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Leveraging Fog Computing for Geographically Distributed Smart Cities

Rasha S. Gargees
Department of Electrical Engineering & Computer Science
University of Missouri
Columbia, Missouri, USA
rsgt3b@missouri.edu

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***Abstract*—Recently, the emergence of smart cities (SC), where data streams come from various geographically distributed places, has posed new challenges. Cloud Computing provides excellent services for smart cities, such as powerful computation and storage. However, processing the geographically distributed data using cloud computing only is not an ideal solution in some cases. Additionally, moving all the big raw data to the remote cloud is another challenge for cloud computing since there will be shortcomings in terms of delay and high bandwidth consumption. A solution that allows fog-to-cloud or fog-to-fog communication can address these limitations as fogs are typically located locally near the data sources. However, the questions related to the efficient frameworks design, workload distribution, cost, and various key technologies and communication challenges remain. To this end, this research investigates the impact of fog, employing our proposed architecture, on the efficient utilization and management of resources in highly distributed systems through experiments. The comparison showed that fog computing reduces the cost in terms of time and resource utilization. Additionally, the collaboration of autonomous agents locally (within one fog) or globally (across multiple fogs and cloud) supports scalability and automation. It also facilitates large-scale data processing across various real-world distributed locations.**

***Index Terms*—fog/edge Computing, cloud computing, smart city, geographically distributed framework**

I. Introduction

Smart cities aim to deliver better services and quality of life to their inhabitants using the developments of cutting-edge technology. Many countries worldwide have already started enormous projects to transform their main cities into smart cities. Such projects are around Asia, Australia, China, Europe, and North America. A smart city is an urbanized region where various fields cooperate to accomplish sustainable results by analyzing contextual, real-time information. In a smart city scenario, lots of devices are connected, and various computations are performed simultaneously [1]. Cloud computing has attracted attention as the truly promising and appreciated computing paradigm for both clients and service providers. Cloud computing provides computing services such as hardware, application development platform, and computer applications. Although cloud computing has various benefits compared to traditional computing paradigms, it also has some restrictions. The evolving developments in networking such as large, distributed Internet-connected sensor networks, mobile data networks, real-time streaming applications, and Internet of Things (IoT) have characteristics that cannot be fulfilled by cloud computing alone [2], [3].

The emergence of these developments in networking challenges centralized data centers and has led the Internet society to pay attention to the design and development of architectures. To this end, edge computing (EC), also known as fog computing (FC), has developed as a new computing paradigm that complements the cloud and addresses numerous limitations in cloud computing. Unlike cloud data centers, fog nodes are geographically distributed in closeness to users [4]–[6]. Cisco introduced fog computing to overcome the shortcomings of cloud computing in the Internet of Things (IoT) by moving some of the core functions of cloud computing to the edge of the network to deliver low latency, real-time, and location-aware services essential for billions of edge devices [7]. In addition, it acts as a bridge between the cloud and the distributed smart city devices. Hence, by distributing intelligence through a distributed fog computing construction to the network's edge, latency, bandwidth requirements, and cloud resource consumption can be cut [8].

Since an effective fog nodes deployment method can reduce the service response time and improve energy consumption efficiency, the selection of fog node locations is vital [9]. FC is a distributed computing infrastructure that is highly virtualized. It provides computing, storage, and network services between edge and cloud servers [10]. Although fog computing is considered a complementary solution to the centralized cloud infrastructure, with the growth of streaming and delay-sensitive applications, FC also needs to address the higher latency issue when forward compute-intensive jobs to a remote cloud. Therefore, there is a need to study computational resources utilization at the edge of the network [11]. Fog computing eliminates the gap between centralized cloud and a variety of geographically distributed applications. It operates by deploying fog nodes throughout the Internet [10]. FC is a promising future generation solution that enables a new generation of cloud applications [12], [13]. The remainder of this paper is organized as follows. Section II details our solution that leverages fog and cloud computing for efficient resources utilization. Results are presented and analyzed in Section III. Finally, Section IV concludes the paper.

Fig. 1. *The geographical view of the cloud, source fogs, and destination fogs:* ***a)*** *The imagery data are moved from source to the cloud then to the destination.* ***b)*** *The imagery data are moved directly from the source to the destination without passing through the cloud, however, still some metadata is moved through the cloud.*

II. Proposed Method

Due to the evolution of the data generated from various geographical locations of smart cities that need to be processed in real-time, centralized cloud computing could not efficiently handle geographically distributed data. Thus, in this paper, we compare the performance of the cloud computing environment against the performance of the fog-cloud computing environment (i.e., allows fog-to-cloud communication or fog-to-fog communication) utilizing our smart framework. Consequently, we explore the workload distribution, cost, and various communication issues. Furthermore, we utilized intelligent agents to autonomously handle imagery data that need multiple processing stages.

