

Machine Learning and Analytical Power Consumption Models for 5G Base Stations

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Abstract—The energy consumption of the fifth generation (5G) of mobile networks is one of the major concerns of the telecom industry. However, there is not currently an accurate and tractable approach to evaluate 5G base stations (BSs) power consumption. In this article, we propose a novel model for a realistic characterisation of the power consumption of 5G multi-carrier BSs, which builds on a large data collection campaign. At first, we define a machine learning architecture that allows modelling multiple 5G BS products. Then, we exploit the knowledge gathered by this framework to derive a realistic and analytically tractable power consumption model, which can help driving both theoretical analyses as well as feature standardisation, development and optimisation frameworks. Notably, we demonstrate that such model has high precision, and it is able of capturing the benefits of energy saving mechanisms. We believe this analytical model represents a fundamental tool for understanding 5G BSs power consumption, and accurately optimising the network energy efficiency.

I. INTRODUCTION

The fifth generation (5G) of radio technology has brought about new services, technologies, and networking paradigms, with the corresponding societal benefits. However, the energy consumption of the new 5G network deployments is concerning. Deployed 5G networks have been estimated to be about $4\times$ more energy efficient than 4G ones. Nonetheless, their energy consumption is around $3\times$ larger, due to the larger number of cells needed to provide the same coverage at higher frequencies, and the increased processing required by its wider bandwidths and more antennas [1]. To put this number into context, it should be noted that, in average, the network operational expenditure (OPEX) already accounts for around 25 % of the total operator's cost, and that 90 % of it is spent on large energy bills [2]. Notably, most of this energy—more than 70 %—has been estimated to be consumed by the radio access network (RAN), and in more detail, by the base stations (BSs), while data centres and fibre transport only account for a smaller share [3], [4].

To decrease the RAN energy consumption, third generation partnership project (3GPP) new radio (NR) Release 15 specified intra-NR network energy saving solutions, similar to those developed for 3GPP long term evolution (LTE), e.g., autonomous cell switch-off/re-activation capabilities for capacity booster cells via X_n/X_2 interfaces. Moreover, 3GPP NR Release 17 has recently specified inter-system network energy saving solutions, and is currently taking network energy saving as an artificial intelligence use case. However, data gathered about the benefits brought by 3GPP LTE and NR

energy saving solutions have shown that they are not enough to fundamentally address the energy consumption challenge [5].

To continue tackling this challenge, 3GPP NR Release 18 has recently approved a new study item, titled “*Study on NR network energy saving enhancements*”, which attempts to develop a set of more flexible and dynamic network energy saving solutions [5]. In more details, the main objectives of this study item are:

- 1) Identify new energy saving scenarios beyond that of the capacity booster cell, e.g., compensation cells;
- 2) Study enhancements to allow a faster adaptation of networking resources to traffic needs through, e.g., *i*) user equipment (UE) assistance information reports, *ii*) BS information exchange to share traffic predictions and support both beam-level operation and transmit power adjustment coordination, and *iii*) downlink (DL)/uplink (UL) channel measurement enhancements.

Importantly, to analyse the gains brought by such new schemes, there has been consensus on the need for new models to accurately estimate the 5G network power consumption. 3GPP NR Release 16 defined a power consumption model for 5G UEs [6]. However, there is no 5G network counterpart. Ongoing 3GPP discussions have suggested that such new 5G network power consumption model should be a function of the number of BSs in the area of study, their frequency of operation, bandwidth, transmit power, number of transceivers, signalling configuration, physical resource blocks (PRBs) load, multiple-input multiple-output (MIMO) layers usage, as well as energy saving functionalities and their related sleep states and transition times.

To fill this gap, in this paper, we introduce a new power consumption model for 5G active antenna units (AAUs), the highest power consuming component of a BS¹ and in turn of a mobile network. In particular, we present an analytically tractable model, which builds on a large data collection campaign and our machine learning (ML)-based analysis. The proposed model is realistic, as it is characterised by a high precision, and generalises well to a high number of 5G AAU types/products. For example, it accounts for multi-carrier AAUs embracing the widely used multi-carrier power amplifier (MCPA) technology [7].² This allows to share some of the PA hardware among multiple carriers managed by

¹In 5G terminology, a massive MIMO BS is divided into three parts: the centralised unit, the distributed unit and the AAU.

