

Fog-to-Cloud (F2C) Data Management for Smart Cities

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Abstract—Smart cities are the current technological solutions to handle the challenges and complexity of the growing urban density. Traditionally, smart city resources management rely on cloud based solutions where sensors data are collected to provide a centralized and rich set of open data. The advantages of cloud-based frameworks are their ubiquity, as well as an (almost) unlimited resources capacity. However, accessing data from the cloud implies large network traffic, high latencies usually not appropriate for real-time or critical solutions, as well as higher security risks. Alternatively, fog computing emerges as a promising technology to absorb these inconveniences. It proposes the use of devices at the edge to provide closer computing facilities and, therefore, reducing network traffic, reducing latencies drastically while improving security. We have defined a new framework for data management in the context of a smart city through a global fog to cloud resources management architecture. This model has the advantages of both, fog and cloud technologies, as it allows reduced latencies for critical applications while being able to use the high computing capabilities of cloud technology. In this paper, we present the data acquisition block of our framework and discuss the advantages. As a first experiment, we estimate the network traffic in this model during data collection and compare it with a traditional real system.

Keywords—Smart City; Fog-to-Cloud (F2C) computing; Data Management; Data Lifecycle Model (DLC); Data Aggregation

I. INTRODUCTION

Data are the essential fuel for smart cities development because they provide the required information for services to proceed according to the contextual state, and can generate higher value knowledge extracted after some complex data analysis. In fact, smart cities constitute an ideal scenario to generate abundant data from any source type. For instance, data is mainly obtained from the sensors network deployed throughout the city, but also from the increasingly popular participatory sensing (e.g. sensors integrated in citizens' smartphones), from social media or any other third party application, streams of data from surveillance cameras and devices, or any other city resource sensitive to contribute with valuable information.

Managing and organizing efficiently all these diverse sources and tremendous volumes of data in such a context is a critical challenge for an effective smart cities' success. We have estimated that 8 GB of data could be generated every

day in the city of Barcelona [1], only considering some basic public sensors' data (for instance, surveillance or traffic control cameras were not considered). However, not many researchers are paying attention to explicit data management strategies in the context of smart cities.

We have defined a novel architecture for efficient data management in the context of a smart city, based on a fog to cloud distributed model for resources management. The advantages of such a model is that it combines the advantages of both the cloud and the fog computing technologies, these are: keeping high performance capabilities for computational intensive applications, reducing communication latencies for real-time or critical services, reducing network data traffic and enhancing fault tolerance and security protection. As a first stage of our research, in this paper we focus on the data acquisition phase, we describe some basic data aggregation optimizations that can be easily implemented in our fog to cloud model, and estimate the effects of such optimizations on the network data traffic reduction.

The rest of this paper is organized as follows. Section 2 discusses some relevant related work about resources and data management models in Smart Cities. Then, Section 3 presents the details of the new architecture for data management in smart cities using the fog to cloud distributed model, and discusses the advantages of this new approach. In Section 4, we describe and implement some basic data aggregation optimizations to illustrate the potential of our proposal. Finally, in Section 5 we conclude this work and present our future research directions.

II. RELATED WORK

Several efforts have traditionally been made to handle data management technologies, generally focused on Relational Database Management (RDBMS) technologies and, more recently, the Extract-Transform-Load (ETL) process for modeling data life stages in the concept of data warehousing environments [2, 3]. Furthermore, the big data paradigm constrained additional challenges to the traditional data management systems in the recent decades [4].

Alternatively, Data LifeCycle (DLC) models represent one great solution towards developing an integral data management framework beyond any specific technology [2, 4]. Several DLC models generated for specific scenarios

(such as smart cities [5, 6]), sciences and environments (for instance, big data [2, 7]) have been proposed by several researchers from academia and industries.

