EE-BSMU: Energy-Efficient Base Station Monitoring Unit for Smart Communication in Smart Cities

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Abstract—Internet-of-things (IoT) is used in almost every aspect of our daily life and it is widely used in smart city application. In order to monitor an environment and to provide services to a citizen, IoT uses various devices to sense, actuate, send data, receive data. Sensing is being done by various sensors and these data are stored in the cloud through a communication system. Mobile communication is one of the major players for transmission of data from end devices to cloud. As the demand for mobile communication increases more number base stations (BS) are deployed to facilitate services. In addition to traditional services, mobile communication systems are improvised to support newer services like IoT devices. So, it is important to impart the smartness of the base station in order to provide efficient services with reduced carbon emission. In this work, we proposed a base station monitoring unit (BSMU) to increase the smartness of BS, a base station monitoring unit is used to collect, compute and transmits data and an Intelligent unit is embedded within the BSMU uses MapReduce algorithm and HDFS to reduces the size of the file to be transferred to the distributed cloud where the distributed cloud is used to store data and send notification about the abnormalities to the administrator. Thus the proposed BSMU achieved improved quality-of-service (QoS) of BS with minimized resource usage and carbon emission.

Index Terms—energy efficiency, smart communication, smart city, base station monitoring unit, Mapreduce

I. INTRODUCTION

According to a latest UN report, 68% of the world’s population would be living in urban areas by 2050 [22]. This outlook accentuates the need for smarter cities: cities which would use the latest information and communication technologies (ICT) to improve the economic and social aspects of mammoth populations within minimum operational cost and optimum utilization of resources. One solution to the burgeoning smart cities is presented by the notion of Internet-of-Things (IoT), which transforms the idea of a city into a network of interconnected variety of nodes, encompassing sensors, actuators, vehicles and controllers along with the computational and analysis units to process the huge volumes of data [23]. A smart city consists of various sub-systems such as smart grids, smart home, intelligent energy management systems and smart traffic management [24].

Communication plays a major role in the Internet of Things, and also defining mobile communication as one of the main platforms for IoT [3] since the number of connected devices will be up to 100 billion by 2030 [2]. This would drastically increase the contribution of mobile communication in net global energy consumption and therefore increasing not only the operational expenditures (OPEX) but also contributing to the global rise in carbon footprint. Hence, it’s imperative that more energy-efficient and environment friendly networks be developed and deployed to mitigate the environmental threats in smart cities. This has opened the gates for a new area of research in the recent past, for which the coined term is ‘greener cellular networks’. As evident, apart from converging to perfection in data rates spectrum efficiency and delays, the new researches have also encompassed environmental issues as well as minimizing the energy consumption [17]. Recently, more research studies have encompassed the energy aspect of the mobile communication networks due to its substantive share in the carbon footprint, equivalent to almost 8 million cars per mobile network [25]. Another study shows that the carbon footprint of mobile communications by the year 2020 would be around 30% from Radio Access Network (RAN) operation, around 20% from data centre and data transport and around 12% from mobile device operation [6] as given in the Fig. 1.

![Fig. 1: Carbon footprint of mobile communication.](image)

Typically, the biggest chunk of energy is consumed by the base stations (BS) in mobile networks, accounting for around 60-80% of the network’s total energy consumption [26].
Furthermore, a base station devours 90% of its peak power even in the case of no traffic\cite{25}. Nonetheless, more base stations are being deployed by the network operators in order to cope with the ever-increasing traffic demand. Therefore, an energy efficient solution is required to minimize the energy consumption and carbon footprint along with the reduction in the OPEX of the mobile operators.

A. Contribution and Organization

In this paper, we have presented an efficient solution for reducing the energy consumption by introducing a base station monitoring unit (BSMU) consisting of a ‘Hard Unit’, which samples, computes and transmits data using sensors and micro-controllers along with an intelligent unit which reduces the size of the data to be transmitted to the distributed cloud. The intelligent unit incorporates HDFS and MapReduce algorithms to significantly reduce the file size and therefore less energy is expended in the Base Station. The Hadoop Distributed File System (HDFS) makes it possible to process the large dataset by breaking it into smaller parts and then using commodity hardware such as commonly available low-cost servers\cite{13}. MapReduce\cite{8} is an efficient tool for processing large datasets as well as producing large datasets, since many real world tasks can be modeled. The data is compressed at the MapReduce and sent to the distributed cloud for storage. The cloud can coordinate with the individual user devices via the BS to send important notifications.

