Estimating Base Station Power Consumption Using Regression

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***Abstract*—Global warming is becoming a paramount concern in the world. One way to decrease the effect of global warming is by decreasing carbon emission and using renewable energy. In particular, there are many works on using renewable energy technologies in mobile communication systems. In order to enable such technologies in mobile communication systems, we should be able to estimate the required energy. Most of research was focusing on techniques to be used to exploit renewable energy sources assuming that the required energy to run the base stations is known. Only few works were focusing on the estimation of the energy based on transmitted energy, and fewer relating the former to traffic. In this paper, we present a regression-based power consumption estimation method based on voice and data traffic provided by base stations with 2G and 3G capabilities. Our results show that the power consumption of different base stations as a function of the provided traffic can have different patterns. Furthermore, the same base stations can have different energy consumption models at different period of time. Therefore, we advocate the use of machine learning algorithms inside each base station to learn its specific pattern.**

I. Introduction

The development of energy efficient and green systems is a major concern in international governmental and non-governmental organizations and industry.

Organizations are mainly interested in such systems due to their positive impact on the environment by reducing pollution generated by energy sources. In particular, the telecommunications industry contributes 2% of the total $CO2$ emissions worldwide, and it is an increasing contribution that is expected to reach 4% in 2020 [1]. The pollution is due to the high energy consumption, especially on the radio interface of mobile networks where base stations consume around 57% of the operator total consumed energy [2]–[4]. Therefore, it is crucial, from environmental point of view, to either reduce the energy consumption of the BS or use green sources of energy. Industry is highly investing in such systems due to the capabilities of reducing operational costs by using natural sources of energy, and providing reliable services to their customers by having multiple sources as backup. Energy budget occupies a big portion of operators' Operational Expenditure (OPEX). It can reach up to 32% of the OPEX using power grid, or even 50% otherwise [5], [6]. The use of renewable or green energy sources (e.g. solar panels, wind turbine) to power base stations of mobile networks has a momentous importance for operators for two main reasons: The presence of BSs in some areas where the power grid is not present or not reliable and the cost of such renewable sources have proved to be much more cost-effective than diesel generators. Furthermore, the loss of the energy source on one of the BSs will generate a cut in the service in a given area, and thus will lead to customer non-satisfaction and possible switch of service provider. Therefore, operators are highly interested in deploying green sources of energy in addition to power grids and generators.

In the last two decades, many problems related to energy efficient wireless base stations have been considered, such as energy efficiency definition, modeling power consumption as a function of traffic, call traffic dynamics modeling, BS on-off solutions, scheduling mechanisms, energy source switching, and energy source dimensioning [6]–[13].

Any design of green networking system based on renewable energy sources should include a model for energy consumption evolution over time. Therefore, a good energy consumption model is required. Most of the existing work on this topic focus on modeling the energy consumption as a function of transmit power [14]. The main problem with this approach is that one cannot predict transmit power, especially based on offers and business models used by operators. A better approach is modeling the energy consumption as a function of traffic [15]–[20]. In this approach, all the existing models related to traffic growth that are available to the operator can be used to estimate the energy consumption over long period of time. These approaches use fixed parametric models, which are based on measurement performed on specific models at given temperature, humidity, and condition. However, the relation between traffic and energy consumption, in practice, changes depending on the environment and the type of hardware used. In this paper, we show that different base stations may have different models and we propose a framework, where the BS learns its own model using regression techniques. This is possible as measurement on the amount of traffic and consumed energy can be available in the OSS of the mobile networks.

The remainder of this paper is organized as follows: In Section II, we show two regression models relating the energy consumed by a base station and its traffic, and we analyze the results. In Section III, we propose a learning-based framework allowing each based station to determine its own model using traffic, energy consumption, and environmental measurements. In Section IV, we discuss the complexity of implementing the proposed framework, and in Section V we conclude the paper and we discuss some future work.