With respect to resource management in smart cities, there are two main different trends: i) centralized (cloud) data management, and ii) distributed data management. In the one hand, in the centralized data management model all physical data resources send the sensed data to the cloud data center through a broad area communication network, such as internet. In this context, the cloud environments are the responsible to collect, aggregate, and convert data into meaningful information [6, 8]. On the other hand, the alternative option is the distributed data management model that uses fog technology [9, 10]. Fog computing proposes the use of physical devices at the edge for further processing and preservation. Other authors [11] propose a Fog-to-Cloud (F2C) computing framework that combines the cloud computing (centralized view) with the fog computing (distributed view) models. Although there is few related work about distributed data management [5] in the context of smart cities, it is not yet mature enough how this distributed data management model can manage all data life stages from fog to cloud layers.

In this paper, we argue that data can be organized and managed in any smart city scenario at the fog layers (including data acquisition, data preservation and data processing) while using the all facilities (such as deep computing and unlimited data storage) at the cloud layer. In addition, we show that the F2C distributed data management model provides an excellent opportunity to perform some data optimizations during the data acquisition phase, which provides several advantages, such as reducing latencies for critical applications, reducing network traffic, while being able to use the high computing capabilities of cloud technologies.

III. F2C DATA MANAGEMENT

The distributed hierarchical F2C resources management architecture provides an interesting framework for data management in the context of smart cities, according to our Smart City Comprehensive Data LifeCycle (SCC-DLC) model proposal [5]. In this section, we present a novel architecture for efficient fog to cloud data management in smart cities, consisting on the SCC-DLC model mapping onto the smart city F2C resources management architecture. The model is illustrated in Fig. 1. The SCC-DLC consists of three main blocks, named the data acquisition, the data processing, and the data preservation. Data acquisition is mainly performed at fog layer 1, as well as some basic data processing and data preservation actions. The fog layer 2 can enhance the data processing and data preservations capabilities of level 1 by providing higher computing capabilities. And finally, the cloud layer is the responsible of a more complex and more sophisticated data processing over a much broader set of (presumably historical) data, as well as the responsible for permanent data preservation. In the following subsections, the functionalities of each data block are further described, as well as the advantages of the model.

A. Data acquisition

Data acquisition is mainly performed at fog layer 1. In fact, all sensor devices (such as the sensors network deployed throughout the city, but also surveillance cameras

or sensor data from smart phones) are part of the fog nodes at this level according to their physical location. So most data is collected at fog layer 1. There can eventually be some additional data collected at cloud level, such as data from web services or third party applications, but these will be smaller compared to the vast volumes of sensor generated data.

As long as data are being collected, the following phases from the data acquisition block can also be performed at fog layer 1, where a reasonable amount of computing resources is available. For instance, the data filtering phase can apply filters to remove redundant data and can apply some additional data aggregation techniques to further reduce the amount of data to be managed. Data quality can also be implemented at this fog layer, assessing and guaranteeing higher data quality. And data description can be performed in order to tag data according to the city business model considered, for instance, timing information (creation, collection, modification, etc.), location positioning (city, country, GPS coordinates), authoring, privacy, and so on.

Data collected at fog layer 1 will be periodically moved upwards to layer 2, and data collected at layer 2 from a set of fog nodes at layer 1 will be combined and periodically moved upwards to the cloud level, which will collect the whole data set from the city and keep it for historical references. Note that data at fog layer 1 can be immediately used at this same level (real-time data), so there is not any need to urgently move these data to higher levels and, therefore, the frequency for the periodical upwards data movements can be strategically decided in order to accommodate it to the network traffic loads.

B. Data storage

Data are generated at fog layer 1, but gradually moved upwards to the fog layer 2, and upwards to the cloud layer, where they will be permanently preserved. So, in fact, the F2C hierarchy acts as a reversed memory hierarchy, where data are created and the lowest cache level (fog layer 1) and moved upwards to “main memory” (cloud layer) instead of being created at the main memory and moved to lower cache levels of the memory hierarchy.

