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Power Profiling and Monitoring in Embedded Systems: A Comparative Study and a Novel Methodology Based on NARX Neural Networks

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Abstract

Power consumption in electronic systems is an essential feature for the management of energy autonomy, performance analysis, and the aging monitoring of components. Thus, several research studies have been devoted to the development of power models and profilers for embedded systems. Each of these models is designed to fit a specific usage context. This paper is a part of a series of works dedicated to modeling and monitoring embedded systems in airborne equipment. The objective of this paper is twofold. Firstly, it presents an overview of the most used models in the literature. Then, it offers a comparative analysis of these models according to a set of criteria, such as the modeling assumptions, the necessary instrumentation necessary, the accuracy, and the complexity of implementation.

Secondly, we introduce a new power estimator for ARM-Based embedded systems, with component-level granularity. The estimator is based on NARX neural networks and used to monitor power for diagnosis purposes. The obtained experimental results highlight the advantages and limitations of the models presented in the literature and demonstrate the effectiveness of the proposed NARX, having obtained the best results in its class for a smartphone (An online Mean Absolute Percentage Error = 2.2%).

Keywords: Data fitting, Embedded Systems, Machine learning, Modeling, NARX, neural Networks, Power Consumption, Power profiling, Smartphone

1. Introduction

Since the introduction of the modern smartphone in 2007, there has been a great deal of research dealing with the duality performance-battery life in these systems [1]. One of the earliest challenges in mobile devices' power consumption was to predict the remaining battery life [2]. This decade-old question is still generating studies aiming to enhance accuracy while accounting for newly released technologies [3]. Furthermore, with the emergence of new factors, such as the Internet of Things (IoT), and the ubiquity of embedded systems in general, the interest in power consumption is no longer limited to just mobile devices, and now includes most embedded electronics [4, 5].

The main issue is how to increase the performance of the system while maintaining sustainable—if not minimal—power consumption levels. Hence, both the scientific and industrial communities have been working actively to improve power efficiency [6, 7]. Most solutions focused on the optimization of resource utilization and varied widely. For instance, some of the proposed solutions were algorithmic like the Dynamic Voltage and Frequency Scaling (DVFS) for CPUs [8] and GPUs [9], and new scheduling and task distribution algorithms [10]. Alternatively, other works focused on empirical approaches in reducing power consumption, like reducing screen resolutions [11], or using large-scale statistical methods to study the impact of the

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user’s behavior on power consumption [12]. The interest in power consumption went even further than just improving efficiency. Researchers have studied power consumption to detect and solve energy bugs [13], create energy-aware software [14], and even to creatively deal with cyber-security issues [15, 16] and detect anomalies [17, 18].

This paper is a continuation of our previous works on the modeling and monitoring of mobile and embedded systems [19]. In this work, the main focus is on building a power model and profiler for the online monitoring of onboard embedded systems [18].

Power profilers are tools that allow for the measurement or the estimation of power consumption on a system-wide level [20] or down to components [21] or applications [22]... Moreover, not only these tools allow users to estimate the power consumption or the remaining battery life, but they also help developers decrease energy loss [12] and create energy-friendly [23] or reliability-aware algorithms [24].

The specialized literature is rich with power profilers and models that were indexed into several surveys [1, 25, 26]. These surveys included profilers made by software and hardware companies [27], as well as those made by researchers like *PowerBooster* [28] and *Sesame* [29]. While these surveys are relatively recent, the generational differences between components (and hence their power profiles [30]), coupled with the changes in user-device interactions, deprecate the use of old models [31]. Thus, the continuing trend in power profiling and the flux of new power models [20, 32, 33, 34, 35]. Some of these models offered more accessible construction and implementation [36], while others focused on accuracy [33].

As it will be demonstrated hereafter, all these models and profilers differ in their purposes and techniques. Thus, explaining why there are so many of them). The aim behind this work is to complement the available research by compiling and comparing the methods and ideas found in the literature and then offering a step-by-step methodology on how to build power profilers, then, use this methodology to build a new accurate profiler that uses a Nonlinear AutoRegressive eXogenous (NARX) neural network model. The profiler, which is called N^3 , is built to be used as a power consumption monitoring tool to detect anomalies in power consumption. In the results section, it will be shown how N^3 improves upon the accuracy reported in the literature while maintaining low power and computational overhead.

In the next section, the main steps of building a power profiler are outlined. The differences between each type of profilers are also highlighted with examples from the literature alongside the different design choices to be made. Then, in the following sections, the use of these steps to design and build a neural network-based power profiler is detailed. Henceforth, this work will serve as both a tutorial to building power profilers and a paper presenting a novel work. In the last section, the obtained results are discussed, validating the profiler.

2. Design and Construction of Power Profilers

All power profilers found in the literature or the industry share the common task of delivering power consumption values, whether by measurement or estimation. Through this commonly shared task, some other standard features and techniques that these profilers use to achieve their results may be outlined. In the following paragraphs, these features are streamlined into manageable steps through which the design choices to be made are explained, starting with the goal of building the profiler.

2.1. Defining the purpose of the profiler

Power profilers are built to accomplish a very specific task energy-wise. For instance, they might be used to measure the consumed energy of the device [37], or some specific component [38], or monitor the device for anomalies [16, 39]. Therefore, the granularity—the level at which the profiler can deliver power measurement or estimation [25]—would differ from one case to another.

Accordingly, to choose the type and the structure of the profiler, the first step in building one, is to state the goal that the profiler has to achieve, which will also indicate how fine the granularity should be. For instance, if the profiler is built to help developers estimate the amount of energy consumed by their applications, it should have an application-level granularity [40, 41] or even higher [42].

Design choices:

- **Purpose:** Monitoring, diagnosis, software optimization...
- **Granularity:** Device-level, component-level, application-level...

2.2. Defining the profiling scheme and measurements source

Once the purpose of the profiler is defined, the next step is to set which profiling scheme to use. There exist two main ones: the hardware-based method and its software counterpart [25].

As their name suggests, hardware-based profilers use external sensors and equipment to collect and report measurements [43]. They generally use multimeters or power monitors, which requires the device to be opened and connected at all times to the monitoring equipment. On the other hand, software-based profiling uses a program to collect power measurements or generate estimations. These profilers rely on several techniques such as self-metering [1], or the state of charge of the battery, or the battery Application Programming Interface (API) [25].

The use of hardware-based power profiling has dwindled over the years since their main advantage (accurate power measurement) no longer outweighs their main drawback (physical intrusion of the device). Furthermore, with recent advancements, software power metering is reaching the accuracy of hardware measurements [41] and has thus gained popularity, since its delivering estimations that are comparable to hardware-based profiling with no physical intrusion.

The purpose of the profiler and the needed level of granularity would also dictate which scheme the profiler will use to deliver power estimations. If the purpose is to observe the power consumption of the whole device, there would be no need for a fine level of granularity, and the physical recordings measurement would be sufficient [43]. However, if the purpose is to monitor a specific component—such as the CPU—then a finer granularity is needed [24]. Moreover, since obtaining physical measurements of the individual components is not always possible, it would be wiser to use a power model to generate estimations. These profilers are called model-based profilers [1]. An even finer granularity, such function-level, would require models based on techniques such as code analysis [40]. The latter is mainly used to help developers optimize their code and avoid energy hogs [44].