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$$P = C_0 + C_1 \times CS2G + C_2 \times CS3G + C_3 \times Data2G + C_4 \times Data3G. \tag{1}$$

$$\begin{aligned} P =& C_0 + C_1 \times CS2G + C_2 \times CS3G + C_3 \times Data2G + C_4 \times Data3G + C_5 \times CS2G \times CS3G \\ &+ C_6 \times CS2G \times Data2G + C_7 \times CS2G \times Data3G + C_8 \times CS3G \times Data2G + C_9 \times CS3G \times Data3G \\ &+ C_{10} \times Data2G \times Data3G + C_{11} \times CS2G^2 + C_{12} \times CS3G^2 + C_{13} \times Data2G^2 + C_{14} \times Data3G^2. \end{aligned} \tag{2}$$

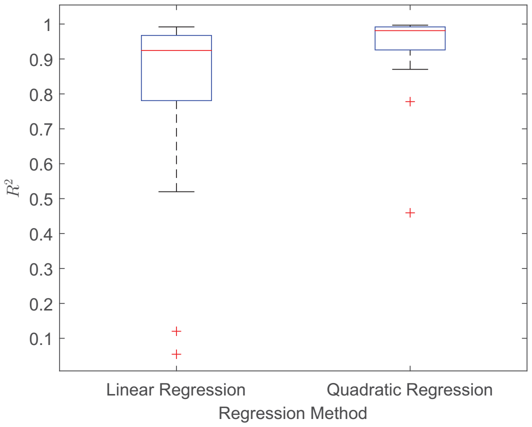

Fig. 1: The boxplot of the R^2 of the two proposed methods.

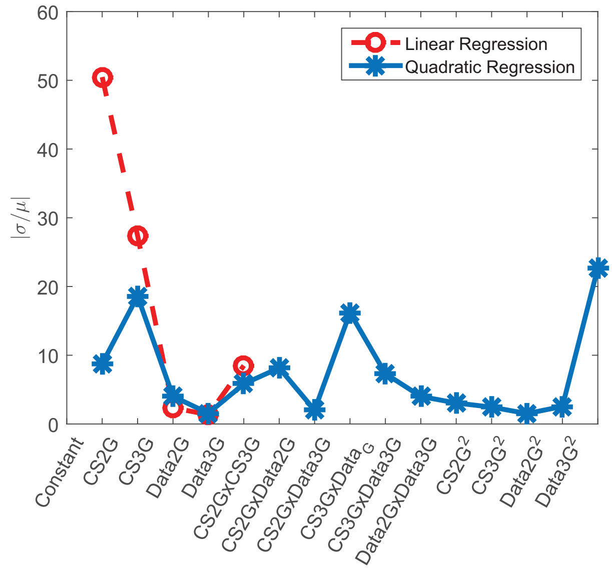

Fig. 2: The normalized variance of the different observation variables for both regression models over all base stations.

II. Measurement-based Model

A campaign of measurements was held on 16 sites serving 2G and 3G cells of an operator in the middle east. The measurement campaign was conducted for 4 months, where 2G and 3G circuit-switched (CS) and packet-switched (PS) traffic were collected in addition to the consumed power. The traffic and the consumed powers were averaged over 24 hours. It should be noted that 3 out of 16 base stations serve only 2G cells.

In order to find the relation between the traffic and the power consumption, we developed two regression models. The first model is linear model and the second is quadratic. The linear and quadratic models are defined in (1) and (2), respectively, where P is the consumed energy in KWH. Moreover, CS2G, CS3G, Data2G, and Data3G represents the 2G circuit-switch traffic in Erlang, the 3G circuit-switch traffic in Erlang, the 2G packet-switch traffic in Mbps, and the 3G packet-switch traffic in Mbps, respectively. Finally, C_i are the coefficient of the observation variables. In particular C_0 is the constant independent of the traffic.

Furthermore, we normalized the variables using z-score:

$$X' = \frac{X - \bar{X}}{s}. \tag{3}$$

where X is the original value, X' the normalized value, and $\bar{X}$ the mean of the sample.