Data generated at fog layer 1 will be temporarily stored at this level, allowing real-time applications an instant access to these data. The smart city business model can decide the amount of temporal data that will be stored at this level, as well as the frequency of updating to upper levels. Similarly, data gathered at fog layer 2, consisting of data received from several fog nodes at layer 1, will be temporarily stored at this level 2. This will make up a set of less recent data (as it has been received after some period of time) but from a broader area, comprising the combination of the respective fog nodes’ areas at layer 1. Finally, data will be moved upwards and permanently preserved at cloud layer, unless any expiry time is defined.

The different management phases included in the data preservation block will be mainly executed at the cloud level, where the permanent storage is performed. Note that these phases are not urgent and, therefore, their execution can be delayed to the time in which data are received to the cloud layer. This is the case of the data classification phase, responsible for classifying and ordering data before storing, and eventually implementing the appropriate techniques for

data versioning, data lineage or data provenance. And the data dissemination phase, responsible for providing a user interface for public or private access to stored data, and responsible for implementing any protection, privacy, sharing or security policies according to the city business requirements.

C. Data processing

Data processing can be performed at any layer from the F2C hierarchy, according to the requirements of the application or service. For instance, critical or real-time services will be executed at fog layer 1 in order to have a faster access to the (just generated) real-time data. Note that accessing data locally inside the boundaries of a fog node is much faster than moving the data to a centralized cloud data center and, afterward, reading these same data from the cloud to the local node.

Alternatively, deep computing complex applications will be executed at the cloud layer. Note that i) in the cloud the computing resources are unlimited and, ii) the data set of a high performance computing application will presumably be very large and, therefore, be part of the historical data set stored at the cloud layer. Note that in this case, when computation requires very high capabilities, adding more latency to the first data access will not be significant in the overall performance.

For the other applications, they will be executed at the lowest fog layer that both, provides the required computing capabilities and contains the required data set. As a general rule, the closer the layer, the faster responses times. An additional consideration in this case is when the required data is not present in the current fog node at layer 1, but can be accessed from either a node at a higher layer or a neighbor fog node at the same layer 1. This option may eventually be considered and solved using some sort of cost model to estimate the effects of both cases and proceed according to the lowest cost.

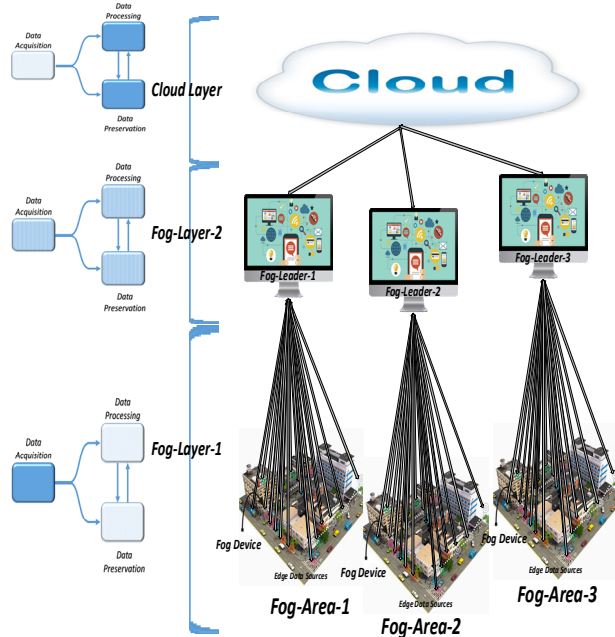


Fig. 1. Mapping of the SCC-DLC model onto the F2C architecture.