II. RELATED WORK

A. Power Optimization at Network Level

In the past, while the main focus of mobile communication was on the enhancement of spectrum efficiency, network capacity and coverage, the recent trend has also shifted to the energy consumption and reduction of carbon footprint due to global warming and exhaustion of natural resources\cite{27}. The academic and industrial research circles have concurred to the rule of increasing the system capacity by 1000x while maintaining at least the current consumption of energy\cite{28}. In terms of mobile communications, there are various fronts at which energy conservation can be applied to reduce the overall carbon front. For example, most of the energy in mobile network is consumed by the BS, in the form of power amplifiers, air-conditioners, RF circuitry etc. The measure of energy consumed by each of the components in the BS is depicted in Fig. 2. \cite{17}. Therefore, controlling the energy consumption at the BS is an intuitive approach, as targeted by many studies in different ways. For example, \cite{29} have introduced a switching-on/off based energy saving (SWES) scheme to switch off the redundant BS in the network based on current network traffic, while monitoring the additional load on neighboring BS’s that might accompany this dynamic switching. This idea is picked by a variety of different researches such as \cite{30}, which have named it discontinuous transmission (DTX) and have studied its impact on the spectral and energy efficiency of the overall system. Several other studies have followed similar approaches to monitor the network traffic and conveniently turning off certain BS, which can save energy expended by power amplifiers and air-conditioning units including \cite{31}, \cite{32}, \cite{33}.

The switch off mechanism of BS’s is easy to implement in the current architecture of mobile networks in which the trend is being shifted towards smaller BS. However, switching off the BS might also result in impact Quality of Service (QoS) because of the decreased system capacity and burdened neighbors unless proper optimization is done and therefore sensitive to non-regularities \cite{36}, \cite{37}. Furthermore, by employing denser networks with optimized smaller cell size also contributes to reduction in energy consumption along with increase in system capacity as corroborated by several studies including \cite{34}, \cite{35}. However, while increasing the density of the BS’s saves energy, one important aspect that must be taken into consideration is their location, which has been done using the stochastic geometry as studied in \cite{36}, \cite{37}.
TABLE I: Techniques for Energy Efficiency at Network Level

| Techniques                  | Advantages                           | Disadvantages                          | Literature |
|-----------------------------|--------------------------------------|----------------------------------------|------------|
| BS switch-off               | High energy-efficient                | Effects QoS                            | [29], [31], [32], [33], [30] |
|                             | Easy to implement on hardware level  | Need proper optimization               |            |
| Network densification       | Energy-efficient                     | Location of nodes must be calculated   | [37], [34], [35] |
|                             | Increase system capacity             | accurately probably using stochastic   |            |
| Massive MIMO                | Increase diversity                   | Increase overall complexity of the     | [40], [41], [42] |
| Efficient resource allocation| Optimal utilization of resources     | relies on trade-offs with other metrics| [49], [50], [47], [48] |
|                             | Easy to implement                    |                                        |            |
| Network offloading          | High energy-efficient                | Security and interference issues       | [43], [44], [45] |
|                             | Reduces delay                        |                                        |            |
|                             | Releases burden from BS              |                                        |            |

Joint frequency allocation etc. However, all these techniques rely on trade-offs between energy efficiency and other metrics such as bandwidth, delay etc[49].