Design choices:

- **Scheme:** Hardware-based or software-based profiling
- **Measurements source:** Instruments or battery API or discharging curve...
- **Measurements generation:** Code Analysis-based estimation, or Model-based estimation, or physical measurement recording

2.3. Model-based profilers

2.3.1. Modeling scheme

White-box modeling of power consumption in embedded systems would result in the building of a model generating accurate power estimation. Such a model would typically use finite state machines [45], or simulate differential equations [46], which would require design level knowledge of all the inner components of the chip [1].

Alternatively, black-box modeling techniques—such as identification and regression—train the model to fit its outputs to observations [1]. In this type of model, the expertise of the factors influencing the output is appreciated, but not required, nor is the formal theoretical proof of the relation between the inputs and outputs [28]. However, these methods require large amounts of data for training and validation to obtain satisfactory results [1].

Grey-box models are the middle ground between white-box models and black-box models, where a part of the model is built through physical knowledge, and the rest is identified using black-box methods [47]. For instance, in a first step, *PowerBooster* defines the power usage of a set of determined states in an FSM, then it uses regression to determine the power consumption of each of these states [48].

2.3.2. Choice of inputs

Hoque et al. [1] state that there exist two types of inputs: Utilization-based and event-based ones. Utilization-based models focus on the direct correlation between the usage of a peripheral or a component and the consumed power. For instance, to account for the power consumed by the Wi-Fi module, its data rate transfer is observed. Event-based models, on the other hand, would instead observe the status of the component (On/Off) [45]. Nevertheless, recent works proved to not stick with either one type for each have their limitation [49], but instead rely on a mixture of them [33, 50, 51, 52].

The choice of inputs depends on two major factors: The available sensors and data on the device and the desired granularity. The most basic model-based profilers need to include at least data from the most relevant components, such as the processors, the communication components, and the most used sensors [26]. In this line of research, Chen et al. [53] demonstrate, in their study, how much each hardware component contributes to the total energy count. Additionally, Ardito et al. [30] also shows the gap between the different generations of materials and technologies in terms of energy consumption.

Finally, finer granularity requires more data to estimate the power correctly. For instance, when profiling the power use of an application, one might call upon code analysis, or use timestamps and systems traces. These two are crucial for estimating software components power consumption—like an application or a function, which encourages the use of time series [54, 55].

2.3.3. Model construction and implementation

Hardware-based profilers, by design, are built to deliver measurements and estimations on the fly. Software-based profilers, on the other hand, can either work online and provide direct estimations of the power consumed by the device or generate estimations from previously gathered data. For instance, for a large-scale study, offline estimation is better suited for the task [12]. However, if the purpose of the profiler is to monitor the device debug and its energy consumption, online estimation is the better solution [19, 56].

Models are also characterized by where they are constructed and trained. Those constructed and trained on the profiled device, require no additional training or tuning [28]. They accurately estimate power consumption and adapt to the device’s specific power profile [1]. However, they require a data gathering and a training time that might come at a high computational cost. Models constructed and trained offline would avoid the drawbacks of the first category [18, 57], but they are always device-specific and their accuracy varies from one device to the other.

The last category is off-device profilers which are constructed and trained off-device [58]. These profilers deliver accurate estimation, notably in fine granularity cases, but require a permanent link to the profiled device.

Design choices:

- **Modeling scheme:** White-box, or grey-box, or black box
- **Estimations availability:** Online or offline
- **Model implementation:** On-device or off-device

2.4. Profiler evaluation and tuning

In the case of model-based profilers, once the model is built and trained, it goes through the validation process. In this process, the model is tested by comparing its estimations or predictions \hat{y} with the measurements y . To validate the model, one should evaluate the goodness of fit, study the accuracy of the estimations, and analyze the residuals.

The goodness of fit is a direct comparison between model estimations and the measurements. It is evaluated through the linear regression of estimations and measurements (R) or the calculation of the coefficient of determination (R^2) [59]. For a test set of n samples, R^2 is equal to:

$$R^2 = 1 - \frac{\sum_{k=1}^n (y(k) - \hat{y}(k))^2}{\sum_{k=1}^n (y(k) - \mu_y)^2} = 1 - \frac{\text{SSE}}{\sum_{k=1}^n (y(k) - \mu_y)^2}, \quad (1)$$

where μ_y is the mean value of the measurements $y(k)$ n , and SSE is the Sum of Squared Errors :

$$\text{SSE} = \sum_{k=1}^n (y(k) - \hat{y}(k))^2 \quad (2)$$

In an ideal case, $y = \hat{y}$. Hence, R and R^2 will be equal to 1. In practice, however, the nearer the value of these indicators is to 1, the better are the estimations of the model.

The calculation of R or R^2 is an indicator of the latter, but the accuracy of the model has to be further evaluated by calculating estimation errors:

$$\varepsilon(k) = y(k) - \hat{y}(k) \quad (3)$$

The study of these residuals makes it possible to conclude if $\hat{y}(k)$ fit $y(k)$ well. These residuals must have a random profile. Their randomness indicates that the inputs and outputs of the model are correlated. Therefore, their distribution must be tested. Among the different tests possible to determine if the residues are random, the most used are the normality test [59] and the Kolmogorov-Smirnov test (K-S test) [60]. These two tests make it possible to deduce if the residuals are normally distributed and centered around an average μ_ε with a standard deviation σ_ε . This variable is also affected by the heteroscedasticity, which indicates the existence of a relationship between the variance (σ^2) and the samples size of the input variables. Thus, in order to verify the homoscedasticity of the residuals, several tests like that of White [59] or Engle’s ARCH test [61] can be used.

Once the goodness of fit is satisfactory, the residuals are analyzed, and the estimation errors are sufficiently small to satisfy the requirements of the designers (MAE lower than the resolution of the sensors, for instance), the model is validated. If the model can not be validated, then the designer must repeat the steps from the choice of the modeling approach. This was the case of this work, where the accuracy of the model has been considerably improved, by changing the type of the model, compared to its first version [19].

In the last step, the performance is also observed to be satisfied or not. During this step, one should look at the time needed to generate estimations, and whether the adoption of some choices outweighs the drawbacks—fine granularity against slower estimations, for instance. Additionally, tweaks can be made to obtain the optimum desired results. For instance, the influence of each input can be observed favoring some inputs to others, leading sometimes to the elimination of some as their influence is marginal. Once the model is validated satisfying all design and performance constraints, the process ends.

2.5. Summary

In figure 1, the general algorithm describing the building of a power profiler is shown. It shows all the steps to follow. It also shows, in case of unsatisfactory results which steps should be revisited according to the constraints underhand. For instance, if the accuracy of the model is not sufficient, one has to review the modeling scheme and onward, until the desired results come through. Furthermore, table 1 displays a compilation of profilers and models found in the literature categorized according to the steps explained above in this section.

Table 1: Summary of some of the profilers available in the literature. —: Information not available or not applicable.