D. Advantages of the F2C data management model

The most obvious advantages of this F2C data management model are that it can benefit from the combined advantages of both, the cloud and the fog computing technologies. This is, high computing and storage capabilities from the cloud layer, and reduced network traffic and communication latencies from the fog layers. However, some additional advantages arise from this hierarchical and distributed model, as listed below:

- Real-time data accesses are much faster than in a centralized architecture. This higher speed is not only due to the reduced communication latencies, but due to the fact that accessing data from a centralized system requires the data to be moved first to the cloud, classified and stored there, and then moved back to the edge. So two times the data transfer through the same path must be considered.
- By having the just collected data available at fog layer 1, the global network load is drastically reduced because some applications will be able to access these data locally, avoiding several remote data accesses through the network.
- By having the just collected data available at fog layer 1, the transmission to the cloud can be delayed without any performance loss. This allows additional optimization implementations, such as:
 - Performing some data aggregation techniques to reduce the volume of data to be transmitted upwards, without any computational constraint, as data do no need to be sent immediately.
 - Adjusting the frequency of the data transmission in order to use the network in periods when the traffic load is low.
- Traditional centralized systems define a low frequency policy for data collection from sensors in order to reduce the total amount of data to be transmitted in the network. By having the real-time data available at fog layer 1, the data collection frequency can be increased at this level without overloading network load and, therefore, providing more precision and accuracy from the sensed data at no additional cost.
- By reducing the data transmission length, the security risks and the probability of communication failure are reduced as well and, for this reason, privacy is easily enhanced.

IV. OPTIMIZING DATA COLLECTION THROUGH AGGREGATION

In this section, we provide some validation for our distributed data management strategy based on a F2C resources management architecture, by estimating the effects of some basic data aggregation techniques and comparing them with a real centralized cloud system, named Sentilo [18], which manages the municipal open data from the city of Barcelona [1].

A. Data Aggregation

Data Aggregation provides a splendid facility as part of data management to do some kind of processing for gathering, reducing, mixing, or presenting information somehow as a summary [12]. The main objective of data aggregation techniques is reducing the amounts of managed data, and can be obtained through diverse techniques, such as data combination, data redundancy elimination, data

compression, bandwidth reduction or power consumption reduction, just to name a few.

Recently, data aggregation has been tailored with the concepts of data and information mining progression, business demands and human analysis techniques, where data must be explored, collected, and presented in a report-based and shortened format in their networks [13]. There are some different view to do data aggregation in theoretical and practical scenarios. Traditional views concentrated to specific network devices and resources such as Wireless Sensor Networks (WSN) to manage data aggregation approaches [14]. The other view extends the previous view to go beyond ubiquitous and distributed scenarios (instead of focusing on specific devices and network) such as big data [13], cloud and distributed computing [13, 15], or real-time systems [16].

In cloud computing environments, cloud computing provides (almost) unlimited, scalable as well as elastic resources. For this reason, cloud computing adopt some data aggregation approaches and techniques to produce high level and sophisticated outcome. In [8], the authors provide a full data model from sensors nodes to cloud computing environments for a smart city scenario. This model has two main layers, which are sensors nodes and cloud computing layers. The sensors nodes collect data from the city and transfer to the cloud computing layer. The cloud layer is responsible to perform data collection and aggregation, data filtering (including classification), and data processing (including preprocessing, processing, and decision making).

With respect to distributed data aggregation, a recent survey presents a taxonomy for distributed data aggregation approaches [15]. They propose two main taxonomies, named communication and computation. The communication taxonomy focuses on the communication aspects (including communication/routing strategy and network topology). It is divided into structured (including hierarchical and ring protocols), unstructured (including flooding/broadcast, random walk, and gossip routing protocols) and hybrid data aggregation approaches. Alternatively, the computation taxonomy encompasses to decomposable functions (including hierarchic, averaging, and sketches basis and principles methods), complex functions (including digests basis and principles methods) and counting (including deterministic and randomized basis and principles methods) data aggregation approaches.