Yet another energy efficient mechanism is the called the ‘offloading’: shifting the cellular traffic to other radio access technologies (such as WiFi, Bluetooth), whenever possible and convenient. One important application of offloading is device-to-device (D2D) communication, which allows co-located devices to communicate directly with each other, thus reducing the energy consumption drastically, since the BS would no more be the intermediary between the two devices and hence creating room for other devices. Several studies have focused on this aspect of offloading such as [33], [34], [35]. One of the major challenges in D2D communication is the proper interference management between the devices, since in certain conditions, the BS does not provide mediation in call setup and resource allocation, which can lead to severe interference and hence a smart interference management is inevitable. Another important challenge is the security concerns when two devices via other intermediary devices, which has serious ramification unless proper encryption protocol is agreed between the two devices[44]. Table I provides a comparison of different techniques for energy-efficiency at network level.

B. Power Optimization in Cloud IoT

Cloud computing is mainly of two architecture namely private and public. In Private cloud, the resources are dedicated to a customer. In public cloud, the resources are shared by many customers and it is hosted on the Internet.

IoT application uses cloud platform efficiently, and power consumption of cloud is given by the energy required to transport one bit from the data center to a user through a corporate network is given by equation (1) [4].

\[
E_c = 9 \left( \frac{P_{les}}{C_{les}} + \frac{P_g}{C_g} + \frac{3 P_{es}}{C_{es}} \right)
\]

where \( P_{les} \), \( P_g \), and \( P_{es} \), are small Ethernet switches, data center gateway routers and the powers consumed by the Ethernet switches, respectively and \( C_{les} \), \( C_g \), and \( C_{es} \) are the capacitances of the corresponding equipment in bits per second. The estimated energy consumption of a private cloud for transmission and switching of a bit is around \( 0.46 \mu J/b \) [4] [18], [19], [20], [21]. The energy EI needed to transmit a bit of data from a data center to a user through the public cloud is given by equation (2) [4].

\[
E_1 = 6 \frac{P_{bg}}{C_{bg}} + 18 \frac{P_{es}}{C_{es}} + 6 \frac{P_g}{C_g} + 108 \frac{P_c}{C_c} + 24 \frac{P_w}{C_w} + 12 \frac{P_{pe}}{C_{pe}}
\]

Where \( P_{bg} \), \( P_{es} \), \( P_g \), \( P_c \), \( P_w \), and \( P_{pe} \), are the powers consumed by the broadband gateway routers, Ethernet switches, datacenter gateway routers, core routers, WDM transport equipment and provider edge routers, respectively and \( C_{bg} \), \( C_{es} \), \( C_g \), \( C_c \), \( C_w \), and \( C_{pe} \) are the capacities of the corresponding equipment in bits per second. The estimated energy consumption of a public cloud for transmission and switching of a bit is around \( 2.7 \mu J/b \) [4] [18], [19], [20], [21]. In this work, A platform service is used in public cloud to transfer and notify the user administrator. The Power consumption of software service per user is given by [4] and for IoT application, the power consumption per BS is rewritten and it is given by equation (3).

\[
P_{bs} = P_t + 1.5 \left( \frac{P_e}{N_s} \right) + 2(B_d)(1.5) \left( \frac{P_{sd}}{B_{sd}} \right) + A(E_1)
\]

Where \( P_t \) is power consumption of user terminal, it uses a simple command to access the network and we estimated this value based on a network switch low-end laptop as 8W. Ps/Ns power consumption of a server to the number of users per that server. From the survey, the average power consumption of the server is estimated as a value 850 W/h and we considered the number of the users to that server is 200. Psd is power consumption of hard disc array of cloud storage, Bsd capacity of hard disc array. Here we have considered for HP 8100 EVA hard disc, the Psd and Bsd value are estimated as 4.9 kW and 604.8 Tb respectively [4]. Where A is a bit rate, data rate between a user and the server and it is approximately estimated as 31.5 Mbs and E1 is energy required to transmit one bit of data and for public cloud, the value estimated is \( 2.7 \mu J/b \) and Bd is the size of a file to be transferred. To reduce the power optimization in a cloud, the data transmitted at the edge side is reduced so that the resource used in the cloud is minimized, this is achieved by including a special unit called Intelligent Unit, Intelligent unit filters the big data into semantic data using MapReduce for BS administrator notification.
III. SYSTEM ARCHITECTURE

The architecture of proposed work includes Base Station Monitoring Unit (BSMU), distributed cloud and end devices (User Equipment - UE) as shown in Fig. 3. Data collection and transmission of data to the cloud are done by the BSMU. Data storage and transmission of user notification are done by the distributed cloud. The end devices are user equipment that receives the notification.