In Fig. 1, we show the boxplot of the R^2 of the two regression methods used. As it can be seen from the figures, the quadratic model provides better results than the linear model. The latter, in some cases, can totally fail to represent the relation between the traffic and power consumption.

In Fig. 2, we show the normalized variance (σ) of the estimated coefficients for the different observation variables over all base stations. The variances are normalized over the mean coefficients (μ). As the figure shows, the variance for the linear regression model can reach a value of 50 for the constant part, and the variance for the quadratic regression model can reach a value of 20 for the coefficient of the square of 3G data. This shows that different base stations, with different properties and traffic patterns, exhibit different energy consumption models, and therefore we should not use generic models for all base stations.

In Fig. 3, we show the normalized variance (σ) of the estimated coefficients for the different observation variables for one base station (BS 1) as an example over 4 months, from January to April. The figure shows that, even for the same base station, the normalized variance is high (e.g., it can reach a value of 16 for quadratic regression). This means that we should have different models for different months, which have different environmental properties such as temperature, humidity, pressure, and rain.

III. Online Learning Model

In the previous section, we showed using the analysis of real measurements that we cannot apply a fixed model for energy consumption, as the model can change from one BS to another and for the same BS over different periods of time. Hence, we propose in this section a framework enabling each base station to learn its own models. These models will be saved in the OSS together with the properties of the base

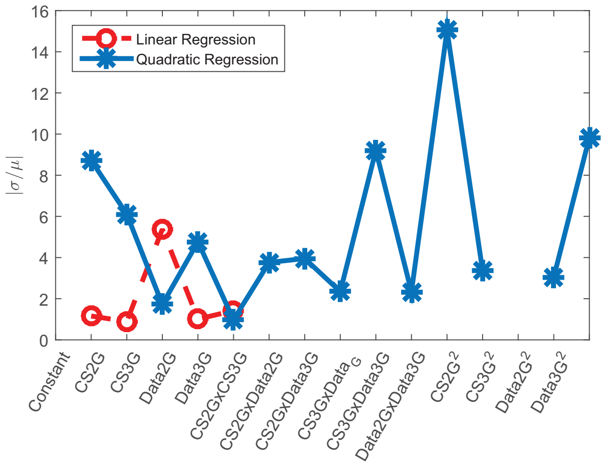

Fig. 3: The normalized variance of the different observation variables for linear and quadratic regression models for base station 1 over 4 months: January, February, March, April.

station (i.e., installed hardware, age, and configuration) and the environmental parameters (i.e., temperature, humidity, rain level, pressure, time, and date). The approach is divided into two periods: Initial period and operational period.

The initial period starts when the base station is turned on. At this stage, the base station would not have any collected measurements. Thus, an initial model is needed. This model can be generated by the OSS using existing models for other base stations that have the same the properties and age.

The operational period starts when there is enough data to generate the model. During the operational period, the base station will make environmental measurements and will send them together with traffic and consumption measurement to the OSS. These measurements will be collected each 15 minutes and a model will be built using two methods as explained below. In case the base station is powerful enough, model extraction will be done by the base station.

In the operational period, the model can be built either periodically or parameter-based. In the first approach, a model will be created for a specific time window. The time window is defined by a month and a range of hours. For instance, a model can be created for the month of March between 12:00 PM and 17:00 PM. The data will be collected for all days in March between these hours and a model will be created for this period. Each year, the model will be updated. In the second approach, the environmental parameters will decide to which model the measurements should be added. In other words, the system will save a model, together with the measurement used to generated the model, for each tuple temperature, pressure, humidity. When enough environmental parameters (i.e. at least 50 records) are received by the system, the model of the matching tuple will be selected. Then the system will create a new model based on the new and existing measurements for the tuple. If the new model is the same, the model will be kept as is. Otherwise, a new model will be created using only the new measurements. This will eliminate the impact of the old measurement on the model, which can change due to the age or traffic properties of the base station. In both cases, the existing measurements will be replaced by the new measurements to keep the model up-to-date. It should be noted that for any change in the hardware or the configuration of the base station, the latter will enter into the initial period. Fig. 4 shows a simple scenario of two base stations of the same model, but with different configuration and thus different models.