In this research, we used four types of agents: SensorAgent, MasterAgent, WorkerAgent(stage1), and WorkerAgent(stage2). We emulated the sensor agents that collect the data and add it to Network File System (NFS). Then MasterAgents pick data piece by piece and publish the corresponding metadata to the WorkerAgents in stage1. The WorkerAgents there request the data they subscribed to its topic. For example, some WorkerAgents subscribe to data from Europe while others subscribe to the data from the USA. Thus, each agent receives the data they subscribed to its topic. This helps save bandwidth and time, especially when there is a huge distance between the agents. It also helps distribute the workload among the agents. Note that agents who subscribe to the same data will collaborate to process the data without repeating the process on the same data.

The WorkerAgents at stage1 can also filter the unwanted data. For instance, they filter the black images that do not contain useful information. In this case, we can save further processing time and the needed bandwidth to move this data to the next stage. Then WorkerAgents in stage1 publish the metadata to stage2, and the WorkerAgents in stage2, which subscribed to this data, obtain the corresponding images they requested. In stage2, the WorkerAgents further process the data. More details about the data processing can be found in our previous works [14], [15]. Unlike our previous works, this research studies the effect of utilizing fog computing, where the nodes are geographically distributed over various regions and continents. Thus, the proposed solution connects various real-world cities/countries as well as facilitates data processing and moving across various distributed locations in the world. Other researchers studied this using prototype or in theory [16]–[18] or through simulation [19], [20]. Also, most of them focused on a specific domain or application [21], [22]. Hence, The proposed framework will fulfill this gap through real-world implementation in various real cities.

For comparison purposes, we use multiple fogs in various areas of this world. For instance, some are in the USA, and some are in Europe. We placed the WorkerAgents of stage1 in the cloud, and in another separated experiment, we moved them to the fogs near the data source. So, in this case, we can study the effect of moving some of the functions to the fog nodes instead of using fog for collecting and distributing data only. In both cases, we will have a database and broker, which help with the communication among the agents, placed in the cloud. The framework employs the publish/subscribe pattern to direct the data from specific source to specific destination. For instance, it moves the data generated in a location (source) in the USA to the another location (destination) in the USA as well. It is worth mentioning here that the framework is flexible in that the data can be directed to any location that needs it. However, for this study and to show the importance of using fog computing, we moved the data to the destination close to the source. We used mesh topology to connect the stages of WorkerAgents. In mesh topology each X number of WorkerAgent at $stage_{n+1}$ is connected to Y number of WorkerAgent at the $stage_n$ in an interleaving pattern.

TABLE I
AWS INSTANCES SPECIFICATIONS

Node	vCPU	CPU Clk	Memory	Bandwidth
MasterAgent, WorkerAgent_$stage_1$	4	3.4 GHz	8 GB	Up to 10 Gb
SensorAgent, WorkerAgent_$stage_2$, Broker, Database	2	3.4 GHz	4 GB	Up to 10 Gb

TABLE II
THE DISTRIBUTION OF THE NODES FOR THE FIRST EXPERIMENT(CLOUD)

Cloud	N. Virginia	Broker 1-3, DB, $Worker_{stage1}$ 1-4
Source Fog	*Oregon*	Sensor 1-2, Master1
	London	Sensor 3-4, Master2,
Destination Fog	*California*	$Worker_{stage2}$ 1-5
	Stockholm	$Worker_{stage2}$ 6-10

TABLE III
THE DISTRIBUTION OF THE NODES FOR THE SECOND EXPERIMENT(FOG)

Cloud	N. Virginia	Broker 1-3, DB
Source Fog	*Oregon*	Sensor 1-2, Master1, $Worker_{stage1}$ 1-2
	London	Sensor 3-4, Master2, $Worker_{stage1}$ 3-4
Destination Fog	*California*	$Worker_{stage2}$ 1-5
	Stockholm	$Worker_{stage2}$ 6-10

III. EXPERIMENTAL SETUP AND RESULTS

To compare the central cloud against distributed fog, we implemented a realistic example of processing and moving imagery data from source regions to destination regions. The data are processed in two stages. In the first stage, the images that do not contain useful information are filtered out, and the rest are cut into smaller images. Then, the small images are processed in the second stage to extract the features using deep learning techniques. Eventually, the extracted features are sent to the final destination for further processing and analysis.