A. Description of BSMU

The BSMU contains two units namely Hard unit and Intelligent unit. The Hard unit consists of various sensors and microcontroller and the Intelligent unit consists of HDFS and MapReduce as given in Fig. 4.

1) Description of Hard Unit: A hard unit consists of various sensors and microcontroller. Sensors include LM35, DHT11, MQ2, fuel level sensor. The LM35 is used to monitor the temperature inside the BS, a DHT11 sensor is used to monitor the humidity, an MQ2 gas sensor is used to find the leakage of gases, fuel level sensor is used to measure the fuel level of the power generator. All these data are collected using Arduino Uno and Arduino IDE is used to transfer the sensed data to the Intelligent unit.

2) Description of Intelligent Unit: The Intelligent unit is a heart of BSMU and consists of Hadoop daemons such as HDFS and MapReduce. Hadoop framework is written in java program used to deal big data [10]. Host machine uses this HDFS, it splits the file into sub file and process those file separately and gives results in aggregated form. MapReduce is a java programming process for a large set of data [11] is used to filter data as per user specification, in this work, we filtered the data which crossed beyond the fixed threshold value. These reduced data from the Intelligent unit is then uploaded to the cloud.

B. Description of Distributed Cloud

Cloud services are characterized as Infrastructure as a service, platform as a service and software as a service depending upon the usage of service and services can also be either public or private cloud. A public cloud is used for this work, hence estimated energy consumption of a public cloud for transmission and switching of a bit is around $2.7 \mu J/b$ [4]. A software service is used for notification. The power consumption per base station to access this service is given by equation (3).

C. Description of End Devices

End devices are user equipment which receives the filter data or the notification about the abnormalities in the environment via a developed application. In this work, a BS administrator mobile phone act as an end device to receive a notification.

IV. EXPERIMENTAL SETUP

To monitor a Base Station, a hard unit is used. In this, various sensors are deployed near BS. Sensors like LM35, DHT11, MQ2 and fuel level sensor are used to monitor various efficient factor of BS. Various values from each sensor are collected using Arduino Uno and Arduino IDE is used to load into the system and these are given as input to the Intelligent unit, which includes Hadoop MapReduce and this reduces the BigData into the Semantic data. Hadoop MapReduce processes the data as many chunks in a distributed cluster and aggregates the final data on the Hadoop Distributed File Systems (HDFS).

A. Intelligent Unit Output

The input to the Intelligent unit consists of raw big data from the various deployed sensors in hard unit and output from the Intelligent unit are semantic data. These are obtained by reducing the data with respect to the fixed threshold value of each sensor. If the temperature is more than 50°C and humidity is above 50% then it will affect the equipment in the BS, so the user administrator should be intimated and hence the threshold value for temperature and humidity are fixed with upper limit of 50°C and 50% respectively, if the smoke sensor output is greater than 30 ppm implies that there is a gas emission in the BS so the value greater than that should be notified and it is fixed as threshold value. If the fuel level in the power generator is lower than threshold value 1000 Kpa with respect to fuel container, then it should be intimated to the administrator that battery is running in reserve mode. The sensor data beyond these threshold values are filtered using MapReduce process. Hence, the big data is now converted into meaningful semantic data. The big data from the hard unit and the semantic data for temperature sensor from the Intelligent unit is shown in Table II.