²An MCPA operates, in contrast to a single-carrier power amplifier (PA), on multiple carriers as input, and provides a single amplified output.

an AAUs, thus reducing its power consumption. Moreover, our model also captures the benefits brought by complex, standardised shutdown schemes, i.e., carrier shutdown, channel shutdown, symbol shutdown, and deep dormancy [4], when operating in the field.

About the methodology adopted in this paper, it should be highlighted that the parameters of the proposed analytical model are derived for a selected AAU product by using data collected from a real network deployment. Unfortunately, however, it is generally not possible to obtain exhaustive data for all possible input configurations for all AAU products deployed in real networks. Importantly, the inaccessibility of AAU measurements of power consumption under some conditions may prevent the derivation of the analytical model parameters. Therefore, we implemented a methodology, in which a ML framework is designed and trained to gather knowledge from many different types of AAU with different hardware configurations. Notably, this modeling approach allows, taking advantage of the ML generalization properties, generating synthetic data covering scenarios that may not be directly observable in the collected data but that are needed to derive the proposed analytical model.

II. RELATED WORKS ON BS POWER MODEL

It has been reported that 73 % of the total network energy is consumed by the BSs [3], where the power amplifier, the transceivers and the cables consume about 65 % of the total BS energy [4]. Therefore, significant attention has been directed towards reducing the energy consumed by the BSs during the last years, and various BS power consumption models have been proposed and investigated, as a result.

The work in [8] proposed one of the most widely used BS power consumption models in the literature. In particular, such model explicitly shows the linear relationship between the BS power consumption and its transmit power. Embracing the model in [8], the work in [9] proposed an extension, which additionally supports massive multiple-input multiple-outputs (mMIMOs) and energy saving capabilities, considering different sleep depths and transition times between different energy states. However, multi-carrier and/or carrier aggregation (CA) capabilities were not considered, and mMIMOs power consumption estimations seem inaccurate [10], with an optimistic 40.5 W per BS.

With regard to mMIMO, the work in [11] extended the BS power consumption model in [8], considering a linear increase of the power consumption with the number of mMIMO transceivers. More advanced works followed in this area, highlighting the importance of taking the impact of multi-UE scheduling and other mMIMO BS components into account in the modelling of 5G BS power consumption, such as power amplifiers, transceivers, analog filter and oscillators. Specifically, the cornerstone research in [12] provided a more complete model, which considers the mMIMO BSs architecture, both DL and UL communications, as well as the number of UEs multiplexed per PRB, and a large number of mMIMO BS components.

When modelling the power consumption of a system using multiple carriers and/or CA, it is also necessary to take into

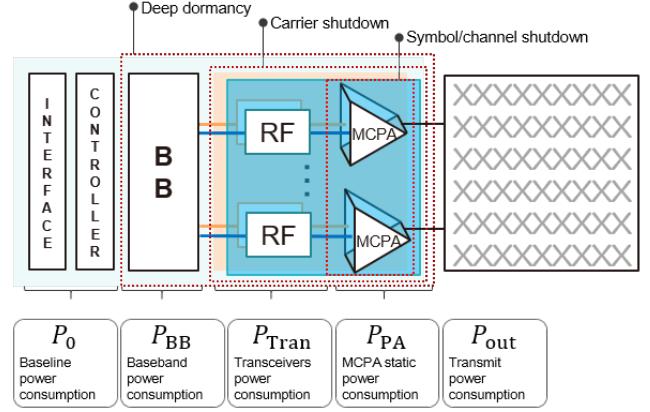


Figure 1: AAU with MCPAs handling 2 CCs in 2 different bands, which transmits over the same wideband antenna panel.

account how the power consumption scales with the number of component carriers (CCs) managed by the BS. The work in [13] captures this relationship using a linear model, but the literature is sparse in this area.

The work in [14] further combined and extended the linear version of the above presented works, jointly considering mMIMO and multi-carrier capabilities features, such as CA and its different aggregation capabilities, i.e., intra-band contiguous, intra-band non-contiguous and inter-band.