In this work, we will apply some basic aggregation techniques as an example to show the facility and efficiency of our model to use such kind of optimizations. The data aggregation techniques explored are:

- Redundant data elimination: With this technique, we focus on providing a basic yet effective solution to easily reduce the amount of duplicated data collected from the sensors layer. For example, in case of weather measurement, each sensor sends the current temperature measurements, but this type of data is prone to repetitions, so eliminating them may easily reduce such amount of data.
- Compression: As data are collected and transmitted to an upper level delayed, several interesting options arise to accumulate a reasonable amount of data and compute compression, in order to obviously reduce the amount of data transfer.

Many other data aggregation techniques could be easily applied in this architecture; however, these two basic techniques are enough to illustrate the facility and effectiveness of such optimizations in our model.

B. Experimental results

In a previous work [1], we estimated the amounts of data that can be generated (and therefore transmitted through the network to the main cloud data center) in the city of Barcelona, through their data management platform, named Sentilo [18]. In this experimental section, we compare these figures with the estimated data that should be transmitted using a F2C data management model as the one described in the previous section.

The data aggregation and data compression tasks can be performed at the fog device (in fog layer 1), at the fog leader (in fog layer 2), and at the cloud layer as part of the data classification phase, as shown in Fig. 2. According to the current distribution of districts and sections in Barcelona, we estimate that our fog layer 1 should be covered with 73 fog areas, which corresponds to the number of sections in Barcelona. In this case, our fog area covers almost 1 km², which is a reasonable fog area size. In addition, the fog layer 2 can be defined as 10 main areas (at fog layer 1) which corresponds to the number of districts in Barcelona.

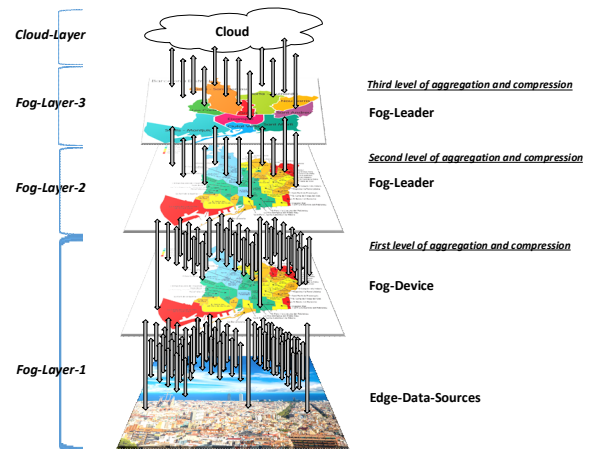


Fig. 2. Representation of the F2C data management in Barcelona.

The data classification phase is the responsible to classify and organize all data collected from the different categories of sensors. In our use case, Sentilo provides five categories of information and services, which are energy, noise, urban, garbage and parking. Each category is divided into different types of information. For instance, the energy category contains electricity meter, external ambient conditions, gas meter, internal ambient conditions, network analyzer, solar thermal installation, and temperature. The noise category includes three different types of information. The urban category encompasses to air quality, bicycle flow, people flow, traffic and weather. The garbage category has container glass, container organic, container paper, container plastic, and container refuse. And finally, the parking category has only one type of information.

The Sentilo platform provides a part of sensors network in Barcelona smart city. In our last paper, we calculated that the Sentilo generated different amount of data per day for different categories of information (including, energy

monitoring, noise monitoring, garbage collection, parking spot monitoring, and urban lab monitoring) as shown in below:

- Energy Monitoring category: 2,390,344,704 byte per day.
- Noise Monitoring category: 641,280,000 byte per day.
- Garbage Collection category: 360,000,000 byte per day.
- Parking Spot Monitoring category: 320,000,000 byte per day.
- Urban Lab Monitoring category: 4,723,200,000 byte per day.

We realized that each category of information produced huge amount of the redundant data in every transaction (by different sensors) and per day. Therefore, we monitored a single day of data generation in Sentilo platform. Then, we observed that the redundant data for energy, noise, garbage, parking and urban is almost 50%, 75%, 70%, 40%, and 30% respectively. Therefore, we have an initial thought to absorb this amount of data through the layers of our F2C data management architecture.

