An Autonomic SLA Management for IoT Networks

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Abstract

Management of SLA requirements of heterogeneous IoT consumer devices in diverge applications are the leading strategic challenges in IoT networks. This paper proposes a genetic algorithm and reinforcement learning based integrated algorithm for autonomic management of SLA in IoT networks. The SLA fulfillment problem is formulated as Markov decision process (MDP) then states and actions are defined as the populations and operators of genetic algorithm. The performance of the proposed algorithm is studied through simulation and we observed the higher utility of IoT devices as the function of rewards of reinforcement learning. The balancing of utility distribution is also analyzed in simulation study.

1. Introduction

Internet of Things (IoT) is a prominent research domain, where all physical objects are connected to the internet to develop and deliver smart services [1]. Therefore, it is essential to maintain and manage service level agreement (SLA) [2] of IoT networks to ensure the service quality received by the consumer devices. However, managing SLA in IoT networks is challenging because of the heterogeneity of IoT devices and also heterogeneity in used applications. The device heterogeneity means different categories of IoT devices e.g., smart phones, google glasses, music players and smart vehicles. Even the same device types have different hardware configurations based on their CPU, memory, connectivity, screen size and screen resolution.

Conversely, various types of applications run on the IoT devices and SLA requirements of those applications are also diverges. Moreover, multiple applications may run on the same IoT device in a same time slot. The SLA requirements of different applications are presented in Table 1 [3]. Therefore, managing SLA requirements of such diverged IoT devices in dynamic IoT networks are thought-provoking. Because of the dynamic nature of the IoT networks and uncertainty of SLA fulfillments, we proposed an integrated algorithm by combining the real-time reinforcement learning [4][5] strategy with genetic algorithm [6] to determine the near optimal parameter configuration for IoT devices to maintain the SLA requirements.

Table 1. SLA requirements of different applications

Application type	Data rates in Kbps (μ)	Delays in millisecond (d)	PER
Video streaming	800	2000	0.05
Audio streaming	320	200	0.08
File downloading	200	3000	0.1
VoIP	512	150	0.01

2. System Description

The system model of IoT networks for management of SLA requirements of heterogeneous IoT devices are presented in Fig. 1. We proposed a layered architecture, where physical IoT devices are considered as edge network devices. The IoT device runs a number of service applications of video, audio, VoIP and text. It is required to maintain SLA for those application services. The IoT devices are connected with gateways for communicating with internet and the content or other service providers as well [7]. We proposed an SLA management layer on top of the gateway layer for autonomic management and fulfillment of service requirements of different application services for heterogeneous IoT devices. The proposed SLA manager applying the novel integrated reinforcement learning and genetic algorithm for autonomic SLA management.

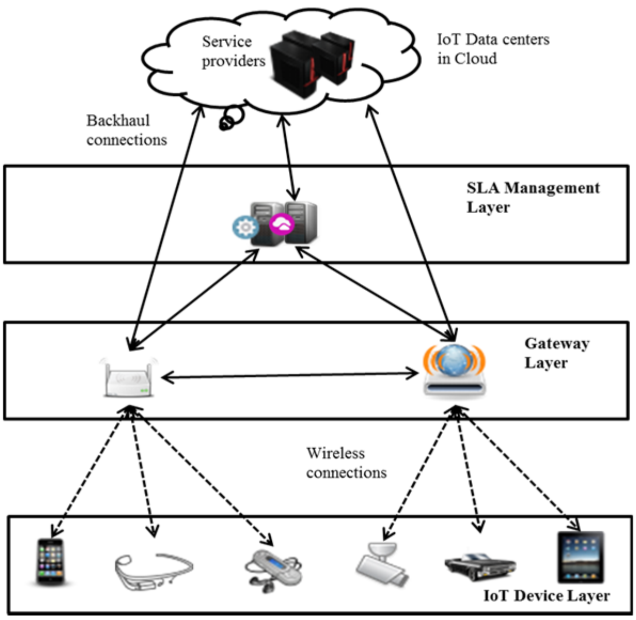

Fig. 1. System model of IoT networks for SLA management of IoT devices

We assumed that the service provider's data center resides in cloud for serving required contents to IoT edge devices.