Two experiments have been performed on Amazon Web Service (AWS): In the first experiment, WorkerAgents in stage1, brokers, and database are placed in the cloud. In the second experiment, brokers and database only are placed in the cloud while WorkerAgents stage1 are moved to the fog nodes. Table I lists the specification of the AWS instances utilized in the experiments. In this research, there are two types of fog: source fog and destination fog. Source fog nodes for both experiments contain SensorAgents and MasterAgents, while destination fog nodes contain WorkerAgents stage2. In the case of the fog experiment, we moved WorkerAgents stage1 nodes to the source fogs. The source fogs are located in Oregon and London, while destination fogs are located in California and Stockholm.

In total, for each experiment there are 4 SensorAgents, 2 MasterAgents, 4 WorkerAgents (stage1), 10 WorkerAgents (stage2), one database, and 3 Brokers. The distribution of the nodes for the first experiment is shown in Table II while The distribution of the nodes for the second experiment is shown in Table III. Fig. 1 shows the locations of the cloud and fogs on a map in addition to the directions of data transfer. Stockholm Fog subscribed to the data from London. At the same time, California fog subscribed to the data from Oregon fog. This demonstrates the advantage of moving part of the processing from the remote cloud to the fog. The data moves directly from one fog to another fog, which is closer than the remote cloud. Red circles represent source fog; green circles represent destination fog; orange circles represent clouds. Fig. 2 shows the distribution of the agents in both experiments. In the case of the second experiment (fog) we also use the cloud for brokers and database since the metadata moves to them is small compared to the imagery data that moves among the agents. The total size of the images data is 10 GB divided among 4 SensorAgent equally. It contains about 12,000 images, including 1000 black images. (Do not contain useful information; should be filtered out).

Fig. 3 revealed a comparison of the network input of two of WorkerAgents at stage2 measured by bytes and averaged every 5 minutes. One of the WorkerAgents is located in the USA, and another one is located in Europe. As can be seen, the network input is almost the same for both cloud and fog experiments; however, the time for the fog experiment is less than the cloud computing, which means it uses less bandwidth than the cloud. This is due to sending data to a remote cloud, while in the case of fog experiments, WorkerAgents stage1 are placed in the source fog, which saves the bandwidth. Fig. 7 in the Appendix shows the network input for the rest of WorkerAgents in stage2 for both experiments. Note time of WorkerAgents in the USA is less than that in Europe because of the shorter distance between the source and destination in the USA.

Fig. 4 shows CPU utilization comparison of two of the WorkerAgents in Stage2, one in the USA and one in Europe. The CPU utilization for the agents of the fog experiments is higher than the ones in the cloud, although they process the same data because it is processing more data in less time. As can be seen from the figure, the time for the fog experiment was less than the time for the cloud experiment because the imagery data moved directly from source fog to destination fog without going through the remote cloud. Fig. 8 in the Appendix shows the CPU utilization for the rest of WorkerAgents in stage2 for both experiments. Note that the CPU utilization of the agents in the USA is higher than that of the agents in Europe because there is a shorter distance between the source and destination in the USA than Europe, which means faster data transfer as well as handling more data in less time. We use deep learning techniques, specifically the

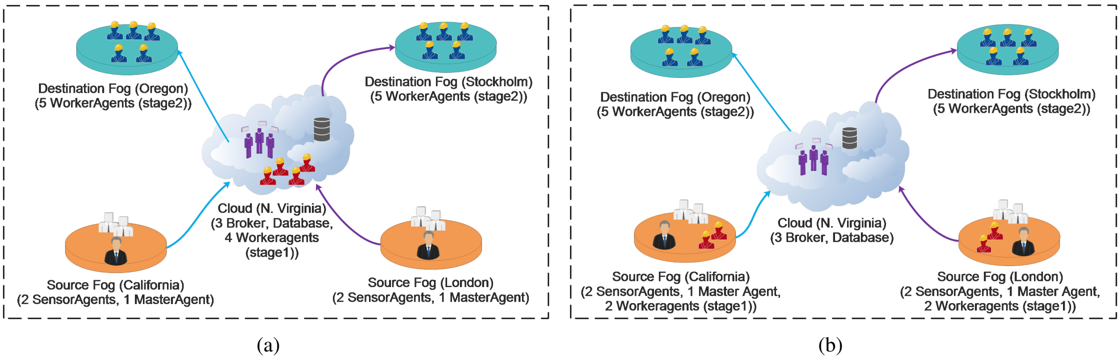

Fig. 2. *Distribution of agents in case of:* ***a)*** *Cloud.* ***b)*** *Fog. Note the WorkerAgents(stage1) are moved from the cloud to source fogs. The colors of the arrows indicate the imagery data flows from sources to destinations.*

