A Predictive Model for Minimising Power Usage in Radio Access Networks

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Abstract. In radio access networks traffic load varies greatly both spatially and temporally. However, resource usage of Base Stations (BSs) does not solely depend on the traffic load; auxiliary devices contribute to resource usage in a load invariant manner. Consequently, BSs suffer from a large underutilisation of resources throughout most of the day due to their optimisation for peak traffic hours. In this paper an energy saving scheme is proposed with the use of an Artificial Neural Network (ANN) predictive model to make switching decisions ahead of time. The optimum set of BS to turn off while maintaining Quality Of Service (QoS) is formulated as a binary integer programming problem. We validated our model and found large potential savings using an extensive data set spanning all network usage for three months and over one thousand BSs covering the entirety of Dublin city and county.

Keywords: Cellular usage · Traffic prediction · Cellular networks · Temporal dynamics · Spectrum sharing · Green networks

1 Introduction

In the past two decades mobile phones and devices utilising the mobile phone network have become ubiquitous in modern society. Mobile phone penetration has approached and in some nations exceeded 100 % [1]. Cellular networks are undergoing, and will continue to experience, a large and sustained increase in demand for network resources [2]. Demand is particularly acute at the radio access level where service is constrained by the availability of valuable licensed spectrum [3]. Concomitant with the growth of cellular usage there has been a large increase in the energy used by cellular networks [4]. It is estimated that cellular networks account for approximately 10 % of the total carbon emitted by the Information and Communication Technology (ICT) sector with this expected to increase further in the future [5]. In addition to the environmental concerns there are real economic benefits for network operators to minimise power consumption [6].

It is currently estimated that 80 % of the overall infrastructure power consumption takes places in the Radio Access Network (RAN), particularly Base Stations (BSs) [7]. Despite significant temporal and spatial variations in demand [8–10], networks are currently optimised for peak throughput at peak demand. As shown in [3] large

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underutilisation of RAN resources are present and particularly pronounced at the cell level. Unfortunately, the infrastructure of currently deployed networks is largely load invariant meaning largely underutilised cells stay active despite a lack of demand. This is a costly inefficiency in terms of power consumption but it also underutilises valuable licensed spectrum which could be made available for secondary usage [3].

Accurate short and medium term predictive models of load (primary usage) at the local level (cell, BS, local grid etc.) are critical if Self-Organising Networks (SON) are to ameliorate the network's inefficient usage of power and spectrum. For example, if it can be predicted that traffic in a particular cell or group of cells falls below a certain threshold at certain times then SON algorithms can use this information to alter the network to save energy [11–13]. Also, if low demand by primary users of valuable licensed spectrum can be predicted in certain cells/areas at for example off-peak times this can provide opportunities for secondary usage in these bands [14].

Much work has gone into algorithms and techniques to dynamically switch on/off cells or BSs [11–13]. However, most work in the area simply uses historical static load profiles or assumes that switching decisions can be made instantaneously. However, real world measurement results such as presented in [15] show that switching can take up to 30 min due to the heating systems. Thus, predictions of the need to perform a switch ahead of time are important.

2 Background

The infrastructure of the 3G network is comprised of two main parts: the RAN and the Core Network (CN). The RAN is comprised of the User Equipment (UE), the Radio Network Controller (RNC), and the BS which can be further subdivided into cells. Each RNC manages many BSs which are split into cells and service subscribers through their air interface with the UE [16] (Fig. 1).

There are two primary subsystems: the communications subsystem and the support subsystem. The communications subsystem is comprised of the Remote Radio Unit (RRU), the Feeder, and the Base Band Unit (BBU). The RRU provides the radio hardware for each sector of the base station. Each BS may have several RRUs near the antennas to allow for varying coverage and capacity [15]. The BBU is responsible for all the other communication functions such as control, Iub interfaces to the RNC, base band, scrambling, link quality measurements, soft handovers etc. [16]. Each BS may also have several BBUs. The feeder is a fiber optic pair cable connecting the RRUs to the BBUs. The supporting subsystem is comprised of the cooling subsystem and supporting devices. The cooling subsystem maintains an appropriate operating temperature at the BS.