III. 5G AAU ARCHITECTURE MODEL

Although various aspects related to the power consumption of a 5G BS have been considered in the research presented in Sec. II, the true complexity of a 5G multi-carrier mMIMO AAU, where a single power amplifier may accommodate for multiple carriers, using MCPA technology, is not embraced in any of them. Our paper fills this gap, by defining a general and practical AAU architecture, and providing first the corresponding data-driven power consumption model, and then an analytical formulation fitted with realistic values for a particular AAU type.

In more detail, in our AAU architecture, we assume that:

- The AAU has a multi-carrier structure, and uses MCPA technology;
- The AAU manages C carriers —or CCs, using a CA terminology— deployed in T different frequency bands;
- The AAU comprises T transceivers, each operating a different frequency band, and M MCPAs, one for each antenna port;
- A transceiver includes M radio frequency (RF) chains, one per antenna port, which comprehend a cascade of hardware components for analog signal processing, such as filters and digital-to-analog converters;
- Antenna elements are assumed to be passive. For example, one wideband panel or T antenna panels may be used per AAU;
- Deep dormancy, carrier shutdown, channel shutdown, and symbol shutdown are implemented, each switching off distinct components of the AAU.

Fig. 1 shows the AAU architecture and its main power consumption components. In more details, the overall AAU

consumed power includes: *i*) the baseline power consumption, P_0 , which accounts for part of the AAU circuitry that is always active (e.g., circuitry used to control the AAU activation/deactivation), *ii*) the power consumption, P_{BB} , required for the baseband processing performed at the AAU, *iii*) the power consumed by the T transceivers in the AAU, i.e., P_{Tran} , *iv*) the static power consumed by the MCPAs, i.e., P_{PA} , and *v*) the power consumed to generate the transmit power required to transmit the data over the C CCs, i.e., P_{out} .

As described in [7], it should be highlighted that the implementation of MCPAs results in an increased energy efficiency with respect to single-carrier power amplifiers. In more details, by integrating multiple carriers together, the total transmit power managed becomes greater, thus enabling MCPAs to operate at higher efficiency areas. Moreover, the static power consumption of the MCPAs increases sub-linearly with respect to the number of carriers, as part of the signal processing components can be shared among them. However, it is worth highlighting that the implementation of MCPAs entails increased complexity in the management of the network energy saving, and thus, in the estimation of the power consumption. In fact, contrarily to what commonly considered by simplistic models, the deactivation of just one carrier may not bring the expected energy savings, if the MCPAs need to remain active to operate other co-deployed active carriers.

IV. ARTIFICIAL NEURAL NETWORK MODEL

In this section, we describe the measurements gathered during our data collection campaign. Moreover, we provide a detailed description of the implemented artificial neural network (ANN) architecture for modelling and estimating power consumption, as well as an analysis of its accuracy. Note that ANNs were selected after evaluating and comparing their performance with those of other ML methods. The better performance of ANNs emanates due to their better capabilities to deal with the available tabular data and superior generalisation properties.

A. Dataset

We collected hourly measurements for 12 days from a real deployment with 7760 5G AAUs in China, comprising 25 different types of AAU from a single vendor. Note that such data contains sensitive information regarding proprietary product hardware specifications, which cannot be made publicly available. The gathered information contains 150 different features, which can be divided into four main categories:

- *Engineering parameters*: Information related to the configuration of each AAU (e.g., AAU type, number of RF chains, numbers of supported and configured carriers);
- *Traffic statistics*: Information on the serviced traffic (e.g., average number of active UEs per transmission time interval, number of used PRBs, traffic volume);
- *Energy saving statistics*: Information on the activated energy saving modes (e.g., duration of the carrier, channel and symbol shutdown as well as dormancy activation);
- *Power consumption statistics*: Information on the power consumed by the AAUs.

B. Inputs of the model

Feature importance analysis was performed to identify the most relevant input features in the available dataset. Such features are the type/model of AAU, together with the key characteristics of the configured carriers. To give an example, such key characteristics comprehend, among others, frequency- and power-related engineering parameters, such as the carrier frequency, bandwidth and transmit power, the DL PRB load, and the amount of time for which each energy saving mode is activated. See Fig. 2 for a detailed description of all the selected input features. Note that the identified features are fundamental parameters, which are available in the products of any vendor. Moreover, feature importance analysis can extend the inputs of our ANN model to consider proprietary and not standardised energy saving schemes.