Work	Purpose	Granularity	Profiling scheme	Measurement source	Model-based?	Modeling scheme	Availability of estimations	Training	Implementation
<i>Snap-Dragon Profiler</i> [58]	Power estimation and logging	Device	Software	<ul style="list-style-type: none"> • API • System traces 	Yes	Linear (Regression)	On-line	Off-line	Off-device
<i>Trepn</i> [27, 62]	Power estimation and logging	Device	Software	<ul style="list-style-type: none"> • API • System traces 	Yes	Linear (Regression)	On-line	Off-line	On-device

<i>Work</i>	<i>Purpose</i>	<i>Granularity</i>	<i>Profiling scheme</i>	<i>Measurement source</i>	<i>Model-based?</i>	<i>Modeling scheme</i>	<i>Availability of estimations</i>	<i>Training</i>	<i>Implementation</i>
Ahmad et al. [40]	Estimation of energy consumption of Application code	Instruction set	Mixed	Hardware	Yes	Linear	Off-line	Off-line	Off-device
Huang et al. [23]	Energy consumption optimization	CPU	Software	System traces	Yes	Polynomial (non-linear)	Off-line	Off-line	Off-device
Niu and Zhu [24]	Improving optimization	CPU	Software	System traces	Yes	Linear	Off-line	Off-line	—
Bokhari et al. [6, 63]	Energy consumption optimization	Application	Software	Battery API	Yes	Application specific	On/Off-line	On/Off-line	On/Off-device
Alawnah and Sagahyoon [51]	Power estimation and prediction	Device	Software	<ul style="list-style-type: none"> • API • System traces 	Yes	ANN	Off-line	Off-line	Off-device
Yoon et al. [31]	Power modeling and estimation	Application processors	Software	System traces	Yes	Linear (Regression)	—	—	—
Walker et al. [35]	Power modeling and estimation	CPU	Software	System traces (PMC)	Yes	Linear (Regression)	On-line	On-line	On-device
<i>PETrA</i> [33]	Power estimation	Application	Software	System traces	Yes	Linear (Regression)	Off-line	On-line	On-device
Djedidi et al. [19]	SoC Monitoring	SoC (CPU, GPU, RAM)	Software	System traces	Yes	Neural networks	On-line	Off-line	Off-device
<i>Deep Green</i> [54]	Energy consumption prediction	Device	Mixed	System traces + <i>Green-Miner</i> [64]	Yes	RNN (SVR)	Off-line	Off-line	Off-device
<i>pProf</i> [20]	Power profiling with reduced overhead	Device	Software	API	Yes	Linear (Regression)	On-line	Off-line	On-device
Bokhari and Wagner [65]	Energy consumption optimization	<ul style="list-style-type: none"> • Device • Applications 	Software	<ul style="list-style-type: none"> • Battery API • System traces 	No	—	—	—	—
Carvalho et al. [66]	Prediction of power consumption	Device	Mixed	<ul style="list-style-type: none"> • Hardware • System traces 	Yes	<ul style="list-style-type: none"> • ANN • <i>k</i>-NN regression 	Off-line	Off-line	Off-device
Kim et al. [3]	Prediction of remaining battery	Application	Software	System traces	Yes	AppScope [67]	On-line	Off-line	On-device
Lu et al. [68]	Improving screens power models	Screen	Software	System Traces	Yes	Linear	On-line	On-line	On-device
Cavaglione et al. [15]	Malware detection	Device	Software	<ul style="list-style-type: none"> • Battery sensors • System traces 	Yes	Modified version of PowerTutor [28, 69]	On-line	On-line	On-device
Chowdhury and Hindle [34]	Modeling software energy consumption	Application	Software	<ul style="list-style-type: none"> • Battery sensors • System traces 	Yes	<ul style="list-style-type: none"> • SVR • Linear regression 	On-line	On-line	On-device
<i>Green-Oracle</i> [34]	Software energy estimation	Applications	Software	System Traces and calls	Yes	<ul style="list-style-type: none"> • Linear Regression (Ridge) • Lasso • SVR • Bagging 	Off-line	Off-line	Off-device
Dzhagaryan et al. [37]	Energy consumption measurement	Applications	Hardware	—	No	—	On-line	—	Off-device
Linares-Vázquez et al. [11]	Device power measurement	CPU	Software	Systems traces	No	—	On-line	—	Off-device
Li et al. [70]	Device power measurement	CPU	Software	Systems traces	No	—	On-line	—	On-device
Altamimi and Naik [44]	Estimating energy consumption	<ul style="list-style-type: none"> • CPU • Storage 	Mixed	<ul style="list-style-type: none"> • Hardware (Power reading) • System traces 	Yes	Linear	—	—	Off-device
<i>PowerTap</i> [46]	Estimating energy consumption	Components	Software	<ul style="list-style-type: none"> • Hardware (Power reading) • System traces 	Yes	Linear	On-line	Off-line	Off-device

<i>Work</i>	<i>Purpose</i>	<i>Granularity</i>	<i>Profiling scheme</i>	<i>Measurement source</i>	<i>Model-based?</i>	<i>Modeling scheme</i>	<i>Availability of estimations</i>	<i>Training</i>	<i>Implementation</i>
WattsOn [21]	Estimation of energy consumption of app	• Device • Components	Software	Systems traces	Yes	Linear	On-line	Off-line	Off-device
Li et al. [71]	Wi-Fi power modeling	Wi-Fi	Software	• Hardware • System traces	Yes	FSM	Off-line	Off-line	Off-device
Merlo et al. [16]	Intrusion detection	Device	Software	System traces	Yes	PowerTutor [28, 69]	On-line	On-line	On-device
Jin et al. [72]	GPU power modeling	GPU	Software	System traces	Yes	Linear (Regression)	—	—	—
Kim et al. [32]	GPU power modeling	• Device • GPU	Software	System readings	Yes	Linear (Regression)	On-line	—	On-device
Demirbilek et al. [7]	Improving battery performance	Device	Hardware	—	No	—	On-line	—	Off-device
Martinez et al. [5]	IoT nodes power modeling	Device	Software	System readings	Yes	Linear	On-line	—	—
Sun et al. [38]	Modeling Wi-Fi power consumption	Wi-Fi	Software	System traces	Yes	Linear	—	—	—
Lee et al. [73]	Automated power modeling	Application	Software	System traces	Yes	• Power Doctor [74] • Linear (Regression)	—	—	—
<i>FEPMA</i> [36]	Power metering	Applications	Software	System traces	Yes	ANN	On-line	—	—
Kamiyama et al. [52]	Test the energy-efficiency	Application	Software	—	Yes	Linear (Regression)	On-line	—	On-device
Park et al. [9]	Improving energy efficiency	Components	Hardware	• System traces • Power meter	No	On-line	Off-line	—	Off-device
Arpinen et al. [75]	Dynamic power management	Components	Software	System traces	Yes	FSM	On-line	On-line	On-device
Holleis et al. [43]	Power measurement and logging	Device	Hardware	—	No	—	On-line	—	Off-device
König et al. [76]	Power measurement	Sensors	Hardware	—	No	—	On-line	—	Off-device
Shin et al. [56]	Battery life estimation	System Traces	Software	Components	Yes	Regression (Nonlinear)	On-line	Off-device	Off-device
<i>eLens</i> [77]	Power estimation	Code level	Software	Application	Yes	Regression	On-line	On-line	On-device
Nacci et al. [78]	Adaptive power modeling	Software	System traces	Yes	Linear (ARX)	On-line	On-line	On-device	—
Kim and Chung [79]	GPU power modeling	Components	Software	System traces	Yes	Linear (Regression)	—	—	—
Ardito et al. [30]	Power profiling	Components	Hardware	—	No	—	Off-line	—	Off-device
<i>V-edge</i> [55]	Power profiling	Components	Software	System traces	Yes	Linear (Regression)	On-line	On-line	On-device
Kim et al. [80]	Power modeling	• Device • Components	Software	System traces	Yes	Linear (Regression)	On-line	—	—
<i>AppScope</i> [67]	Energy metering	• Device • Components	Software	• System traces	Yes	DevScope [57]	On-line	On-line	On-device
<i>Power Doctor</i> [74]	Power Modeling	• CPU • Screen	Software	• API • System traces	Yes	Regression	On-line	On-line	On-device
Murmuria et al. [81]	Measurement of power consumption	• Component • Application	Software	System traces	Yes	Linear (Regression)	Off-line	On-line	On-device
<i>DevScope</i> [57]	Online power analysis	Components	Software	• Battery interface • System traces	Yes	Linear (Regression)	On-line	Off-line	On-device
Minyong Kim et al. [82]	Online power estimation	Components	Software	System traces	Yes	Linear (Regression)	On-line	—	—
<i>eProf</i> [45, 42]	Fined grained power modeling	Threads and systems traces	Software	System traces	Yes	FSM	On-line	On-line	On-device
<i>Sesame</i> [29]	Automated power modeling	Device	Software	Battery interface	Yes	Linear (Regression)	On-line	Off-line	Off-device