The cooling subsystem coupled with some of the transmission modules are responsible for the consumption of a significant amount of the power in a BS (over 50 % [15]) but are load invariant i.e. their power consumption does not proportionately scale down with low demand. Thus, the RAN can conserve large amounts of power by powering down certain BSs under low load conditions.

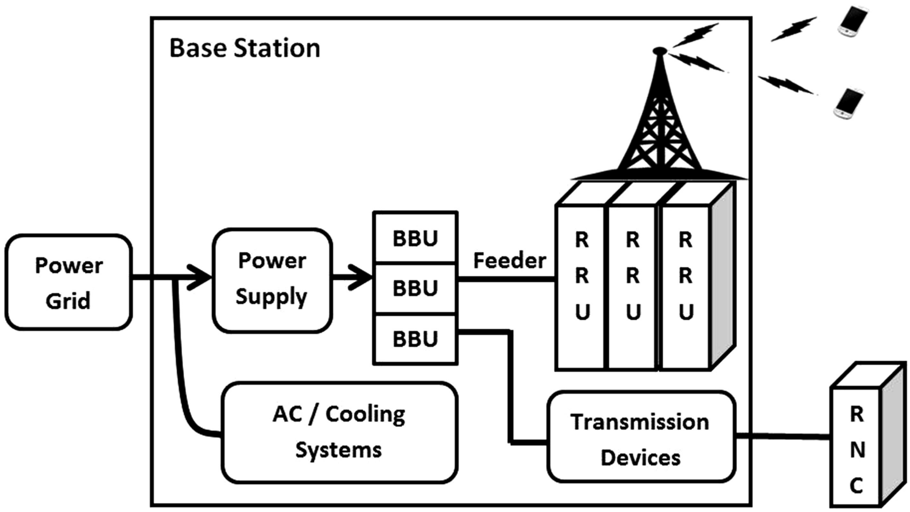

Fig. 1. A typical BS in a 3G Network

For base stations we employ the power consumption models outlined in [15, 17] where the total power consumption P at a given BS is given by:

$$P = P_{tx} + P_{misc} \tag{1}$$

where P_{tx} accounts for the power used to provide network access to subscribers UE. This includes power consumed by the RRUs, the BBUs, the feeder, and the RNC transmissions. P_{misc} is the power consumed by cooling, monitoring and the auxiliary power supply.

P_{tx} can be linearly approximated as:

$$P_{tx}(L) = P_{\alpha} \cdot L + P_{\beta} \tag{2}$$

where L is the traffic load factor on a BS. P_{tx} varies as a result of both the RRU and BBU. For example, during periods of high traffic the RRU consumes more power servicing more active links. Thus, the power consumption varies with traffic load. Conversely, the BBU carries out base band processing for all frequencies used by the BS. Its power consumption is mainly determined by the number of frequency carriers and not the number of active links. Also, other operations such as such as signaling over control channels use energy even under low loads. The coefficient P_{α} depends on the transmission distance of the base station as greater power is consumed communicating over a greater distance.

P_{misc} as outlined in [15] is mainly a function of external conditions such as temperature. It is largely invariant with load and thus we assume that the supporting subsystem power consumption stays constant in this work.

3 Artificial Neural Network Traffic Load Prediction

As demonstrated in [3, 18, 19] several factors can affect the traffic load: time of the day, day of the week, location, special events etc. Thus, a useful prediction method must be capable of learning the relationships between these factors and load. There are several possible methods available such as Auto-Regressive Moving Average (ARMA) models, Seasonal ARMA models (SARMA), Auto-Regressive Integrated Moving Average Models (ARIMA), Artificial Neural Networks (ANN), wavelet based methods, compressed sensing based prediction methods etc. With due consideration to the accuracy and the computational complexity of traffic prediction we employ ANN as recommended by [20, 21].