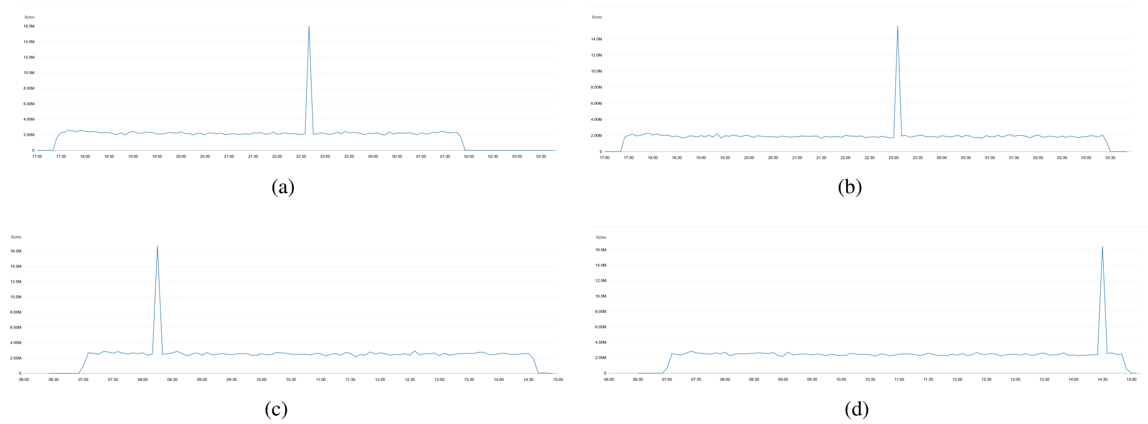

Fig. 3. *Network input comparison of two of the WorkerAgents at stage2 measured by bytes and averaged every 5 minute.* ***a)*** *WorkerAgent in cloud that handles USA data.* ***b)*** *WorkerAgent in cloud that handles Europe data.* ***c)*** *WorkerAgent in fog that handles USA data.* ***d)*** *WorkerAgent in fog that handles Europe data.*

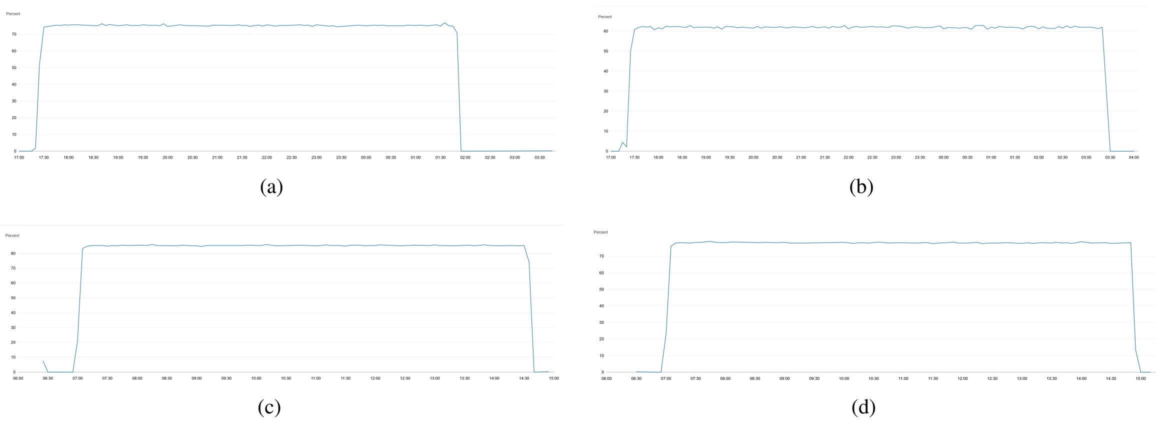

Fig. 4. *CPU utilization comparison of two of the WorkerAgents in Stage2. The CPU utilization for the agents of the fog experiments is higher than the onces in the cloud due to the faster coming data.* ***a)*** *WorkerAgent in cloud computing that handles USA data.* ***b)*** *WorkerAgent in cloud computing that handles Europe data.* ***c)*** *WorkerAgent in fog computing that handles USA data.* ***d)*** *WorkerAgent in fog computing that handles Europe data.*

pre-trained ResNet50 model for features extraction from the images in the second stage, which is why it consumes CPU power in stage 2 more than in stage 1. It can be concluded that moving some functions from the cloud to the fogs leads to faster processing and, as a result, enhance the response time. This is especially important for real-time applications that need a faster response.