<i>Work</i>	<i>Purpose</i>	<i>Granularity</i>	<i>Profiling scheme</i>	<i>Measurement source</i>	<i>Model-based?</i>	<i>Modeling scheme</i>	<i>Availability of estimations</i>	<i>Training</i>	<i>Implementation</i>
<i>Power-Booster</i> [28]	Automated power modeling	<ul style="list-style-type: none"> • Device • Components 	Software	<ul style="list-style-type: none"> • Battery sensors • System traces 	Yes	PowerTuTor (Regression with varying parameters) Zhang et al. [28]	On-line	On-line	On-device
Yusuke et al. [83]	Power consumption monitoring and analysis	<ul style="list-style-type: none"> • Device • Micro-processor 	Software	System traces	Yes	Linear (Regression)	On-line	Off-line	On-device
Gurun and Krantz [84]	Energy consumption estimation	<ul style="list-style-type: none"> • CPU • Networks 	Software	<ul style="list-style-type: none"> • HMPs • BMU 	Yes	Regression (Linear, dynamic)	On-line	Off-line	On-device

3. Case study devices

The systems on which N^3 is validated are a smartphone and a development board running Android. These systems were chosen for three main reasons. Firstly, these devices are available on a wide scale and are easily programmable, making all the developed programs easily transferable between them. Secondly, these devices run on the kernel used by most of the embedded systems in the world—Linux—extending the portability of the N^3 profiler to, virtually, all devices running this kernel (with some device-specific adjustments). Finally, these devices are well-instrumented and need no external or invasive measurement schemes.

Table 2 shows all the significant specifications of both the development board and the smartphone. The board is a system used to develop prototypes. The one used in this work has only one core CPU and no extra peripheral making a perfect case study for basic systems. Figure 2 shows the board alongside a multimeter used to measure its power consumption.

4. Constructing the power profiler

In the previous section, the steps and the design choices for building a power profiler were outlined. The paragraphs in this section demonstrate how those steps are to be undertaken, starting with the purpose of the profiler.

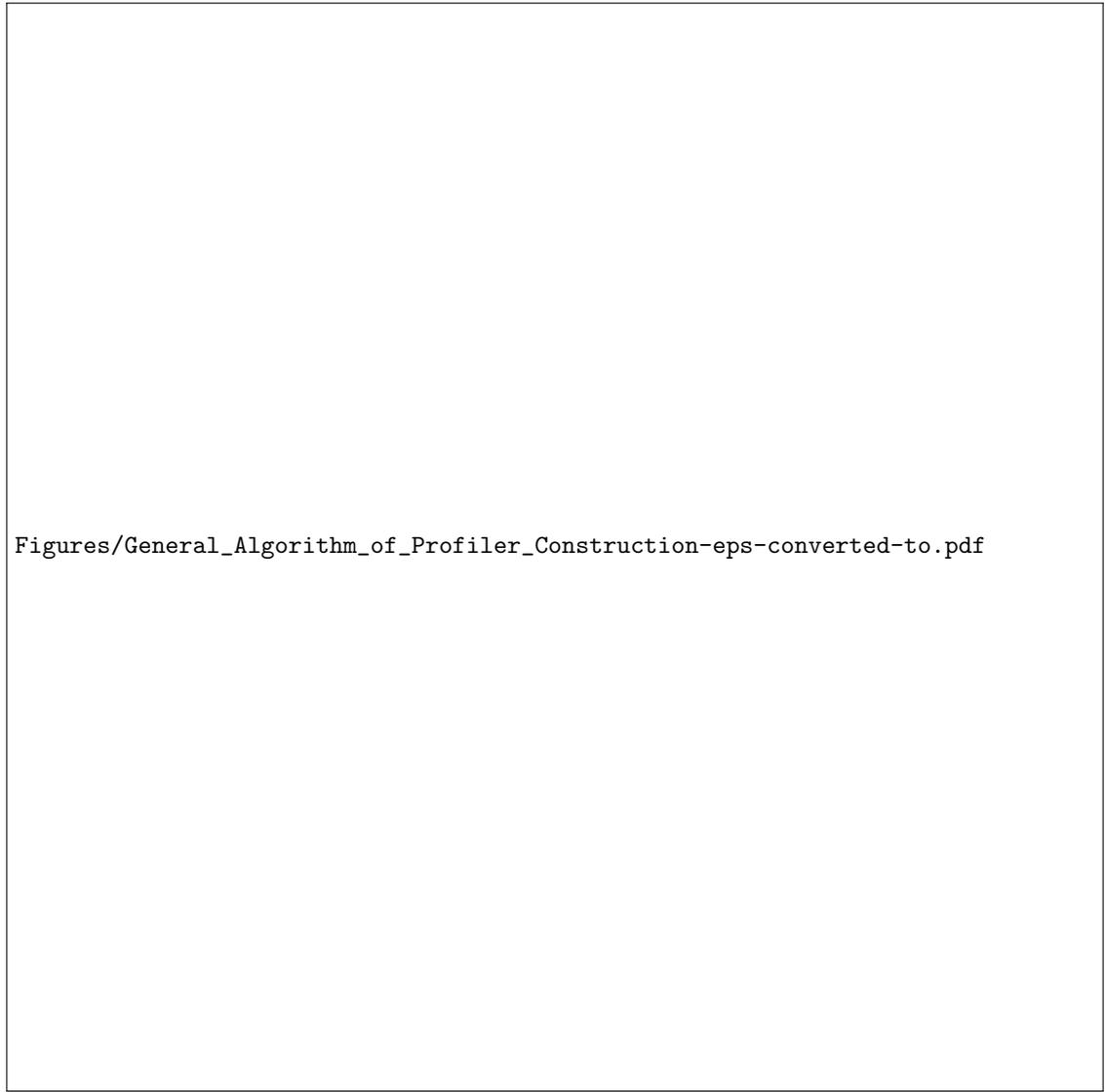
4.1. Purpose of the profiler

The N^3 power profiler is meant to serve as a power monitor for an embedded or a mobile device and its components. It is meant to be a component of an incremental model and a monitoring framework previously presented by Djedidi et al. [18], it is also an improvement and a generalization of their previous works [19].