In this work we chose an ANN employing Back Propagation (BP) due to its simple structure and plasticity. The traffic prediction process can be divided into three sections: create the BP network, train the BP network, and predict the traffic.

The BP network outputs the predicted traffic at a given time *t*. Different cells service many diverse areas with differing demands and thus have disparate load profiles [3]. Thus, we do not use the same model for different cells; every cell has its own BP network model. We chose day of the week (*D*), time of the day (*t*), and past traffic which is relevant to the predicted value as input parameters. As in [21] the relativity R_τ between $\rho_m(t\text{-}\tau)$ and $\rho_m(t)$ is measured by:

$$R_\tau = \frac{\sum_{t=1}^{T}\left(\rho_m(t) - \bar{\rho}_{m,1}\right)\left(\rho_m(t-\tau) - \bar{\rho}_{m,2}\right)}{\sqrt{\sum_{t=1}^{T}\left(\rho_m(t) - \bar{\rho}_{m,1}\right)^2}\sqrt{\sum_{t=1}^{T}\left(\rho_m(t-\tau) - \bar{\rho}_{m,2}\right)^2}} \tag{3}$$

where T is the total number of points in time, $\bar{\rho}_{m,1}$ and $\bar{\rho}_{m,2}$ are the mean values of $\rho_m(t)$ and $\rho_m(t\text{-}\tau)$ respectively. If the load at time $t\text{-}\tau$ (denoted $\rho_m(t\text{-}\tau)$) has a $R_\tau > 0.8$ it is considered to be strongly related to time $\rho_m(t)$; the number of related past time points $\rho_m(t\text{-}\tau)$ is denoted M.

The number of hidden layers and neurons is application dependent; output sensitivity is used to estimate the effect of each input or neuron to ensure efficiency. We denote an input or a neuron as θ, the output sensitivity of θ at t is defined as

$$S_\theta(t) = \frac{\delta\rho_m(t)}{\delta\theta} \tag{4}$$

the variance of sensitivity can be estimated by:

$$\sigma_{s_\theta}^2 = \frac{\sum_{t=1}^{T}\left(S_\theta(t) - \bar{S}_\theta\right)^2}{T-1} \tag{5}$$

where $\bar{S}_\theta$ is the mean value of $S_\theta(t)$. Based on the variance of S_θ, $v_{S\theta}$ describes the availability of θ and

$$v_{s_\theta} = \frac{(T-1)\sigma_{s_\theta}^2}{\sigma_0^2} \tag{6}$$

where σ_0 is a regularization parameter; increasing σ_0 leads to more θ being discarded and a simpler network architecture. However, a network architecture that is too simplistic may also lead to a poorer predictive performance. Assuming zero variance, $v_{s_\theta} \approx \chi^2(T-1)$, a critical value v_c can be found in the χ^2 distribution table:

$$v_c = \chi^2_{T-1,(1-\alpha/2)} \tag{7}$$

where α denotes the significance level which we set to 0.05. Values of $v_{s_\theta} < v_c$, result in a θ being abandoned. This procedure is carried out for each input parameter and neuron to build a network with a simple but effective structure.

The BP network is trained with the Levenberg-Marquardt (LM) algorithm [21, 22]; training is a cyclical process where t, D and traffic from *t-M* to *t-1* are provided to the BP network at the start of each iteration. The difference between the predicted traffic $\rho_m^p(t)$ and real traffic $\rho_m(t)$ is:

$$\xi(w) = \frac{1}{T}\sum_{t=1}^{T}\left(\rho_m^p(t) - \rho_m(t)\right)^2 \tag{8}$$

which can be rewritten as:

$$\xi(w) = \frac{1}{T}\sum_{t=1}^{T}(\mathrm{f}(\omega, \mathrm{t}) - \rho_m(t))^2 \tag{9}$$

where the output $\rho_m^p(t)$ is expressed as a function of the weights ω and t represented by $f(\omega,t)$. The weights ω are adjusted as:

$$\omega = \omega_{last} + \Delta\omega \tag{10}$$

with,

$$\Delta\omega = -\frac{\boldsymbol{d}}{\boldsymbol{H} + e^{\beta}\boldsymbol{I}} \tag{11}$$