As we mentioned in the previous section, we applied two different techniques to reduce the number of data transfer among F2C layers. First, we used data aggregation techniques to eliminate the number of redundant data in the layer. Second, we used data compression techniques (for example, one solution proposed by PKWARE [17]) to compress data size after applying aggregation techniques. Note that data aggregation and data compression techniques can be implemented in each layer of F2C data architecture. Therefore, in the following paragraph we will explain how much data will be reduced at each layer.

The fog device is in the first level of our aggregation model. With respect to number of the redundant observation, we calculated that sensors data would be reduced to 1,194,834,432 bytes for energy monitoring, 160,320,000 bytes for noise monitoring, 108,000,000 bytes for garbage collection, 192,000,000 bytes for parking spot monitoring, and 3,306,240,000 bytes for urban lab as shown in Table I and Fig. 3 (blue lines). Then, the amount of data can be further decreased to smaller sizes through data compression. Therefore, the data size will be 262,863,575 bytes for the energy monitoring, 35,270,400 bytes for the noise monitoring, 23,760,000 bytes for the garbage collection, 42,240,000 bytes for the parking, and 727,372,800 bytes for the urban lab as shown in Table I and Fig.3 (green lines).

Similarly, the fog leaders at Fog-Layer-2 (city sections) play a second level for performing data aggregation and data compression techniques. Therefore, the data volume will be reduced to 597,586,176 bytes for energy monitoring, 39,498,840 bytes for noise monitoring, 32,462,370 bytes for garbage collection, 115,106,400 bytes for parking spot monitoring, and 2,318,823,158 bytes for urban lab as shown in Table I and Fig. 3 (blue lines). Then, the number of data can be shifted to smaller sizes through data compression. Therefore, the data size will go to 131,468,959 bytes for the energy monitoring, 8,689,745 bytes for the noise monitoring, 7,141,721 bytes for garbage collection, 25,323,408 bytes for the parking, and 510,141,095 bytes for the urban lab as shown in Table I and Fig. 3 (green lines).

Next layer are the fog leaders at Fog-Layer-3 (city districts) to handle data compression and data compression techniques. In this layer, data size goes to 298,793,088 bytes for energy monitoring, 9,874,710 bytes for noise monitoring, 9,738,711 bytes for garbage collection, 69,063,840 bytes for parking spot monitoring, and 1,623,176,211 bytes for urban lab after handling data aggregation as shown in Table I and Fig. 3 (blue lines). Then, the number of data can be further reduced through data compression. Therefore, the data size will change to 65,734,479 bytes for the energy monitoring, 2,172,436 bytes for the noise monitoring, 2,142,516 bytes for garbage collection, 15,194,045 bytes for the parking, and 35,098,766 bytes for the urban lab as shown in Table I and Fig. 3 (green lines).

After these computations, we conclude that: i) aggregation efficiency rate at fog devices, fog leaders in Fog-Layer-2 (city sections), and fog leader in Fog-Layer-3 (city districts): is almost 49.98%, 50.01%, and 50.08% efficiency rate for energy monitoring information. Similarly, the noise monitoring efficiency rate is 24.96%, 25.02%, and 25.05%. Then, the garbage collection rate is 29.99%, 30.05%, and 30.08%. In addition, the parking spot monitoring rate is 59.95%, 59.99%, and 60.01%. Indeed, the urban lab monitoring rate is 68.93%, 69.13%, and 70.01%. ii) compression efficiency rate: is almost 22% for all layers (including Fog device, Fog-Leader (in Fog-Layer-2 layer), and Fog-Leader (in Fog-Layer-3 layer)).

