimal scheduling

The following inequality:

$$L_t \leq \min\left\{\sum_{i=1}^{M} f_i^{\max}\Delta(i); \frac{C_{max}}{2}(T_t - \Delta_{max})\right\}, \tag{4}$$

is necessary and sufficient condition for the feasibility of the constrained optimization problem in *COP*.
Let the constrained optimization problem in *COP* be feasible. Thus, its solution equates (Case of quadratic energy consumption function).
As already pointed, the form assumed by $\Phi(\eta)$ for DVFS-based CMOS CPUs is generally well approximate by quadratic one. In this case, for the optimum rate we have the following simple expression:

$$f_i^* = \left[\gamma_i f_i^0 + \delta_i[\mu^* - 2P_i^{net}/C_{max}]_+\right]_{f_i^{min}}^{f_i^{max}}, \tag{5}$$

$$L_i^* = \mathbf{1}_{[\mu^* > 2P_i^{net}/C_{max}]}(f_i^*\Delta(i)), \tag{6.1}$$

$$C_i^* = C_{max}\mathbf{1}_{[L_i^*>0]}. \tag{6.2}$$

where γ_i and δ_i are given by:

$$\gamma_i \triangleq \frac{2k_e}{2k_e + 2\mathcal{E}_i^{max}/(f_i^{max})^2}, \ \ \delta_i \triangleq \frac{\Delta(i)}{2k_e + 2\mathcal{E}_i^{max}/(f_i^{max})^2}. \tag{7}$$

The scalar $\mu^* \in \mathbb{R}_0^+$ in f_i^* plays the role of a Lagrange multiplier and it is computable as the solution of the following algebraic equation: $\sum_{i=1}^{M} L_i(\mu) = L_t$. The optimal scheduler hibernates VM(i) when the following *hibernation condition* is met (see Fig. 7):

$$\mu^* < 2P_i^{net}/C_{max}, \ i = 1, \ldots, M. \tag{8}$$

Average energy consuption under random workload

The plots of Fig.8 may be considered representative of application scenarios where the energy due to frequency switching energy overhead is low (e.g., $k_e = 0.005$ $Joule/(MHz)^2$), medium (e.g., $k_e = 0.05$ $Joule/(MHz)^2$) and high (e.g., $k_e = 0.5$ $Joule/(MHz)^2$). Interestingly, these plots show that: *i)* the average energy consumption (quickly) increases for increasing k_e's; and, *ii)* the optimal number M^* of VMs to be instantiated decreases for growing k_e's.
The plots of Fig.9 reports the optimal allocations of the processing rates at the 1*th* round (red bars) and at the 10*th* round (blue bars) for the aforementioned heterogeneous networking case of Fig.7. The trend emerging from the plots of Fig.9 is that, round-by-round, some of VMs tend to be consolidated and permanently loaded, while the remaining ones gracefully pass from the hibernation state to the off one.

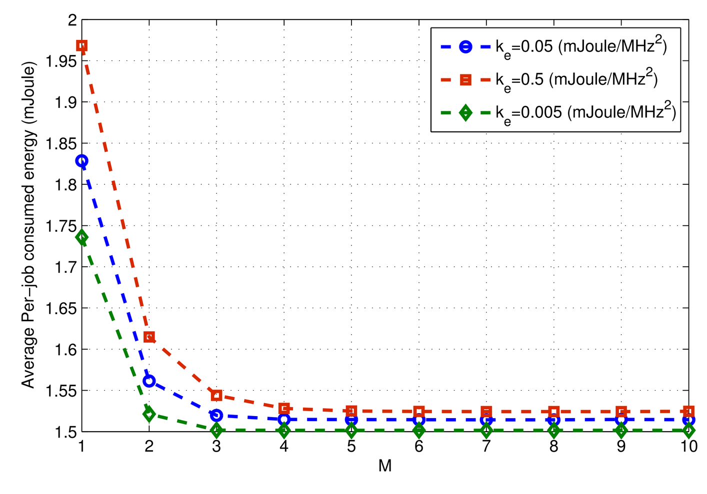

Fig. 8: Average energy consumption of the optimal scheduler in the presence of randomly time-varying workload.

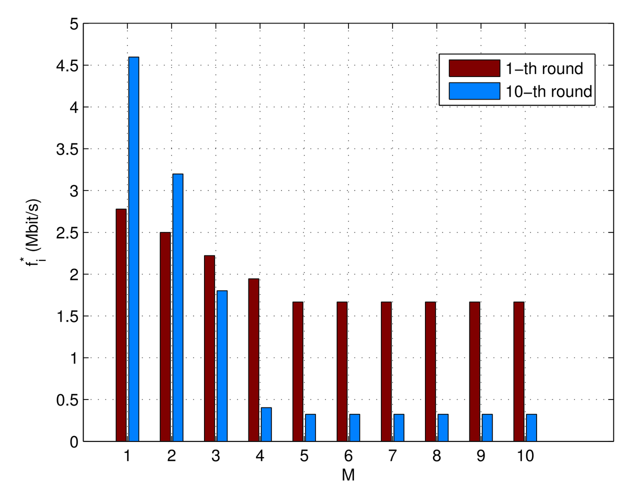

Fig. 9: Allocation of the processing rates at the 1*th* round (red bars) and 10*th* round (blue bars).

Conclusion The obtained results confirm that attaining Green in real-time Cloud platforms requires a dynamic tradeoff among several contrasting objectives, together with an optimized planning of the overall networking-plus-computing Cloud infrastructures.