After selection, each of the input features was pre-processed, and then represented by one or more neurons at the input layer of the ANN. The numerical features were normalised before being input to the model, whereas the categorical ones were input by using one-hot-encoding.

Since a 5G AAU can operate multiple carriers through a MCPA, to make our ANN model the most general and flexible, the input layer takes input from the maximum number of carriers that can be managed by the most capable AAU in the dataset. When less carriers are deployed in an AAU, the input neurons related to the none deployed carriers are set to zero. This approach allows to implement our ANN model with a fixed number of input neurons, and thus construct a single model for all possible AAU types and carrier configurations, with a minimal accuracy loss. The maximum accuracy loss observed when comparing this single model approach with respect to training different models for the different AAU types and carrier configurations is 1.86 %.

C. Outputs of the model

Different power consumption values are observed in the data for the same input feature values due to missing input features and/or errors in the measurements or in the collection/processing of the data. To embrace such noise, we define the measured power consumption in our ANN model as the expected power consumption for a given input configuration plus a noise, originating from the mentioned errors. The analysis of the available data highlighted that such noise is normally distributed. It thus follows that the measured power consumption is normally distributed.

With this in mind, the goal of our ANN model is to produce, for a given input configuration, an estimate of the mean and standard deviation of the power consumption distribution. This allows having an evaluation of the confidence interval for each of the performed power consumption estimations during training and testing, and in turn, increase the reliability of the whole estimation process.

D. Model architecture

We consider the multilayer perceptron as basic architecture for the ANN, consisting of multiple fully connected layers of neurons [15]. The overall architecture of the proposed ANN model is also depicted in Fig. 2.

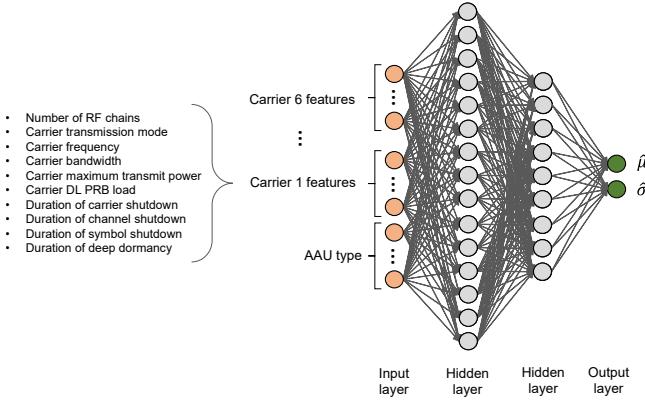


Figure 2: Architecture of the designed ANN.

In our specific scenario, we collected data for 25 different AAU types, where the most capable AAU supports up to 6 CCs. The input layer is thus composed of 85 neurons, and it is followed by two hidden layers, which are comprised of 100 and 50 neurons, respectively. These dimensions were chosen after an optimisation process targeted at maximising the model accuracy. Finally, the output layer is composed of two neurons, which capture the mean and the standard deviation of the power consumption, as explained earlier.

E. Training of the model

The model is trained with the objective of reducing both the prediction error and its uncertainty. In particular, the training is considered successful, if the distribution outputted by the model for a given input matches the distribution of the power measurements in the data.

In terms of data management, we split the available dataset related to 7760 AAUs into two parts: a training set and a testing set. The training set contains data collected for 10 days, whereas the testing set contains the data collected for the 2 remaining days. The model training was performed by adopting the Adam version of the gradient descent algorithm [15], and required 75 minutes to perform 1086 iterations.

F. Model performance evaluation

To assess the performance of the proposed ANN model, we compared the estimated power consumption during the testing phase with the real measurements available in the data. Overall, the model achieved a root mean square error (RMSE) of 25.02 W, a mean absolute error (MAE) of 12.21 W and a remarkably low mean absolute percentage error (MAPE) of 6.55 % when estimating the power consumed by each AAU in each hour of the testing period.