The profiler will collect data, generate power estimation with its incorporated power model for the system as a whole, and its components individually, then log this data. Hence, the granularity is chosen to be at the components' level. The monitored components are:

- **The system on chip (SoC):** In most embedded systems, it is composed of the CPU and a Graphics Processing Unit (GPU) when needed.
- **The Random Access Memory (RAM)**
- **The LTE module**

¹The Vivante GC400T and GC320 are modules handling 3D and 2D graphics. However, they does not fall under the modern definition of a GPU [87].



Figures/General_Algorithm_of_Profiler_Construction-eps-converted-to.pdf

Figure 1: A general algorithm for constructing a power profiler for embedded and mobile devices.

Table 2: Highlights of the specifications of the smartphone and the development boards used in this study [85, 86]. —: Not Applicable.

	Mobile Device	Development board
OS	Android 8.0.1 (Oreo)	Android 6.0.1 (Marshmallow)
SoC	Exynos 8895	MCIMX6SX
• CPU	Octa-core (big.LITTLE) <ul style="list-style-type: none"> • 4 × 2.3 GHz Mongoose M2 • 4 × 1.7 GHz Cortex-A53 	One core + microcontroller <ul style="list-style-type: none"> • 1 GHz ARM Cortex-A9 • 0.2 GHz ARM Cortex-M4
• GPU	Mali-G71 MP20	3D : Vivante GC400T / 2D : Vivante GC320 ¹
RAM	4 GB	1 GB
Communication		
• Cellular	GSM/HSPA/LTE	—
• Wi-Fi	Wi-Fi 802.11 a/b/g/n/ac	—
• Bluetooth	5.0	—
• GPS	Yes	—
I/O		
• Touchscreen	QHD+ Super AMOLED	HD LCD
• Speakers	2 Speakers	—
• Camera	2 (Front and back)	—
• Microphone	Yes	—
• Vibration	Yes	—
Power supply	Battery 3500 mA h	plugged

- **The GPS module**
- **The wireless module:** Wi-Fi and Bluetooth.
- **The touchscreen**
- **The speakers and the microphone**
- **The camera module** containing the front facing camera, the rear facing camera(s), and the flash.

These components are the major factors when it comes to power consumption [26]. The smartphone contains other peripherals, but their power draw is considered to be marginal [88] and a part of the static power consumed by the device. For instance, the capacitive touch layer on the screen is considered to be consuming a marginal and static amount of power [89].

This assumption was tested and confirmed experimentally. In figure 3, the measured power consumption is drawn during multiple stages. In the first stage (Blue dots), the frequency is set to its minimum, and the screen is kept off by a custom app. During the second stage (Plain magenta), the fingerprint sensor is activated and used. Nevertheless, the power draw is unchanged. The same draw is observed in the third stage (Red dashes), during which the heartbeat sensor was used instead. The power draw significantly increased in the last stage (Green dashes), when the frequency was no longer limited, and the screen was turned on again.

4.2. The profiling scheme and measurements source

Modern smartphones are abundantly available, and developing applications for them is relatively cost and risk-free. The N^3 profiler is software-based that will rely on system files system and traces for its power

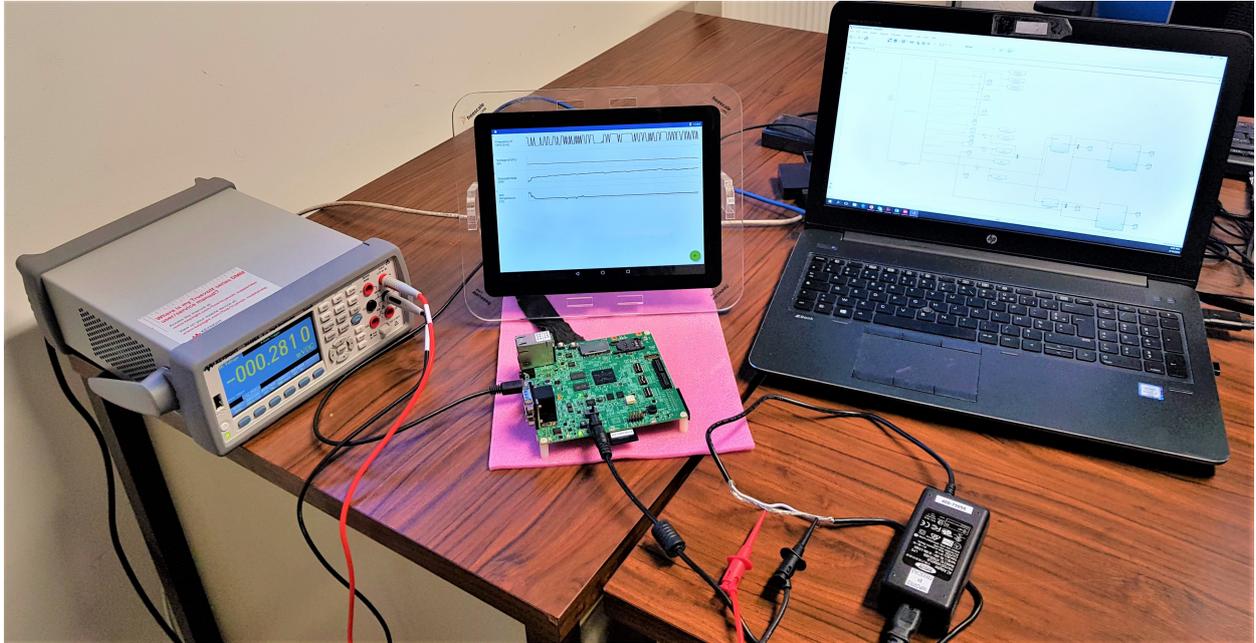
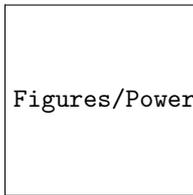


Figure 2: The development board alongside the multimeter and the monitoring PC.



Figures/PowerConsumptionWithMarginalSensors-eps-converted-to.pdf

Figure 3: The measured overall power consumption of the device during multiple stages with different components activated and deactivated at each stage.

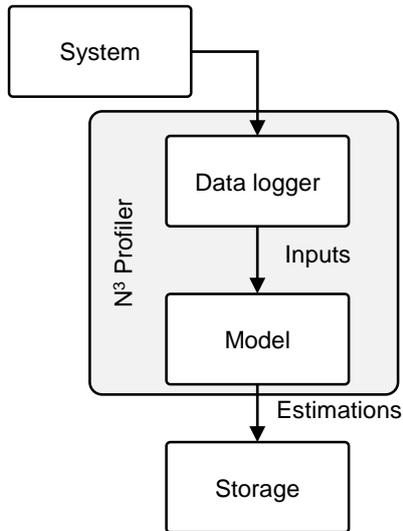


Figure 4: General architecture of the N^3 profiler.

readings and inputs’ readings. This profiling scheme and measurement source are adequate for the chosen level of granularity in this work. Moreover, the results obtained with these methods are on par with the accuracy of hardware-based measurements [41].

Accordingly, the profiler will be composed of two parts: a data logger and a model (Figure 4). Firstly, the data logger will collect relevant information from the device. Then, the model will use these pieces of information as inputs to generate power estimation.

