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On Intelligent Base Station Activation for Next Generation Wireless Networks

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Abstract

The evolution of mobile communications, during the last decades, has led to a rapid increase in the number of users that mobile operators have to serve. To cope with this increase, mobile operators increment the number of base stations they are using resulting in an escalation of the corresponding energy footprint. This is why; the reduction of the total energy that is consumed from base stations has been the epicentre of many researchers. To achieve that, a common approach is to minimize the number of base stations that are used by activating only the necessary base stations without affecting the corresponding quality of service. In this paper, we present a method for predicting crowded areas based on machine learning techniques. The dataset used contains information about the number of users that have been connected to twenty base stations during the time period of 8 days. Prediction results can be used in order to make appropriate suggestions to mobile operators about bases stations that can be activated or deactivated. We propose a Probabilistic Neural Network and confirm its superior performance against two other types of neural networks.

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Keywords: heterogeneous wireless networks; software defined networks; software-based controllers; learning algorithms; mobile operator recommendations

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1. Introduction

Wireless communications have met great popularity during the past decades, passing through numerous phases of evolution like 2G, 3G and recent 4G networks. In parallel, there has been an explosive progression on users' mobile phones (e.g. smartphones); while by 2020 the traffic originating from portable devices is expected to increment exponentially[1]. Until recent years, mobile operators (MOs) were increasing the number of Base Stations (BSs) in order to satisfy the escalating number of users. This growth in the number of BSs resulted in an increased energy consumption, which is harmful to both the environment and the MOs maintenance costs[2]. Specifically, BSs' energy consumption is estimated to 60-80%, among various elements of a cellular network, reaching 80-90% even in idle or low traffic state[3].

A recent approach that has been addressed from the research community is the dynamic activation and deactivation of BSs in a network, in order to reduce significantly the consumed energy[4,5]. Specifically, in[6] the authors formulate a network utility maximization problem aiming to find an optimal activation schedule for each BS and devise a distributed algorithm based on the Lagrangian dual decomposition. Similarly, in[7] the authors attempt to find an adaptive cell zooming method to reduce the energy consumption of BSs. They formulate an optimization problem taking into consideration varying traffic patterns, interference and service availability.

The authors in[8] attempt to find the minimum set of BSs to be powered on to satisfy a given traffic demand. To achieve that, they propose two switch-off strategies based either on the cell load or the BS coverage overlap. In[9] the authors utilize sparse-promoting techniques and propose formulations to select active BSs in order to (a) minimize the total power consumption; or (b) maximize the sum rate performance. An online reinforcement learning algorithm that adapts to the changing network traffic is proposed in[10] in order to dynamically activate and deactivate the resource units.

In this paper, following the above trend, we propose an intelligent BS activation system, in order to locate areas that will be crowded and provide recommendations to MOs about potential BSs to be activated or deactivated. According to[11] cellular traffic exhibits periodic fluctuations both in time and space. This behaviour can be attributed to diverse usage examples amid days and nights, weekdays and weekends, and crosswise over residential and business regions. This is why our proposed solution focuses on the use of neural networks. Specifically, we propose a Probabilistic Neural Network (PNN) and compare its performance to two other algorithms that are also based on machine learning.

The rest of this paper is organized as follows. In Section 2, we describe the architecture of the proposed system for processing collected data from BSs using machine learning mechanisms. In Section 3, we present the three different approaches that we use based on machine learning, namely Multilayer Perceptron, Support Vector Machine (SVM) and PNN. The dataset that was employed is presented in Section 4, while in Section 5 we provide the results and discuss on the performance of the three proposed algorithms. Finally, the paper concludes in Section 6.

2. System Architecture

The main idea of the proposed architecture is based on the SDN architecture, which enables the abstraction of low level networking functionality into virtual services, allowing the introduction of new services[12]. A representation of the entities involved in the scope of this paper is depicted in Fig. 1. We assume that there is a Centralized Network Controller, based on the SDN architecture, which is responsible for collecting all necessary measurements and reaching the required decisions. In order to enhance the Centralized Network Controller, we introduce the *Intelligent Decision Making* entity.

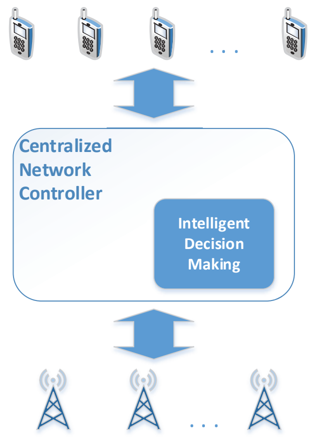

Fig. 1. SDN-based system's architecture.

The *Intelligent Decision Making* entity is responsible for collecting necessary information from BSs that apply to the range of the Centralized Network Controller. In addition, using machine learning mechanisms we can assist the Centralized Network Controller to the decision making process. In Fig. 2, we illustrate the deployment of the main application components of the proposed architecture, using the ArchiMate® notation[13], showing the basic components and their relationship.