where ω_{last} is initially randomly chosen and thereafter the weight from the previous iteration. $\Delta\omega$ is the change in ω between iterations, $\boldsymbol{I}$ is the identity matrix, β is used to maintain stability and adjusted in each iteration [21], and $\boldsymbol{H}$ is the Hessian matrix which provides the learning rate. $\boldsymbol{H}$ can be obtained by taking the second derivative of ξ with respect to all weights. The sum of the gradient is denoted by $\boldsymbol{d}$ and is equal to:

$$\mathbf{d} = \frac{\delta\xi}{\delta\omega} = \sum_{t=1}^{T}\frac{\delta\xi}{\delta\rho_m(t)}\frac{\delta\rho_m(t)}{\delta\omega} \tag{12}$$

The algorithm continues until the prediction error is acceptable or the maximum number of iterations is reached; each network is only trained once.

4 Traffic Prediction Based Energy Savings Scheme

In a typical network many BSs are vastly underutilised for most of the day as demonstrated in [3]. As discussed in Sect. 1, this underutilisation is wasteful of both power and valuable licensed spectrum which could be used by unlicensed secondary usage. As shown in [3], the coverage areas of many BSs overlap to reliably service demand during the short and predictable hours of peak demand. A reduction in the underutilisation of network resources can thus be achieved by putting redundant BSs to sleep at off-peak times. Once redundant BSs are put to sleep, the active BSs can take advantage of modern techniques such as beamforming to cover the spaces left by inactive BSs [23]. When the traffic increases above a certain threshold the inactive BSs are switched on again. However, real world measurements [15] show that the switching process is not instantaneous. Thus, predicting the load ahead of time is important to the smooth operation of such a system.

To tackle the problem we first divide the coverage area of each base station into equal sized squares. As the coverage area of each BS is generally small in the areas of most interest (dense urban [3]) we assume that the traffic load of each BS is evenly distributed between its squares. We then map all the BSs and squares as the vertices of an undirected graph $G = (V,E)$. BS i and square k form and edge $e_{i,k} \epsilon E$ if the entire area of the square falls within the maximum transmission range of the BS. Thus, we want to form a graph with the minimum number of edges while ensuring that: every square is covered by one BS, and every BS is not connected to more squares than it can reasonably service. Thus the problem can be formulated as:

$$\begin{aligned} & min \sum_{i=1}^{n} sgn\left(\sum_{e_{i,k} \epsilon E} I_{e_{i,k}}\right) \\ & s.t. \sum_{e_{i,k} \epsilon E} V_{e_{i,k}} \times I_{e_{i,k}} \leq C_i, \qquad \forall i \in 1\ldots n \\ & \sum_{e_{i,k} \epsilon E} I_{e_{i,k}} \geq 1, \qquad \forall k \\ & I_{e_{i,k}} \in \{0,1\} \qquad \forall e_{i,k} \in E \end{aligned} \tag{13}$$

where $e_{i,k}$ is the edge between BS i and square k; $V_{ei,k}$ denotes the traffic load in square k. If $I_{e_{i,k}} = 1$ then $e_{i,k}$ is included in the optimal solution while $I_{e_{i,k}} = 0$ means it is not. C_i is the capacity threshold of BS i [24]. The first constraint prohibits the distribution of a traffic load to any BS that exceeds the BS's capacity. The second constraint guarantees that every square is covered by a BS.