Additionally, we have measured the total time of the experiments. Time for the cloud experiment was about 10.028 hours while for the fog experiment was 7.871 hours (see Fig. 5).

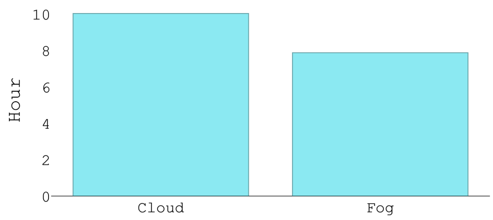

Fig. 5. *Comparison of the total time measured by hour for both cloud and fog experiments. Fogs reduced the time needed to handle the imagery data.*

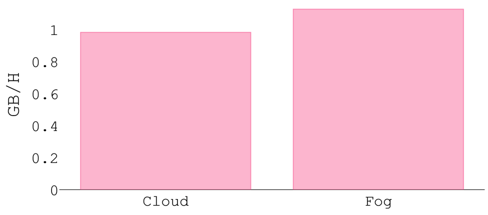

Fig. 6. *Comparison of goodput measured by GB/Hour for both cloud and fog experiments. Fogs increased the goodput of the imagery data handling.*

As can be seen, moving some functions to the fog near the data source decreased the total time by more than 2 hours. This reveals the benefit of the fog. Time-saving is expected to increase with the increase of the data size. The goodput metric for stage2 has been measured as well. Goodput is the ratio between delivered useful information (e.g. images) and the total time. We measured the goodput in this study in GB/H. As shown in Fig. 6, the goodput for the cloud experiment was 0.982 GB/Hour while for the fog experiment it was 1.127 GB/Hour. The goodput of stage2 reveals the final outcome of the experiments because it represents the final stage, which receives the transferred data. This indicates that the size of processed data per time unit in the fog experiment was better than in the cloud.

IV. Conclusion

This paper studied the benefit of the collaboration between fog computing and cloud computing for geo-distributed computing platforms such as smart cities platforms by applying our smart solution to the two environments (cloud computing only and cloud-fog computing) and comparing their performances. The experiments have been carried out on AWS across multiple regions in the USA and Europe. To study the effect of fog computing, we moved some functions to fogs by moving intelligent agents of stage1 from cloud to fogs. Additionally, the data that did not contain beneficial information was filtered out in stage1 before sending it to its destination, which added another benefit of saving bandwidth and time when moving WorkerAgents of stage1 to the fog.

In summary, the experimental results revealed that fog computing was able to reduce the cost in terms of time and bandwidth as well as improve the goodput. Furthermore, the framework successfully connected various cities located in different countries and continents and processed the data autonomously while minimizing the usage of the network resources. Also, the framework can scale easily to new cities and locations by adding more intelligent agents or nodes. For these reasons, fog computing can effectively help enhance the services of smart cities.