To highlight the ability of the model to accurately estimate the power consumption when dynamic energy saving algorithms are activated, Fig. 3 shows an example of the real and estimated power consumption of a particular AAU, which supported up to 6 carriers, and intensively used energy saving features, during the 2 testing days. The confidence region is also reported, representing the interval in which the true power consumption is expected to fall with a 0.95 probability.

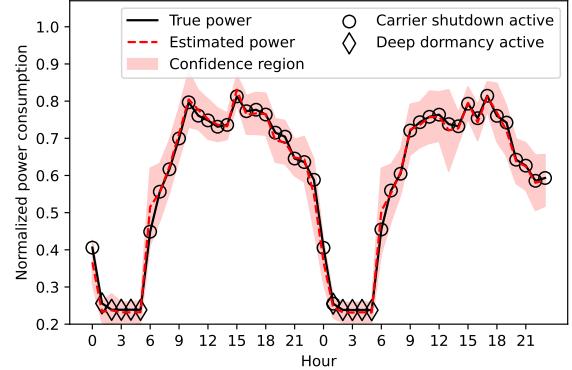


Figure 3: Hourly real and estimated normalised power consumption for an AAU doing carrier shutdown and deep dormancy.

Note that we normalised the power consumption for privacy reasons. From this figure, it can be observed that the deep dormancy feature is activated during night hours (i.e., from 1am to 6am), while the carrier shutdown algorithm is activated and intensively used during the rest of the day. Note that an AAU can only shutdown a carrier when its shutdown entry conditions are met, and that such conditions mostly depend on traffic load, and are independently checked per carrier on a less than a minute basis. Overall, even in this highly dynamic activation/deactivation conditions, the proposed model is able to estimate the power consumption of this AAU with high accuracy (i.e., RMSE 14.43 W, MAE 9.5 W, MAPE 2.5 %).

To highlight the capability of the model to perform in a variety of deployment environments, Fig. 4 also shows the real and estimated power consumption, not of a single AAU as in Fig. 3, but for a popular AAU type also supporting up to 6 carriers, which appears often in our dataset in different scenarios and city areas, with respect to the DL PRB load. For the sake of clarity, we would like to highlight here that the spread of the real and estimated values observed over the y-axis in this figure is motivated, in addition to the noises introduced in Section IV-C, by the presence of multiple carriers deployed within this AAU type, which are generally configured with different maximum transmit powers. As a result, there is not a biunivocal relation between the DL PRB load and the total transmit power (and thus neither with the power consumption). From this figure, it can be seen that this AAU type achieves a 47 % and 70 % reduction in power consumption when doing carrier shutdown and deep dormancy, respectively. Importantly, even if this AAU type was deployed in a heterogeneous set of scenarios, the proposed model is able to accurately estimate the power consumption (i.e., RMSE 18.25 W, MAE 14.48 W, MAPE 2.63 %).

V. ANALYTICAL MODEL

Although accurate and general, the presented ML model lacks tractability to drive energy efficiency feature standardisation, development and/or optimisation. To facilitate these tasks, in this section, based on the knowledge gathered from the previous ML model, we propose an analytically tractable 5G AAU power consumption model, which is easily interpretable and amicable to optimisation.

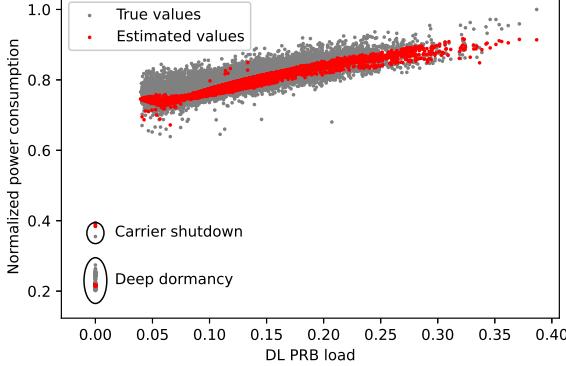


Figure 4: Normalised power consumption, estimated by the ANN model, versus AAU DL PRB load for the selected AAU.