4.3. Data logging

The operating system (OS) generates traces and logs to indicate its current state and the status of the peripherals. Thus, instead of encumbering the system with queries for the values of the inputs, the system files are read in parallel. Data from experimentation also showed that it is also faster to read the system files than to use system APIs (Table 3).

Table 3: The mean time needed to access the value of some variables through Android APIs and through system files, on the smartphone.

Variable	System APIs (ms)	System files (ms)
CPU core frequency	—	~ 2
GPU frequency	—	>2
Screen status	8	2
Screen brightness	8	>2
On call status	15	~ 2
Battery voltage	15	5
Battery current	10	2

An application was constructed to read and organize the necessary data. In order to have a correct correlation between the inputs and output, the application reads the data concurrently to minimize the reading time. It divides the reading queries into two halves and lunches two threads. Each of the threads reads the current time and then proceeds to get the readings from the systems files. Once the reading is finished, each of the threads queries for the time again and add it to the end of the data array (Figure 5).

To ensure the sanity of the data, the application compares the starting time of each of the threads and its ending time (TS3 - TS1 and TS4 - TS2). Then, it compares the start of the thread that started first

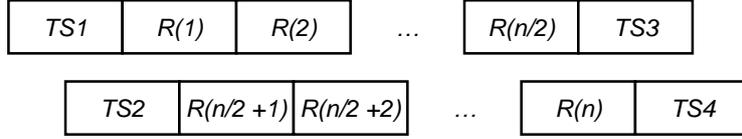


Figure 5: Concurrent readings (R) of n pieces of data with timestamps (TS).

with the end of the second one, to compute the time of the whole process. The process should not take more than 20 ms (the average is around 10 ms), with each thread taking at most 10 ms. Otherwise, the data is considered corrupted and discarded.

The choice of 10 ms for each thread is based on the time the Linux Kernel gives to each process before pausing it and changing to another (Multitasking). The 20 ms limit is imposed to be able to follow the fastest-changing variable, i.e. the CPU frequency [90]. Hence, the sampling time is 20 ms to follow this variable.

$$\begin{cases} TS3 - TS1 \leq 10 \text{ ms} \\ TS4 - TS2 \leq 10 \text{ ms} \\ TS4 - TS1 \leq T_s, T_s = 20 \text{ ms} \end{cases} \quad (4)$$

To keep the model as simple as possible—and consequently as computationally optimized as possible, only the most characterizing and directly influential inputs for each of the components were included.

4.4. The choice of inputs

- **The SoC**

CPU power consumption is a function of its frequency and voltage [44]. Moreover, the voltage in processors with dynamic voltage and frequency scaling (DVFS) is also a function of the frequency [19]. Thus, the input used to estimate power consumption is the frequency f of each CPU core. However, the CPU on the smart-phone was configured to use one frequency for each of the quad-core blocks in its big.Little configuration. Therefore, there will only be two frequency readings for that device [91]. The same input—the frequency—is used for the GPU since it correlates directly with its power consumption [32].

- **The RAM**

The RAM consumes around 10% of the total system power [92]. To account for the power used by the RAM, in the first trials, the value of the occupied RAM was used as an input characterizing the power draw of the RAM. However, that value on its own does not factor the maximum and the minimum possible values of the RAM on the system. Henceforth, the ratio of the occupied RAM over its maximum value is used and called the Memory Occupation Rate (MOR).

- **The communication peripherals**

The communication peripherals are the phone’s LTE module, the wireless chip (Wi-Fi and Bluetooth), and the GPS. Power consumption for these peripherals is mostly characterized by their state of connection and data transfer [52, 83]. For the LTE chip, the inputs are the On-call status (Off, 2G, 3G, LTE), the signal strength, and the connection and data transfer mode. Similarly, for the Wi-Fi and Bluetooth, as their power consumption is heavily influenced by their state of activity and the bandwidth [70], the inputs are the status (On/Off) and the data transfer. Finally, for the GPS, only the status was used.

- **The input and output peripherals**

To account for the power draw of the touchscreen, the status of the screen (On/Off) and its brightness are used as inputs [80, 89], since for modern AMOLED screens, consumed power is a quadratic function of the brightness [89, 52]. The power consumed by the screen is also dependent on the used resolution and scaling [11]. However, since in the case of this work, the resolution will be fixed to the maximum possible value without any scaling, it will be a constant that won't affect the model.

For the speakers, the status (On/Off) and the volume are used as inputs for the model [81]. As for the microphone, only the status was used. Finally, for the cameras and the LED flashlight, the status of the camera its recording status (Camera recording or not) alongside the flash (On/Off) are used.

4.5. The modeling scheme

Microprocessors-based SoCs are very complex and contain a large number of sub-modules. White-box techniques would require the modeling of all those components, making the process of constructing one arduous [25, 42].

The availability of the traces provided by the OS, alongside the complexity of the system, leads us towards the use of black-box modeling techniques. In this modeling scheme, there is a choice between either regression-based identification techniques or correlation and classification ones. Regression-based power models have been thoroughly studied in the literature [28, 29, 80, 32, 20, 55], especially for smartphones. Nevertheless, their accuracy was undermined by the fact that most of them used linear-regression, which led to an increased estimation error when the power dynamics were not as linear.

Nonlinear models like artificial neural networks (ANN) avoid these shortcomings [19, 51, 66]. However, Classic ANN do not account for the sampling time or the different timestamps associated with data. They are also not built to account for feedback loops, where previous values of the output influence the value of the next output. One alternative was recently explored by Romansky et al. [54] who used times series and deep learning to predict energy consumption in their model *Deep Green*.

The solution implemented in this work is the Nonlinear Autoregressive Network with eXogenous inputs (NARX) neural networks. These networks are recursive neural networks build to predict the output of time series [93]. Equation 5 gives their mathematical representation.

$$y(k) = \varphi [y(k-1), \dots, y(k-d_y), u(k-n), u(k-n-1), \dots, u(k-n-d_u)] \quad (5)$$

$y(k)$ and $u(k)$ are the output to be predicted and the input at the time step k , respectively. φ is the characteristic function. The term n is the process dead-time, whereas d_y and d_u are the orders of time delays for the input and output, also called input and output memory. Since the power changes react pretty quickly with changes in the characteristics (inputs), d_y , d_u , and n were all set to the value of 1, giving:

$$y(k) = \varphi [y(k-1), y(k-2), u(k-1), u(k-2)] \quad (6)$$

The NARX model is composed of two layers: a hidden layer and an output layer. The neurons in the hidden layer have sigmoids (ς) as activation functions. The output layer contains a single neuron, representing the total consumed power by the device P_{System} , with a linear transfer function (Figure 6).

The first advantage of using these neural networks is their capacity to estimate nonlinear dynamics while still keeping a relatively simple and computationally light form (2-layers). The second advantage is the component-level granularity.