The above solution allows for adjustments to be made to the coverage areas of BS. However, it does not take into account that (as discussed in Sect. 2) a certain amount of the power consumption is proportional to transmission distances and load. To that end the edge weight $P_{ei,k}$ is introduced to the graph $G = (V,E)$ and denotes the power required by BS i to service the traffic load in square k. The magnitude of $P_{ei,k}$ depends on the load, and the distance between BS i and square k. $P_{ei,k}$ is analogous to P_{tx}, the transmit power discussed in Sect. 2. Following on from the power model in Sect. 2 we incorporate $P_{constant}$ which represents the constant power usage of the BS independent of load and transmission distance. Thus the objective function in (13) is extended to include power consumption:

$$\min \sum_{e_{i,k} \in E} P_{ei,k} \times I_{e_i,k} + \sum_{i=1}^{n} P_{i,constant} \times sgn\left(\sum_{e_{i,k} \in E} I_{e_{i,k}} \right) \tag{14}$$

Equation (14) can be transformed into a more manageable form as in [24]:

$$\begin{array}{rr} \min \sum\limits_{e_{i,k} \in E} P_{ei,k} \times I_{e_{i,k}} + \sum\limits_{i=1}^{n} P_{i,constant} \times I_{s_i} & \\ s.t. \sum\limits_{e_{i,k} \epsilon E} V_{e_{i,k}} \times I_{e_{i,k}} \le C_i, & \forall i \in 1\ldots n \\ \sum\limits_{e_{i,k} \epsilon E} I_{e_{i,k}} \ge 1, & \forall k \\ \sum\limits_{e_{i,k} \epsilon E} I_{e_{i,k}} - I_{s_i} \times N_{s_i} \le 0, & \forall i \in 1\ldots \\ I_{e_{i,k}} \in \{0,1\} & \forall e_{i,k} \in E \\ I_{s_i} \in \{0,1\} & \forall i \in 1\ldots n \end{array} \tag{15}$$

If $I_{si} = 1$ then BS i will be active in the final energy saving scheme while $I_{si} = 0$ means it will be inactive. N_{si} denotes the number of edges connected to BS i. The new constraint in (15) ensures that if BS i is selected to be inactive ($I_{si} = 0$) it does not need to service any of the squares. (15) is a binary integer programming problem which can be approximated by the branch and bound plus primal and dual algorithms [25].

5 Evaluation and Results

To evaluate the performance of our prediction algorithm and energy savings scheme we use three months of real world traffic data taken from 1145 BSs covering the four administrative counties comprising county Dublin in Ireland (Dublin City, Dún Laoghaire-Rathdown, Fingal and South Dublin)[1].

The data set includes information on all calls, SMS and cellular data usage for each of the network's users over the time period. Where appropriate, both voice calls and SMS are treated as an equivalent data service expressed in bytes and added to cellular data to get the Total Equivalent Data (TED). Voice is encoded in mobile phone networks using adaptive multirate (AMR) codecs. In GSM and wCDMA, a narrow-band AMR scheme is used with a typical data rate of 12.2 kbps. A higher quality wideband AMR is used in LTE and offers superior quality at a data rate of 12.5 kbps [26, 27]. Higher and lower data rates are possible, but for this paper a rate of 12.5 kbps will be used in converting voice channels to an equivalent data session. Text messages will be treated as a 200 byte message with 1 s duration.

[1] The boundary files used to define the four administrative counties can be obtained from the Irish Central Statistics Office. (2011, 01/02/2015). *Census 2011 Boundary Files*. Available: http://www.cso.ie/en/census/census2011boundaryfiles/.

The privacy of individual subscribers is paramount, thus all personal information in the dataset is anonymised and cannot be used to identify individual customers. No information was provided relating to the content of any call, SMS or data session.

5.1 Performance of Traffic Load Prediction

To evaluate the performance of our traffic load prediction algorithm we divide the dataset into three sets: 50 % training, 25 % test, and 25 % validation.

In [28] the authors suggest the use of scaled error metrics as an alternative to percentage error techniques when working with data on different scales. They propose the scaling of errors based on the training MAE from a "*naïve*" forecasting method. In the non-seasonal case using the naive method, we compute one-period-ahead forecasts from each data point in the training sample. Thus, a scaled error is defined as:

$$q_j = \frac{e_t}{\frac{1}{T-1}\sum_{t=2}^{T}|y_t - y_{t-1}|} \tag{16}$$

where we denote y_t as the observation of the load y at time t; $\hat{y}_t$ denotes a forecast of y_t T is the number of steps; the forecast error is defined as $e_t = y_t - t$.