IV. Discussion

The widely used model with fixed relation between the energy consumption and the traffic is very simple and facilitates the development of green systems as it provides a static feedback to any planning systems such as the work in [12], [21], [22] or for energy efficient radio resource management techniques such the work in [23]–[26]. However, these models are inaccurate and may lead to errors in the estimation of needed energy.

Although the proposed framework provides more accurate models, they may lead to an increase in system complexity. The periodical approach in the proposed framework can provide the planning and resource management algorithm with the required information to estimate the needed energy in a periodic way, which will provide fixed inputs to energy efficient algorithms for a period of time. Therefore, this approach is comparable to the fixed models in terms of complexity of its integration in energy efficient systems. However, the determination of the periods of time that will have the same model is a difficult problem as it depends on environmental changes that have high dynamics. In addition, the number of models that should be saved are limited.

The parameter-based approach in the proposed framework has less parameters to set as it will dynamically learn the tuples. However, this mechanism generates two problems. The first problem is the presence of a big number of models that will corresponds to all the possible combinations of the environmental parameters. This problem can be solved by using ranges for the environmental parameters instead of absolute values as shown in Fig. 4. The second problem is due to the fact that the models will have a loose relation with time, which will lead to the need to different planning and radio resource management methods than the ones we have today. Fortunately, there are models that can predict the environmental parameters and therefore allow the development of stable energy efficient methods.

V. Conclusions

In this paper, we have studied the relation between energy consumption in base stations and their traffic using the measurements obtained through a campaign of measurement that was led on a regional operator over several months. We have used two regression models: Linear and quadratic. The obtained results have shown that in most of the cases the quadratic model is much better than the widely used linear model, which drastically fails to represent the consumption models in some cases. Furthermore, the results have shown that a unified model for all base stations is not an efficient approach as each base station may have its own model.

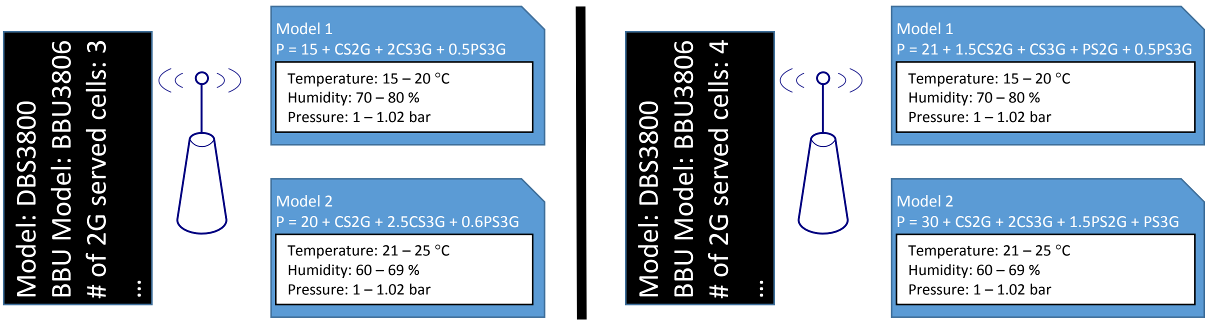

Fig. 4: An Example of online-learning model using the parameter-based approach.

Based on the obtained results, we have proposed a learning-based approach that allows base stations to create their own models based on environmental and traffic measurements. Two approaches have been used to implement the framework in operational environment where the energy consumption model can change over time. The two approaches have been discussed in terms of complexity.

The obtained results and proposed framework can be generalized to other systems where renewable energy can be used such as in IoT, small-cells, D2D, and data center systems. We are working now on implementing the developed approach on small hardware (i.e. Arduino) to study its performance and to investigate more on the environmental parameters that can impact the energy consumption model.

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