To illustrate the capacity of the model to reach this level of granularity, Figure 7 describes the distribution of the total power consumed by a typical device as the sum of the power consumed by each individual component (CPU, Wi-Fi, ...), plus a minimum amount of base still consumed by the device [80], and a negligible amount consumed by the rest of the components whose consumption is marginal (see 4.1). Assuming that the power consumed the components whose consumption is marginal and the base power represents a single static power, the power consumed by the device becomes:

$$P_{Total} = P_{Static} + \sum_{i=1}^n P_i \quad (7)$$

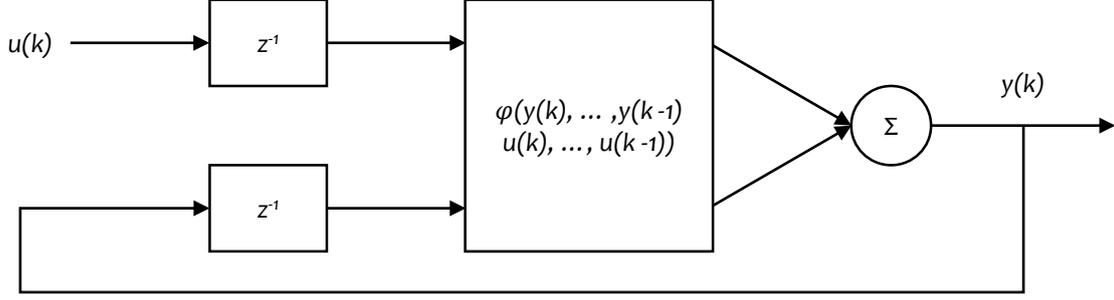


Figure 6: The general structure of N^3 NARX model.

Where i denotes the component number (CPU, GPU, RAM...), and n is the total number of these components. The power consumed by each of these components can be correlated with one of its characteristics. These characteristics will be used as inputs to the power model.

The level of granularity can be ensured by configuring the neurons of the hidden layer so as to achieve component decoupling, by disabling the training of the weights w linking the neurons of the different components. Figure 8 shows the configuration of the power model for an embedded system and showcases the interconnection of the neurons related to three components: the SoC, Camera 1 and the screen. Since the output layer is a linear neuron, the power consumed by the system becomes:

$$P_{System} = w_1s_1 + \dots + w_n s_n + w_{n+1}s_{n+1} + w_{n+2}s_{n+2} + \dots + w_m s_m + w_{m+1}s_{m+1} + w_{m+2}s_{m+2} + \dots + w_j s_j + w_{j+1}s_{j+1} + w_i s_i \quad (8)$$

by disabling all the components except the SoC, as this is the component required for system operation, and training the model with data from this configuration, the power consumption of the system becomes (from Equation 7):

$$P_{Systeme} = P_{Statique} + P_{SoC} \quad (9)$$

whereas for the NARX model (Equation 8), this translates into:

$$P_{Systeme} = \underbrace{w_1s_1 + \dots + w_n s_n + w_{n+1}s_{n+1} + w_{n+2}s_{n+2} + w_i s_i}_{P_{Statique} + P_{SoC}} \quad (10)$$

In order to quantify the individual contribution of each component, the training set is constructed as follows. At first, only the SoC is active for a period of time. Then the components are activated one after the other. Each component is kept active for a duration of time, after which it is deactivated for a period of time before activating the next component. Finally, All the components are returned to their automatic operating state.

Thus, the NARX model gives estimates of the power consumed by the system as a whole, as well as the

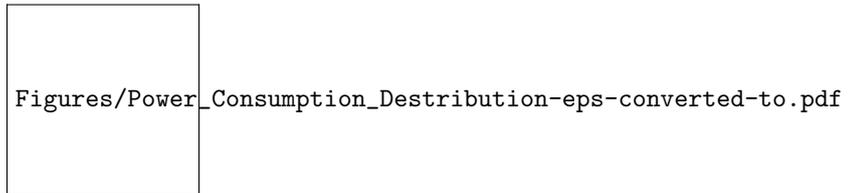


Figure 7: Power consumption distribution in a typical mobile phone.

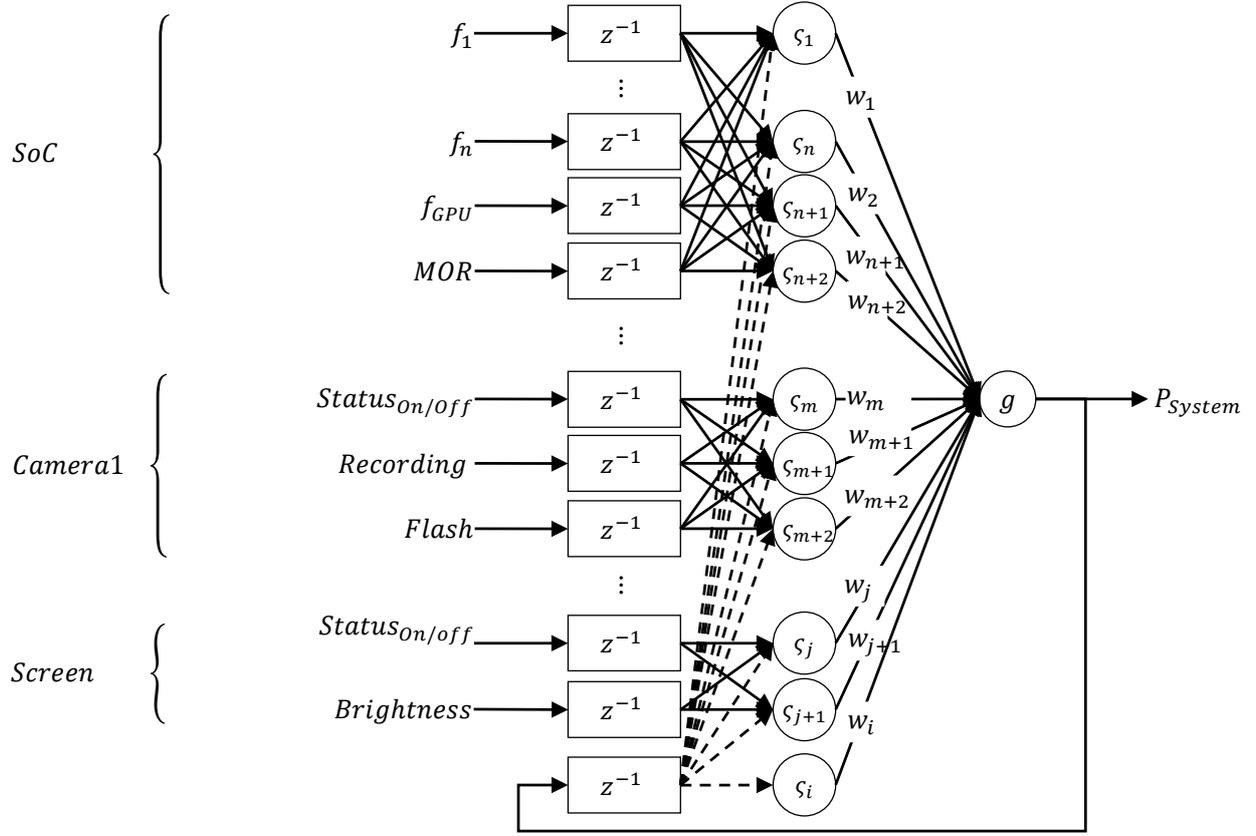


Figure 8: The configuration of the interconnections of neurons in the hidden layer in the NARX power model to ensure the components' level granularity.

power consumed by the components individually:

$$\begin{aligned}
 P_{System} = & \underbrace{w_1\varsigma_1 + \dots + w_n\varsigma_n + w_{n+1}\varsigma_{n+1} + w_{n+2}\varsigma_{n+2} + w_i\varsigma_i}_{P_{Statique} + P_{SoC}} \\
 & \underbrace{w_m\varsigma_m + w_{m+1}\varsigma_{m+1} + w_{m+2}\varsigma_{m+2} + \dots + w_j\varsigma_j}_{P_{Camera1}} + \underbrace{w_i\varsigma_i}_{P_{Screen}} \quad (11)
 \end{aligned}$$

4.5.1. Model construction and Implementation

NARX neural networks require relatively large amounts of data and resources to be trained into accuracy. Mobile CPU are not yet capable of doing such training. In fact, during experimentation, it took around 45 minutes to train N^3 on the device with 8×10^4 data points, and when the number of data points exceeded 1.2×10^5 , the device would just shut down.