As both the numerator and denominator include values on the scale of the original data, the result is independent of the data's scale. A scaled error of less than one results when the forecast is better than the mean naive forecast of the training data. A value greater than one indicates that the forecast was worse than the naive forecast calculated from the training set. As discussed in [3] network load exhibits a strong diurnal i.e. seasonal pattern which must be accounted for in our naive forecast component.

In the case of seasonal data we define the scaled error by employing a seasonal naive forecast:

$$q_j = \frac{e_t}{\frac{1}{T-m}\sum_{t=m+1}^{T}|y_t - y_{t-m}|} \tag{17}$$

where m is the seasonality component of the data. For example, setting m = 24 uses the value of the load 24 h ago as a naïve forecast of the load now.

The Mean Absolute Scaled Error (MASE) is thus defined as:

$$MASE = mean\left(\left|q_j\right|\right) \tag{18}$$

We calculate q_j from (17) for all the BSs, and we then get the MASE of all these results as in (18). We plot the MASE for one representative day for over 1000 BSs.

Figure 2 shows that the MASE value for the ANN prediction is usually less than 0.4 and hence a significant improvement on the naive method. As well as presenting the results for our ANN method we also plot results obtained from a Seasonal Auto Regressive Moving Average (SARMA) method presented in [3]. We see that the SARMA model again outperforms the naive method but is at all times, on average less accurate than our ANN method.

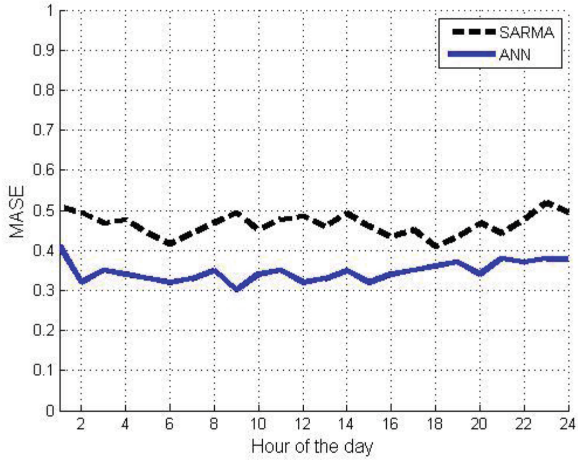

Fig. 2. The MASE over the course of one representative day for both SARMA and ANN.

Figure 3 illustrates the performance of the ANN load prediction method on one representative BS over a 24 h period. Generally the load prediction algorithm is stable under different load conditions; it consistently outperforms the naive and SARMA methods. We will now use it as a basis to perform predictions about the traffic load in our energy savings scheme.

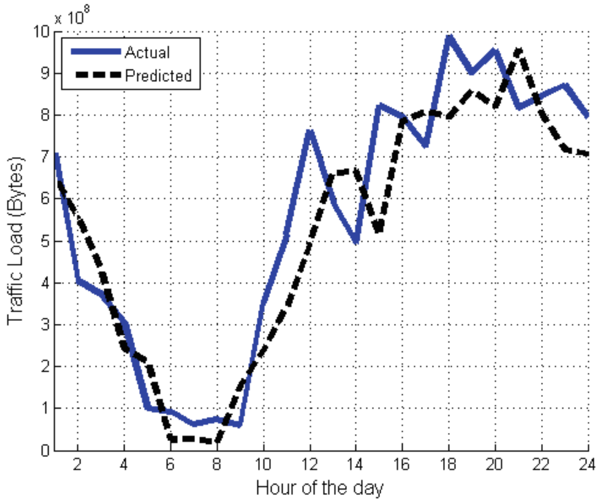

Fig. 3. Performance of the ANN traffic load prediction: Predicted value for one representative BS versus actual value over 24 h.