Indeed, the total efficiency rate (including redundant data elimination and compression) at fog devices, fog leaders in Fog-Layer-2 (city sections), and fog leader in Fog-Layer-3 (city districts) is as shown in below:

- Energy Monitoring category: About 71.98%, 72.01%, and 72.08%.
- Noise Monitoring category: Almost 46.96%, 47.02%, and 47.05%.
- Garbage Collection category: Approximately 51.99%, 52.05%, and 52.08%.
- Parking Spot Monitoring category: Almost 81.95%, 81.99%, and 82.01%.
- Urban Lab Monitoring category: About 90.93%, 91.13%, and 92.01%.

V. CONCLUSION

In this paper, we have presented a novel architecture for hierarchal distributed data management in smart cities based on a distributed hierarchical fog to cloud resources management system. The advantages of this architecture are numerous. The most obvious advantage is that high computing and storage capabilities from the cloud layer can be combined with reduced network traffic and communication latencies from the fog layers, while enhancing fault tolerance and security and privacy protection. However, by providing such a hierarchical and distributed model, some interesting additional advantages arise:

- Real-time data accesses are much faster than in a centralized architecture;
- The network load is drastically reduced because many data can be accessed and used locally;

- Several aggregation techniques can easily be applied to further reduce the volume of data to be transferred through the network;
- The data transmission frequency can be adjusted in order to use the network in periods of low traffic;
- The data collection frequency from sensors can be increased at no additional cost, thus allowing higher precision and accuracy.

We have also explored the effectiveness of this architecture by exploring two basic data aggregation techniques, which are redundant data elimination and data compression, and compared to a real cloud based system from the smart city of Barcelona. We have shown by applying redundant data elimination that, in some cases, the data reduction rate reaches 75%. Additionally, by applying data compression, the data reduction rate increases to up to 78%. Finally, we have explored that the total efficiency rate, by applying both redundant data elimination and data compression, moves to almost 92%, in some cases. Although many other data aggregation techniques could be easily applied in this architecture, these two basic techniques are enough to illustrate the facility and effectiveness of such optimizations in our model.

As part of our future work we will explore more options related to data aggregation, and continue developing other data life cycle phases of our model, including data quality, data processing, data analysis, data storage, and data dissemination.