A. Model description

Our proposed 5G AAU power consumption model, which characterises the relationships between the key characteristics that play a major role on 5G AAU power consumption, is mathematically formulated as

$$P_{\text{AAU}} = P_0 + P_{\text{BB}} + \underbrace{\sum_{t=1}^T M_{\text{av},t} D_{\text{Tran},t}}_{P_{\text{Tran}}} + \underbrace{M_{\text{ac}} D_{\text{PA}}}_{P_{\text{PA}}} + \underbrace{\frac{1}{\eta} \sum_{c=1}^C P_{\text{TX},c}}_{P_{\text{out}}}. \quad (1)$$

In more details, the power, P_{Tran} , consumed by the t -th transceiver in the AAU is the product of the number of available RF chains, M_{av} , and the power consumed by each RF chain, $D_{\text{Tran},t}$. The static power, P_{PA} , consumed by the MCPAs is the product of the number of active RF chains, M_{ac} , and the static power consumed by each MCPA, D_{PA} . Recall that there is an MCPA for each RF chain spanning over the managed carriers. Finally, the power, P_{out} , consumed to generate the transmit power required to transmit the data over the c -th CC is equal to the ratio of the transmit power in use at such CC, $P_{\text{TX},c}$, to the efficiency of the MCPAs and antennas, η , where the transmit power in use usually linearly increases with the number of PRBs utilised.

When symbol shutdown is activated, the AAU switches off the MCPAs, and its power consumption is reduced to the sum of the baseline power consumption, P_0 , the baseband processing power consumption, P_{BB} , and the power consumed by the transceivers, P_{Tran} as they are not deactivated.

When channel shutdown is active, the AAU reduces power consumption by limiting the multiplexing and beamforming capabilities of the cell, i.e., by limiting the number of active MCPAs. This is realised in our model by decreasing the value of the variable, M_{ac} , e.g., from 64 to 32 or 16.

When carrier shutdown is activated, the MCPAs and the transceivers are switched off. Therefore, the power consumption is further reduced to the sum of the baseline power consumption, P_0 , and the baseband processing power consumption, P_{BB} . Finally, when deep dormancy is activated the circuitry for baseband processing is switched off, and the AAU power consumption is further reduced to the baseline power consumption, P_0 .

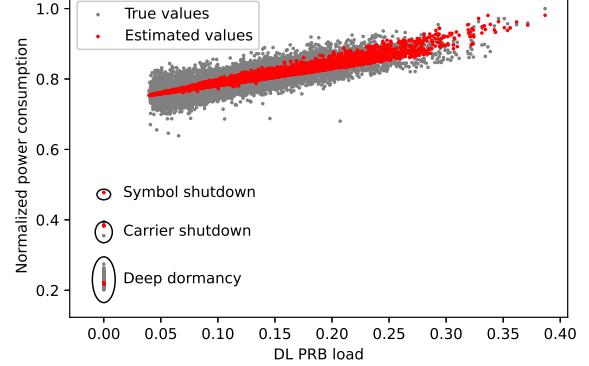


Figure 5: Normalised power consumption, estimated by the analytical model, versus AAU DL PRB load for a popular AAU.

The proposed model has a number of benefits, not captured by other models in the literature, which makes it a cornerstone for accurate 5G network energy efficiency standardisation, development and optimisation:

- 1) It allows to capture different multi-carrier architectures, i.e., intra-band contiguous, intra-band non-contiguous, and inter-band, where distinct carriers may or many not share the same transceiver;
- 2) It characterises realistic multi-carrier AAU products with MCPAs and their intricate shutdown functioning, where deactivating only a subset of the carriers in the AAU does not lead to large energy savings, since the MCPAs must continue operating to support the active carriers;
- 3) It accounts for each of the state-of-the-art energy saving techniques, i.e., carrier shutdown, channel shutdown, symbol shutdown, and deep dormancy, and can be easily extended to more.

B. Model fitting

To analyse the proposed analytical model performance, we have fitted its parameters, for the popular AAU type introduced in Sec. IV, by using power consumption estimations performed through our ANN model. Note that this approach to fitting, not based on the data, but on ANN model created through the data, allows to exploit the generalisation capabilities of our proposed ANN model, which can learn from other AAU types, and perform accurate power consumption estimations for traffic conditions not observed in the data of this AAU type. In more detail, the analytical model parameters have been fitted on the generated data by iteratively solving a nonlinear least-squares regression problem.