3. Problem Formulation and Algorithm Design

As different IoT devices have different hardware capabilities the possible hardware configurations are defined as follows:

- C_{hw}=($Hconfig_1$, $Hconfig_2$, …, $Hconfig_{n-1}$, $Hconfig_n$) =([$device_1$,cpu_1,mem_1,$connectivity_1$,$screen_1$,$resolution_1$], [$device_1$,cpu_2, mem_2, $connectivity_1$, $screen_2$, $resolution_2$] …, [$device_n$, cpu_n, *connectivityn*, *memn*, $screen_n$, $resolution_n$])

The SLA parameter settings mostly depend on hardware configurations and content types. To fulfill the SLA requirement the possible parameter configurations are defined as follows:

- C_{para}=($paraConfig_1$, $paraConfig_2$, …, $paraConfig_n$) = ([C_1, D_1, L_1, PER_1], [C_1, D_2, L_2, PER_2], …, [C_1, D_n, , L_n,, PER_n]); where *C*, *D*, *L* and *PER* represents content type, data rate, delay, and tolerable packet error rate respectively.

Now, the research question is which parameter configuration is required for which hardware configuration to fulfill the SLA requirement. To solve this problem we formulate the problem as a Markov decision process(MDP) [8], so that we can find the solution by applying the proposed integrated reinforcement learning and genetic algorithm. The states of the Markov decision process are defined as X ={x_1 ; x_2 ; …; x_k}={[$Hconfig_1(paraConfig_2)$, $Hconfig_2(paraConfig_n)$,$Hconfig_n(paraConfig_1)$,…]; [$Hconfig_1(paraConfig_1)$,$Hconfig_2(paraConfig_2)$,$Hconfig_n(paraConfig_n)$,…]; …; [$Hconfig_1(paraConfig_n)$,$Hconfig_2(paraConfig_1)$,$Hconfig_n(paraConfig_2)$, …]} which are considered as the feasible population of genetic algorithm.

The set actions for reinforcement learning agent are A={a_1,a_2,…, a_n}={one-point crossover, two-point crossover, uniform crossover, replacing mutation, swapping mutation}; which are also possible operations of genetic algorithm. The reward function for a definite action of reinforcement learning agent i.e., $R(x_p, x_q, a_i)$ is the fitness value of each individuals of state x_q, which is generated from x_p following action a_i and can be determined through equation (1).

$$R(x_p, x_q, a_i) = \sum_{m=1}^{|x_p|} r_m = \sum_{m=1}^{|x_p|} \frac{\mu_m(1-PER_m)}{\sum_{l=1}^{|b^m|} d_l^m(t_l)} \tag{1}$$

Where, μ_m, d_m, PER_m represents as data rate, delay, and packet error rate, and $|x_p|$ and $|b^m|$ represents the length of the state x_p, and the number of application running on the IoT device of application type t.

Algorithm 1: AutonomicSLA (X, A)

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1. {
2. n=0
3. **Repeat** {
4. Select x_p as a randomly selected feasible parent population;
5. **Repeat** {
6. a_i = *get action* (x_p), where a_i is feasible genetic operation
7. x_q=*set transition*(x_p, a_i), where x_q is a new generation
8. Determine reward $R(x_p, x_q, a_i)$=reward (x_p, x_q, a_i) using (1), which determine the fitness of new generation
9. Update the Q value for finding the state and action pair.
10. $Q_{n+1}(x_p, a_i) = Q_n(x_p, a_i) + \alpha * \left[R(x_p, x_q, a_i) + \gamma * \max_{a_j \in A(x_q)}[Q_n(x_q, a_j)] - Q_n(x_p, a_i)\right]$
11. Set $x_p = x_q$
12. n=n+1
13. } **Until** the Q value function has converged
14. } **Until** population has converged
15. **Return** the fittest population
16. }

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4. Performance Evaluation

We evaluated the performance of the proposed method through MATLAB2015a simulator. We considered 5 types of IoT devices with 2 instances each and 10 distinct parameter configurations; therefore we have total 100 feasible states for reinforcement learning agent. Moreover, we also considered 5 actions as discussed in section 3. The considered benchmark for SLA requirements is presented in Table 1. The learning rate α and discount rate γ is assumed as 0.98 and 0.7 respectively.

Fig.2 shows the higher normalized utility of first 25 devices because of the learning agents reward gain in learning phase.