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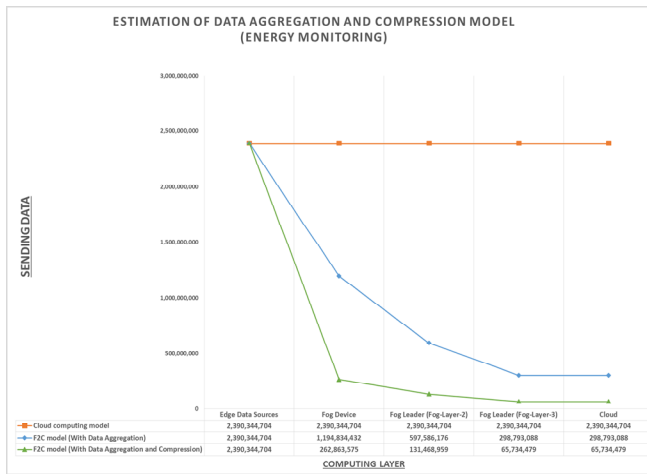
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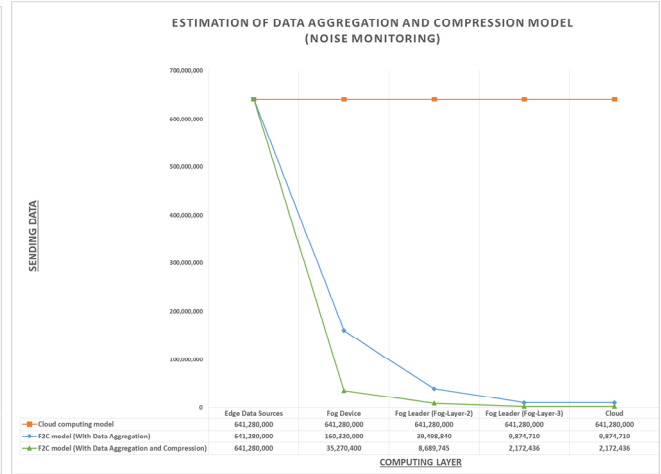
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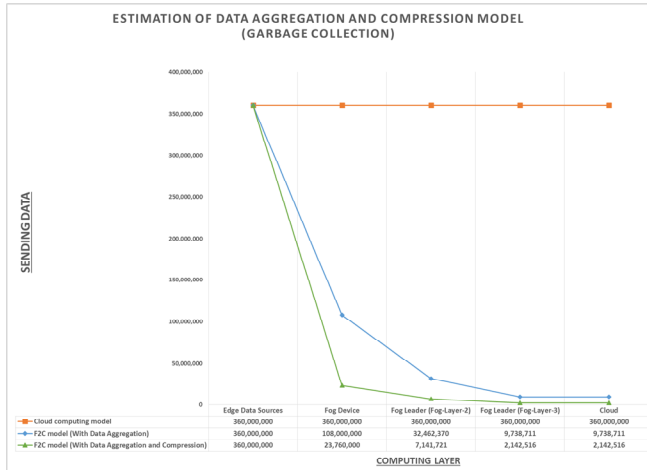
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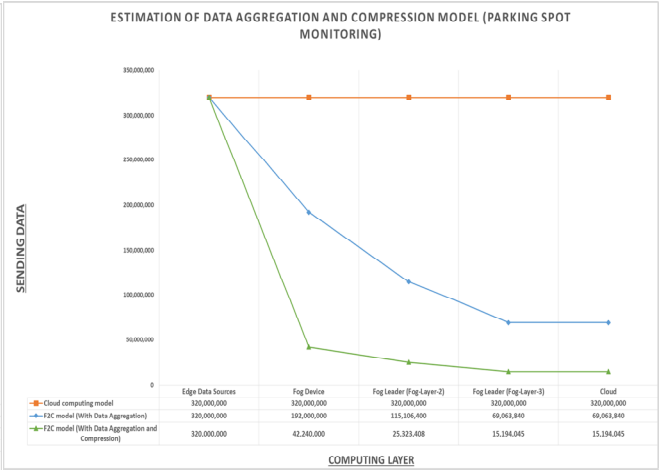
(a) Energy Monitoring category



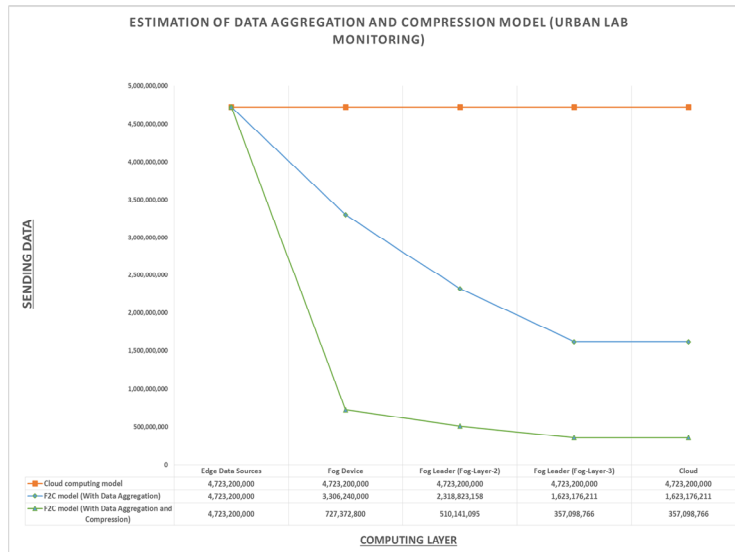
(b) Noise Monitoring category



(c) Garbage Collection category



(d) Parking Spot Monitoring category



(e) Urban Lab Monitoring

Fig. 3. Redundant data aggregation and data compression models in F2C data management architecture.