These reduced data are uploaded to the cloud, the overall results for the LM35 sensor from the Intelligent unit are also shown in Table II. Table II also provide the summary of details such as time taken by the CPU to complete the process in ms, the details of various counters like the number of mapper and
TABLE II: Counter values of the intelligent unit

| Counter                                | Map | Reduce | Total |
|----------------------------------------|-----|--------|-------|
| Spilled records                        | 19  | 19     | 38    |
| Map output materialized (bytes)        | 335 | 0      | 335   |
| Reduce input records                   | 19  |        | 19    |
| Virtual memory snapshot (bytes)        | 3,755,327,488 | 1,890,303,712 | 5,646,131,200 |
| Map input records                      | 101 | 0      | 101   |
| Split Raw bytes                        | 208 | 0      | 208   |
| Map output records                     | 1,505 | 0   | 1,505 |
| Reduce shuffle bytes                   | 0   | 335    | 335   |
| Physical memory snapshot (bytes)       | 398,012,416 | 107,339,776 | 505,352,192 |
| Map input bytes                        | 3,002 | 0     | 3,002 |
| Reduce input groups                    | 0   | 1      | 1     |
| Combine output records                  | 19  | 0      | 19    |
| Reduce output records                   | 19  | 0      | 19    |
| Map output records                     | 101 | 0      | 101   |
| Combine input records                   | 101 | 0      | 101   |
| CPU time spent (ms)                     | 470 | 990    | 1,460 |
| Total committed heap usage (bytes)     | 336,592,896 | 92,798,976 | 429,391,872 |
| Bytes read                             | 4,503 | 0   | 4,503 |
| HDFS bytes read                        | 4,711 | 0     | 4,711 |
| File written (bytes)                   | 112,115 | 56,106 | 168,221 |
| File read (bytes)                      | 0   | 329    | 329   |
| HDFS written (bytes)                   | 0   | 266    | 266   |
| Bytes written                          | 0   | 266    | 266   |

The bytes used to transfer into a cloud for the temperature sensor without the Intelligent unit is 4503 bytes and power consumption for single BS is given by $P_{bs} = 4503 \times 1.944 \times 10^{-10} = 8.76 \times 10^{-4} mW$. The bytes used to transfer into a cloud for the temperature sensor with the Intelligent unit is 266 bytes and power consumption for single BS is given by $P_{bs} = 266 \times 1.944 \times 10^{-10} = 0.5178 \times 10^{-4} mW$. Similarly, Table III provide details of the energy consumption of all other sensors in BSMU from the result summary. It can be seen from the results presented in Table III that by employing our proposed BSMU, the total energy saved is about $33.18 \times 10^{-4} mW$ and thus reduction in energy consumption reaches up to 92%.

V. Conclusion and Future Work

For building a smart city, communication plays a vital role in interfacing devices with each other and for cellular communication, a base station is a key equipment for data transfer and in order to operate this equipment continuously a more energy is required. Hence, an IoT solution BSMU is proposed to monitor the base station and to notify a BS administrator about the abnormalities through a cloud and thereby energy consumption at this context is minimized. An Intelligent unit is also introduced within the BSMU to reduce the data size Bd in a distributed manner for instant notification and the resource usage at the cloud is decreased. The overall energy consumption at the cloud is decreased by 91.43%. Thus BS smartness is increased with minimized resource usage this, in turn, reduces the carbon emission. IoT solution can be given to enhancing the strength of RSSI level of the user of the BS in order to provide better communication.

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### TABLE III: Total Energy Consumption of BSMU

| Sensor         | File Size (\(E_B\)) Before Intelligent Unit (bytes) | Power Consumption | File Size (\(E_B\)) After Intelligent Unit (bytes) | Without BSMU (mW) | With BSMU (mW) |
|----------------|---------------------------------------------------|-------------------|--------------------------------------------------|------------------|--------------|
| Temperature    | 4503                                              | 8.7x10^{-4}       | 70                                               | 0.3x10^{-4}      |              |
| Humidity       | 4500                                              | 8.7x10^{-4}       | 70                                               | 0.3x10^{-4}      |              |
| Smoke          | 4800                                              | 9.3x10^{-4}       | 392                                             | 0.7x10^{-4}      |              |
| Fuel level     | 4883                                              | 9.4x10^{-4}       | 880                                             | 1.7x10^{-4}      |              |
| Total          | 18686                                             | 36.2x10^{-4}      | 1608                                            | 3.1x10^{-4}      |              |

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