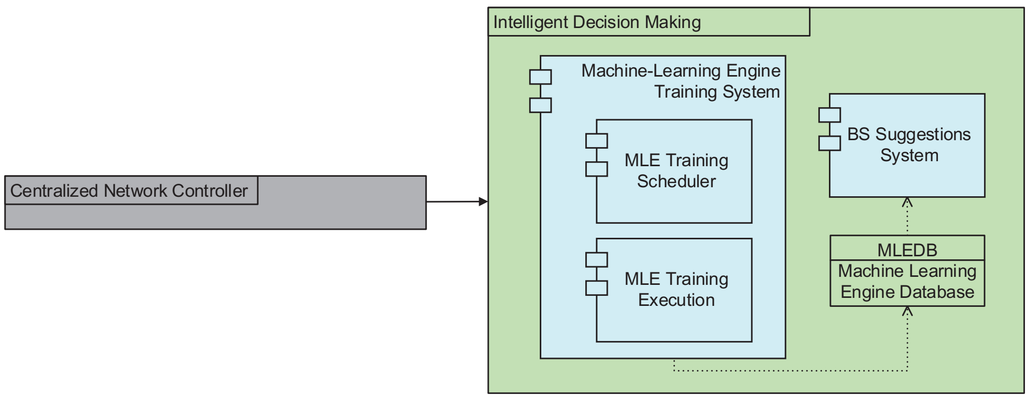

Fig. 2. Intelligent Decision Making System – application layer.

For the *Intelligent Decision Making* entity, we recognize the following components:

- *Machine-Learning Engine Training System*: This system is responsible for the centralized training of the machine-learning engines that will be used by the *BS Suggestions* system. It is comprised of the *MLE Training Scheduler* and the *MLE Training Execution* components.
- *MLE Training Scheduler*: The main purpose of this component is to initiate the generation of new MLEs (such as Multilayer Perceptron, SVMs, or PNNs).
- *MLE Training Execution*: This component is responsible for retrieving all necessary training data and for executing the machine learning engine training algorithm.

- *BS Suggestions System*: This component is responsible for performing estimation about the crowd level that is expected in each BS, according to the traffic records retrieved from the BSs.

3. Prediction Models

In order to provide MOs with recommendations about BSs that can be activated or deactivated, we propose the use of machine learning techniques in order to predict areas that are expected to be crowded, based on input that we retrieve from BSs.

3.1. Multilayer Perceptron

The first approach used as a prediction model is the Multilayer Perceptron Network. Multilayer Perceptrons form one type of feed-forward Artificial Neural Networks (ANNs) according to the taxonomy of neural network architectures presented in[14].

The Multilayer Perceptron's architecture consists of an input layer, a number of hidden layers and an output layer. The number of the necessary hidden layers depends on the problem formulation. However, it has been proved that using more than two hidden layers rarely improves the model, while it introduces a risk of converging to local minima[15]. The nodes are connected by weights and output signals which are a function of the sum of the inputs to the node.

3.2. Support Vector Machine (SVM)

Another category of universal feed-forward network is the SVMs, proposed by Vapnik[16,17], which are widely used for pattern classification and nonlinear regression problems. It is based on statistical learning theory and uses linear, polynomial and radial basis kernels. An SVM, unlike common ANNs, is characterized by the absence of local minima. In addition, the computational complexity of SVMs does not depend on the dimensionality of the input space[18].

Assuming that there exist separable patterns in the context of pattern classification, the main idea of SVMs is to construct a hyperplane as the decision surface in such a way that the margin of separation between positive and negative examples is minimized. A major advantage of SVMs is that they can provide a good generalization performance on pattern classification problems despite the fact that they do not incorporate problem-domain knowledge.

A central notion for the construction of the SVM learning algorithm is the inner-product kernel between a "support vector" $\boldsymbol{x}_i$ and the vector x drawn from the input space. The support vectors consist of a small subset of the training data extracted by the algorithm. Depending on how this inner-product kernel is generated, different learning machines characterized by nonlinear decision surfaces can be constructed.

3.3. Probabilistic Neural Network (PNN)

PNNs are used to perform classification where the target variable is categorical. Compared to the Multilayer Perceptron networks, a PNN is usually much faster to train and more accurate. This is mainly due to the fact that the PNN uses the radial basis function as kernel and interprets the network structure in the form of probability density function. It is noteworthy that PNNs are based on the Bayes' theory, resulting to classifications that approach Bayes' optimal classification[19].

As it can be seen from Fig. 3, a PNN takes as input a n dimensional feature vector $\boldsymbol{X} = \{x_1, x_2, \dots, x_n\}$. The inputs are passed to the neurons in the *Hidden Layer*, where the distance of the test case from the neuron's centre point is computed and then a radial basis function is applied, using a smoothing parameter (σ). The number of units in this layer is equal to the number of samples in the training set. The *Summation Layer* is responsible for summing the input from the hidden layer and produces a vector of probabilities that represent the probability of each feature to belong to a specific class. Finally, the *Output Layer* provides the classification decision, following Bayes' decision rule. It is worth mentioning that the smoothing parameter (σ) is the only parameter of the network that needs to be fixed at the beginning of the training.