Appendix

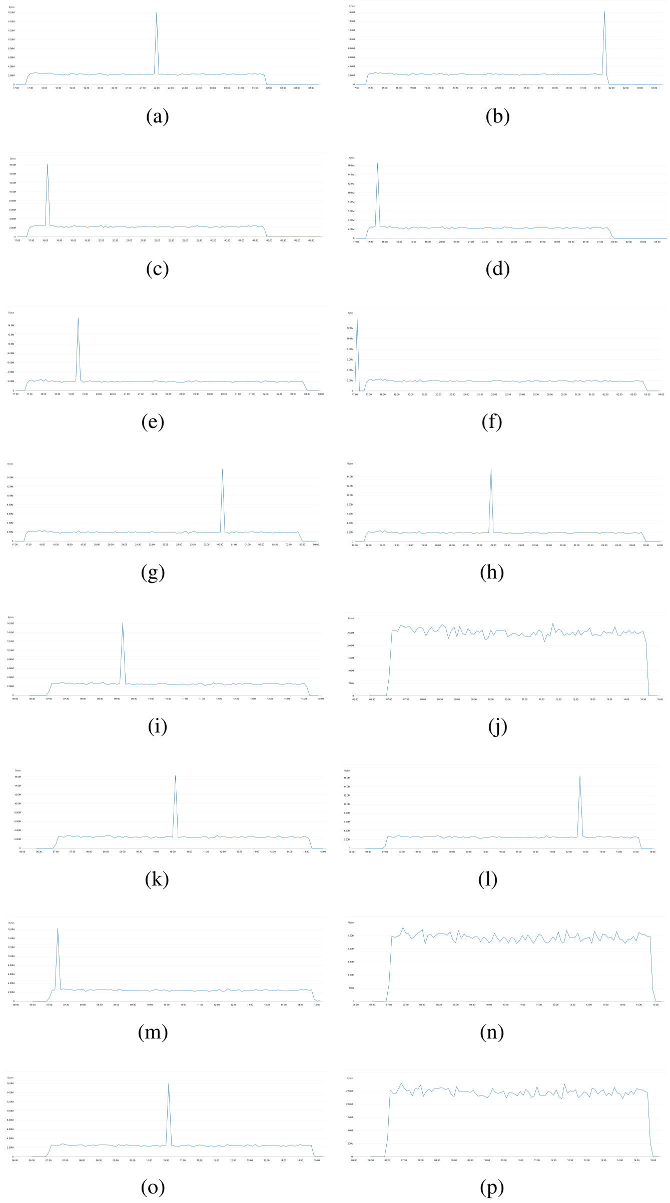

Fig. 7. *Network input of 8 WorkerAgents (stage2) measured in bytes and averaged every 5 minutes.* ***(a-d)*** *WorkerAgents (cloud) handles USA data.* ***(e-h)*** *WorkerAgents (cloud) handles Europe data.* ***(i-l)*** *WorkerAgents (fog) handles USA data.* ***(m-p)*** *WorkerAgents (fog) handles Europe data.*

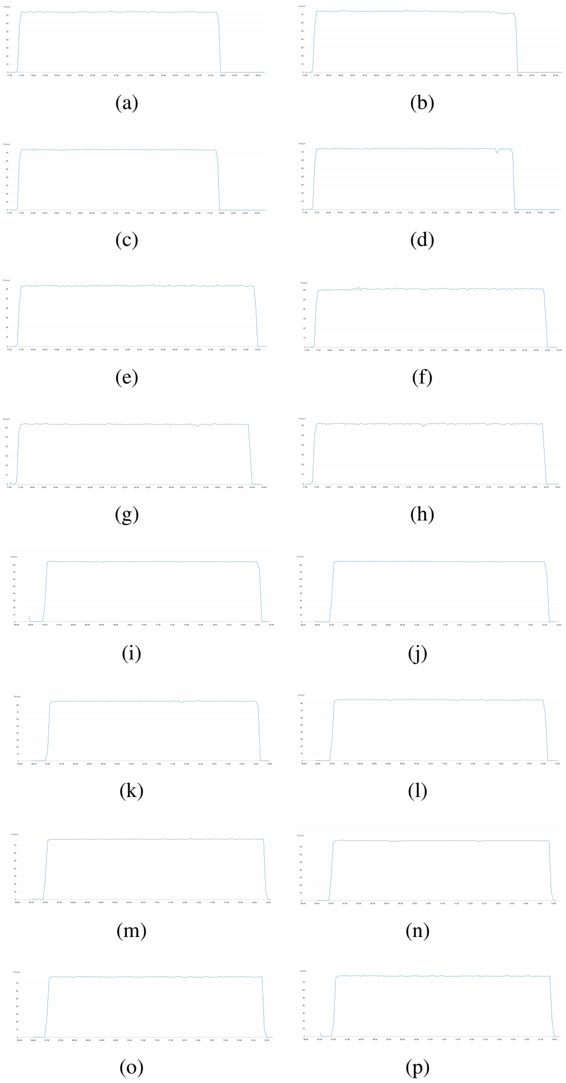

Fig. 8. *CPU utilization of 8 WorkerAgents (Stage2).* ***(a-d)*** *WorkerAgents (cloud) handles USA data.* ***(e-h)*** *WorkerAgents (cloud) handles Europe data.* ***(i-l)*** *WorkerAgents (fog) handles USA data.* ***(m-p)*** *WorkerAgents (fog) handles Europe data.*

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