5.2 Performance of Energy Savings Scheme

To evaluate the performance of our energy saving scheme we inatalise the 1145 BSs to their real world coverage grids (supplied by the network operators). The following parameters are used: (i) the maximum capacity of each BS is set to the peak load observed in that BS over the three month period. This is a conservative estimate and probably underestimates actual capacity. However, in picking parameters we feel that it is more realistic to err on the side of caution as network operators will invariably overprovision for QoS reasons. (ii) The maximum transmission range depends on population/building density. We previously calculated the amount of people working or living in each BS's coverage area from call records [19] and now use these figures as proxy for density. As our area of interest is a densely populated urban region we use a conservative estimate of a 2 km maximum transmission range and scale down to the order of hundreds of meters depending on local density [15]. (iii) The power models $P_{tx} = 6L + 600\ W$ and $P_{misc} = 1500$ W are used at lower transmission ranges; the power model $P_{tx} = 12L + 600\ W$ is used when approaching the maximum transmission range [15_ENREF_15].

To quantify our results we calculate the power saving ratio which is defined as the power consumption of the optimised network divided by the original unoptimised power consumption of the network. Figure 4 shows the power saving ratio for Dublin's 1145 BSs over 24 h and the corresponding traffic load. We see that throughout the entire day there is great scope to conserve energy in the network, particularly at times of low load. For instance, over 70 % of the networks power consumption can be saved during the early morning hours. Even during peak times energy savings of over 35 % are possible.

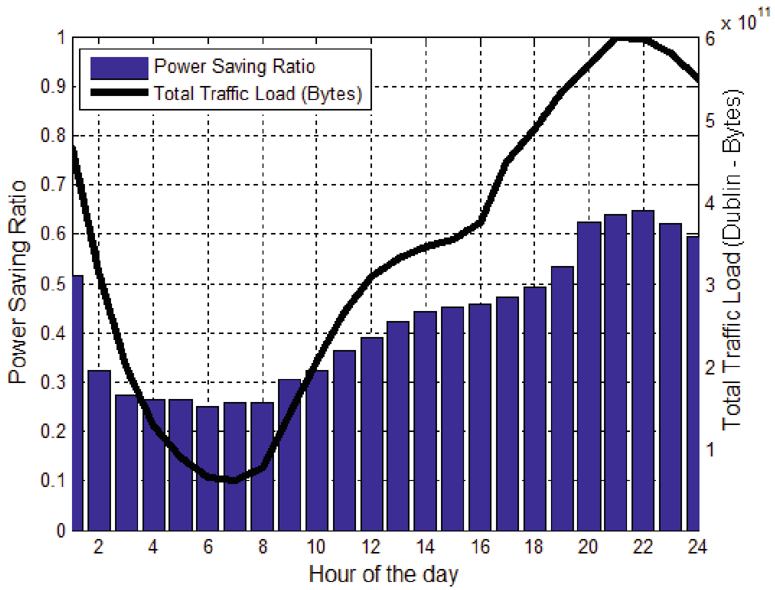

Fig. 4. Power saving ratio for Dublin's 1145 BSs over 24 h and corresponding traffic load.

6 Conclusion and Future Work

In this paper we have shown the potential for large resource savings by switching off underutilised BSs. Unlike other works in the area we use an ANN based predictive model of usage to make the switching decision ahead of time. The optimum set of BSs to turn off while maintaining QoS is formulated as a binary integer programming problem. We verified our results by using an extensive data set spanning all network usage over three months and 1145 BS covering all of Dublin city and county; we used actual BS locations and real world coverage zones provided by a network operator. Although our results are very promising, network operators may be reluctant to turn off BS for fear of degrading QoS. To assuage these fears in future work we hope to improve our prediction algorithm to provide robust prediction intervals based on long term traffic data. We also feel that it would be beneficial to examine the potential for improvements in resource usage at a more fine grained level. For example, dense city center v sparser suburban neighborhood, etc.

In this work we mainly focused on energy savings. However, in future work we wish to focus on identifying spectrum that is being underutilised by primary users. To that end we wish to reformat our optimisation routine to focus on maximising the considerable amount of underutilised spectrum in the network. This valuable licensed spectrum could be made available for secondary usage, particularly at off-peak times.

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