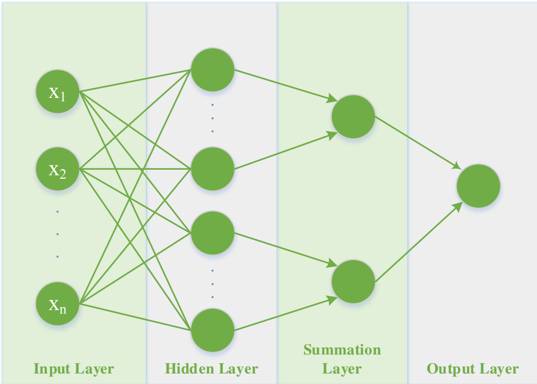

Fig. 3. Architecture of Probabilistic Neural Network.

4. Data Analysis

The dataset used in this paper is based on measurements that were taken for research purposes in[20]. The data were collected from BSs in a median-size city of China, consisting of individuals' activities during a continuous week, with accurate timestamp and location information indicated by connected BSs. Each individual is detected by the hashed International Mobile Subscriber Identity (IMSI). For the purposes of this paper, we used information from twenty BSs.

The above mentioned information is used to create a three-tuple with the variables described in Table 1.

Table 1. Variables and values used.

Variable	Description
base_station	Identity of each cellular base station {20 base stations}
day	Values 1-7, representing each day of the week {Monday-Sunday}
period	Values 1-4, representing the time period of each day {morning, noon, afternoon, night}

Using the described variables, the input set for the proposed algorithms can be defined as:

$$x = (base\_station,\ day,\ period) \qquad (1)$$

In order to provide MOs with recommendations about whether a BS will be crowded or not, we use the methods described in Section 3. Furthermore, we introduce as a target for the used prediction algorithms the $crowd\_level$ variable, which takes values 1-3 according to the level of forecasted crowd {uncrowded, crowded, overcrowded}.

5. Results

To demonstrate the appropriateness of the PNN, we compared the results of the validation process of the PNN ($\sigma = 0.05$), with two other types belonging to the family of neural networks, as described in Section 3. The proposed learning algorithms were used in order to provide recommendations to MOs based on record traffic collected from the BSs, about the level of crowd that is expected in each BS. In Table 2, we present the misclassification percentage that was derived from each learning method, using 10-fold cross-validation method. Specifically, the Multilayer Perceptron was formulated as a 3-9-4 three-layered feed-forward neural network, while the SVM was constructed with an RBF kernel function.

Table 2. Results of validation process.

Learning Method	Misclassification percentage (%)
MLP	10.538
SVM	10.397
PNN ($\sigma = 0.05$)	9.355

It is clear that the PNN network performs better compared t the three-layered perceptron network and the SVM, making it suitable for MOs' recommendations. However, it should be noted that the smoothing parameter (σ) affects the performance of the PNN and need to be appropriately fixed in order to give better prediction results. In Fig. 4, we present the effect of the smoothing parameter with values that range from 0.01 to 0.2. It can be observed that for most possible σ values, the PNN network performs better that the other two prediction algorithms, and for $\sigma \approx 0.04$ it provides minimum misclassification percentage (8.988 %).

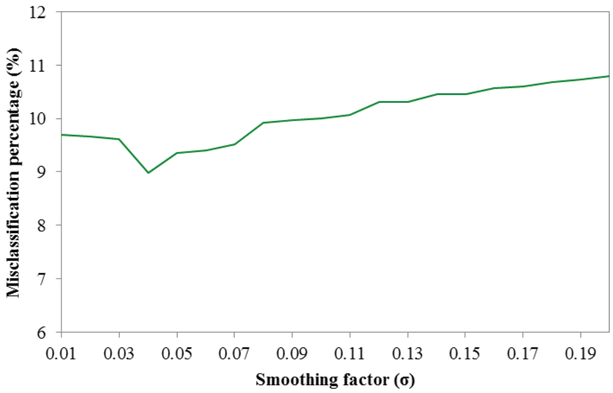

Fig. 4. Misclassification percentage for PNN with respect to σ values.

6. Conclusions

In this paper, we have presented our work on providing recommendations to mobile operators about the activation or deactivation of base stations, using data gathered from users' traffic in base stations. Specifically, we have introduced a system architecture for collecting necessary data from base stations, and for running the machine-learning algorithms in order to provide recommendations to mobile operators about base stations that can be activated or deactivated on specific time periods of the day. Three different learning algorithms based on neural networks, Multilayer Perceptron, SVM and PNN, were used in order to forecast the crowd level of base stations.

The dataset used includes information collected from twenty base stations. From the results we have concluded that the PNN outperforms the other two proposed algorithms, giving predictions with high accuracy.

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