The normalised values for the fitted parameters are $P_0 = 0.22$, $P_{\text{BB}} = 0.16$, $D_{\text{Tran},1} = 1.47 \cdot 10^{-3}$, $D_{\text{PA}} = 3.81 \cdot 10^{-3}$, $\eta = 0.4$. For completeness, let us note that the AAU under study has $C = 2$ CCs with $M_{\text{av},1} = 64$ RF chains.

C. Model performance evaluation

Fig. 5 shows the normalised power consumed by the selected AAU type for different values of the DL PRB load, observed in the dataset, and the values estimated by the fitted analytical model. The analytical model achieves a remarkable

Metric	Analytical model	ML model	ML model gain
RMSE	19.96 W	18.25 W	8.6 %
MAE	15.36 W	14.48 W	5.7 %
MAPE	2.80 %	2.63 %	6.1 %

Table I: Comparison of accuracy performance achieved by the ANN model and the analytical model for a popular AAU type.

performance with RMSE 19.96 W, MAE 16.50 W and MAPE 2.67 %. This estimation accuracy is close to that achieved by the ANN model, highlighting that the most relevant inputs to power consumption have been captured, and the capability of the proposed analytical model to accurately model realistic AAUs, while considering the complex MCPA structure and the existence of different energy saving modes. A comparison of the accuracy performance reached by the ANN and analytical models is reported in Table I.

From Fig. 5, it can also be observed that, for this AAU type, the activation of symbol shutdown provides a 34 % power consumption saving w.r.t to the power consumption at zero load, while that of carrier shutdown results in larger savings, 47 %.

It should be noted, however, that the lower power consumption achieved by carrier shutdown comes at the expense of an increased complexity in the network management. Symbol shutdown operates locally—and usually opportunistically—in every cell at the time scale of hundreds of microseconds when no data needs to be transmitted, and thus it does not generally affect the user performance. On the contrary, carrier shutdown strategies are adopted for longer time periods (from few minutes to few hours), and coordinated across the network, as their activation requires/implies the redefinition of the network coverage and redistribution of its traffic, i.e., user association. Due to its complexity, if the carrier shutdown feature is not appropriately optimised, energy savings may come at the expense of user experience. Even worst, if the optimisation is performed with an inaccurate AAU power consumption model, the energy saving gains may not even be there.

To illustrate this point, we have estimated the power consumption of the selected AAU under the same conditions over the 24 hours of a day with a state-of-the-art power consumption model [12]. Such model provided a $2.5 \times$ overestimation of the power consumption over the ground truth, as it is not able to capture the multi-carrier architecture and the accurate impact of energy saving methods. The error of our analytical model was less than 1 %. This significant overestimation would lead to a suboptimal carrier shutdown configuration, hindering energy savings, and shows how state-of-the-art models may fail to drive network energy efficiency optimisation. Instead, the better accuracy of our proposed model indicates that it may be a more viable tool to drive the optimisation of greener 5G (and beyond) networks.

VI. CONCLUSIONS

In this paper, we presented a novel power consumption model for realistic 5G AAUs, which builds on a large data

collection campaign. At first, we proposed an ANN architecture, which allows modelling multiple types of AAU and different configurations. The discussed results highlighted that the designed ANN architecture is able to provide high accuracy. In a second stage, we exploited the knowledge gathered by the ANN method to derive a novel and realistic but analytically tractable 5G AAU power consumption model. We demonstrated that such analytical model reaches accuracy close to the one of the ML model for a widely used type of AAU. Notably, when compared to a state-of-the-art model under the same conditions, the proposed one was shown to be around 150 % more accurate, as it is able of precisely capturing the MCPA architecture and the benefits of shutdown approaches. Importantly, due to its fundamental nature, the proposed methodology can be adopted to model other types of AAU deployed in different multi-vendor networks. We thus believe that this model is a valuable contribution to both industry and the research community working on wireless network energy efficiency, and its optimisation, and can be of use in the current 3GPP NR Release 18 work on network energy efficiency.

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