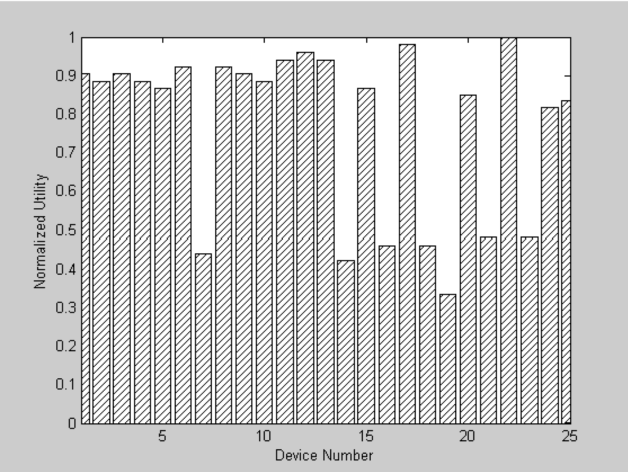

Fig. 2. Normalized utility per device configurations of first 25 device instances

Therefore, the gained knowledge of learning agents ensures higher utility, which gathered by the learning agent in autonomic manner. Fig. 3 also shows the control chart of utility distribution, where the utility balancing is perfectly done by the

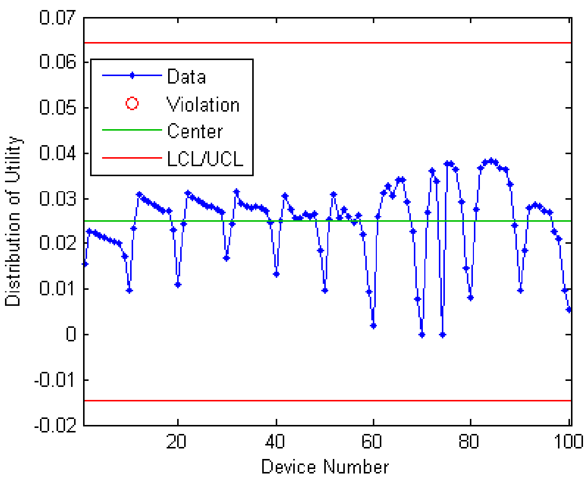

Fig. 3. Normalized utility per device configurations of first 25 device

learning agent as there is no violation and the utility of each of the 100 configurations belongs to the central line and none of the distribution crossed the upper (UCL) and lower control limits (LCL).

5. Conclusion

The proposed integrated reinforcement learning and genetic algorithm for autonomic SLA management is a novel approach for device and application aware SLA maintenance in IoT environment. The proposed method facilitates the autonomic management because of the reinforcement learning strategy, which learns from the environment. The genetic algorithm accelerates the convergence steps while the fitness function controls the utility of IoT devices by rewarding reinforcement learning agent with the utility. Reinforcement learning with epsilon greedy policy may enhance the utility of IoT devices. Matching game can also be another future direction to solve the formulated SLA management problem in IoT networks.

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References

[1] Abedin, Sarder Fakhrul, Md Golam Rabiul Alam, Nguyen H. Tran, and Choong Seon Hong. "A Fog based system model for cooperative IoT node pairing using matching theory." In *Network Operations and Management Symposium (APNOMS), 2015 17th Asia-Pacific*, pp. 309-314. IEEE, 2015.

[2] Palacios, Marcos, Jose Garcia-Fanjul, Javier Tuya, and George Spanoudakis. "Coverage-based testing for service level agreements."*Services Computing, IEEE Transactions on* 8, no. 2 (2015): 299-313.

[3] Pantisano, Francesco, Mehdi Bennis, Walid Saad, Stefan Valentin, and Mérouane Debbah. "Matching with externalities for context-aware user-cell association in small cell networks." In *Global Communications Conference (GLOBECOM), 2013 IEEE*, pp. 4483-4488. IEEE, 2013.

[4] Littman, Michael L. "Reinforcement learning improves behaviour from evaluative feedback." *Nature* 521, no. 7553 (2015): 445-451.

[5] Alam, Md Golam Rabiul, Yan Kyaw Tun, and Choong Seon Hong. "Multi-agent and reinforcement learning based code offloading in mobile fog." In*2016 International Conference on Information Networking (ICOIN)*, pp. 285-290. IEEE, 2016.

[6] Attwood, Andrew, David J. Lamb, and Omar Abuelmaatti. "Position-Relative Identities in the Internet of Things: An Evolutionary GHT Approach." *Internet of Things Journal, IEEE* 1, no. 5 (2014): 497-507.

[7] Abedin, Sarder Fakhrul, Md Alam, Golam Rabiul, Rim Haw, and Choong Seon Hong. "A system model for energy efficient green-IoT network." In*Information Networking (ICOIN), 2015 International Conference on*, pp. 177-182. IEEE, 2015.

[8] Niyato, Dusit, Ping Wang, and Dong In Kim. "Optimal Service Auction for Wireless Powered Internet of Things (IoT) Device." In *2015 IEEE Global Communications Conference (GLOBECOM)*, pp. 1-6. IEEE, 2015.