The evident solution to these limitations is to do the training on a separate device. Therefore, the model construction process would start with data gathering. The data will then be transferred to a separate device to train N^3 . Once the training process finished, N^3 will be installed on the profiled device to generate online estimations.

4.6. Summary

In Table 4, all of the previously described and detailed points are summarized.

Table 5: The training time needed for different numbers of samples alongside the resulted mean absolute percentage error (MAPE), the mean squared error (MSE), and the regression (R) for the test set.

Total number of samples	Smartphone				Development board			
	Training time (min)	MAPE (%)	MSE	R	Training time (min)	MAPE (%)	MSE	R
$\sim 8 \times 10^4$	7	5	7.56×10^{-3}	0.986	4	2.9	4.72×10^{-3}	0.942
$\sim 2 \times 10^5$	12	3	7.23×10^{-3}	0.986	6	2.9	4.68×10^{-3}	0.942
$\sim 4 \times 10^5$	14	2.9	7.18×10^{-3}	0.986	10	2.8	3.67×10^{-3}	0.942
$\sim 8 \times 10^5$	20	2.4	7.60×10^{-4}	0.987	12	2.8	3.56×10^{-3}	0.963
$\sim 1.2 \times 10^6$	32	2.2	7.48×10^{-4}	0.987	15	2.8	3.61×10^{-3}	0.961
$\sim 1.8 \times 10^6$	57	2.2	7.09×10^{-4}	0.987	19	2.8	3.54×10^{-3}	0.961

4 [95], PCMark [96], and 3DMark [97]. These benchmarks are used to test the maximum performance of the systems through multiple calculation tests, 3D renderings... The successive launch of these benchmarks would generate data describing the system under heavy workloads. It would also stress the system and account for its behavior under thermal throttling (if present).

Then, the system—when appropriate, as the development board lacks multimedia and communication functionality—is put through more common tasks: A phone call, an internet video call, local video playback, video streaming, audio playback, file download over the cellular network, then over Wi-Fi, taking a picture without flash, with flash, and recording a 30s video, and finally leaving the phone idle for a while. This data-gathering experiment is repeated multiple times with variations in the order of the benchmarks as well as the tasks.

The gathered data is then divided into three sets: a training set (60%), and a validation set (20%) to train the model, and a test set (20%) to evaluate its performance. The results of the test sets for different sizes of training sets are shown in Table 5. These results demonstrate how the inputs correlate with the output ($R \approx 1$). Moreover, the predictions fit the output, with very low errors (MAPE = 2.2% for the smartphone and 2.8% for the board), indicating the accuracy of the model. Thus, N^3 is validated.

Nevertheless, Table 5 also shows the limitations of using neural networks. Indeed, the MAPE went down from 5% to 2.2% by adding more samples, but it came at the cost of longer training times. Additionally, after a certain number of samples (1.8×10^6 for the smartphone and 2×10^5), the MAPE no longer improved.

5.2. Real-time usage validation

In the model construction process, the profiler was set to generate estimations online. Having validated the model through the test sets, it is, then, incorporated alongside the data logging program into the application and directly deployed onto the device. Then, its accuracy and performance are tested through a non-scripted randomized normal usage of the device. This test, which is set to mimic day-to-day activities, includes making cellular and video calls through applications, sending messages through SMS and applications services (Smartphone only), video playback and streaming, taking and sending pictures (Smartphone only), browsing the web, and finally playing two different games (Smartphone only).

Table 6 highlights the online performance of the model on both devices, while in figure 9 and figure 11, the measured power consumption of the smartphone is drawn against values estimated by N^3 for the smartphone and the development board, respectively. For the smartphone, the model accurately predicts the power consumed by the phone with minimal estimation errors. It has an estimation MAPE of only 2.82%, and the recorded Mean Absolute Error (MAE) is 0.0168 W, whereas the Mean Squared Error (MSE) is 7.04×10^{-4} . Moreover, 97% of the estimation sample made by the model had an error value of zero (or less than the precision of the measurements which is 10^{-3}). Furthermore, the errors are normally distributed for both devices (verified by K-S test, Figure 10). For the smartphone, the estimation errors had a mean $\mu_\varepsilon = 1,178 \times 10^{-4}$ W and standard deviation $\sigma_\varepsilon = 0,0265$. Whereas for the development board, $\mu_\varepsilon = 0.0116$ W and $\sigma_\varepsilon = 0,037$. Both residuals present no heteroskedasticity (Engle’s ARCH test).

Finally, on the development board, as can be seen in figure 11, the estimations had a delay (of about 0.2s). This delay is a result of the wait time needed by the board to receive the measurements from the external multimeter to the device. Once accounted for this delay, the model performance results were practically the same as they were on the smartphone.

Table 6: Online testings results of the model on both devices.

	Smartphone	Development board
Test Duration	2.25 h	1.5 h
Number of Samples	$\sim 403 \times 10^3$	$\sim 280 \times 10^3$
MAE (W)	0.0168	0.038
MAPE (%)	2.82	2.88
MSE	7.04×10^{-4}	5.74×10^{-3}
Perfect fits (%)	97	96.6

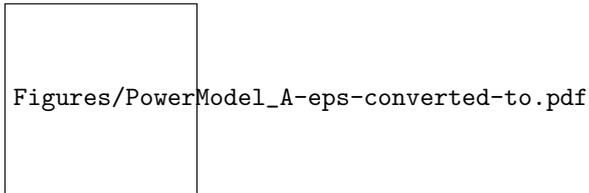


Figure 9: Online N^3 Power estimation against the measurements for the smartphone.

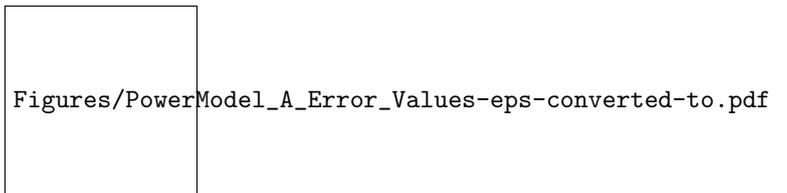


Figure 10: N^3 Online estimation error distribution for the smartphone.

5.3. Performance evaluation and comparison

Performance-wise, the average sampling time was 19.8ms which satisfies the previously stated design constraint. Additionally, N^3 caused no issues or bottlenecks for the system, as indicated by its overhead. The overhead is computed by running the system with the profiler and then comparing its power consumption and load to data from instances that had no profiling [37]. N^3 it had only a 3% load overhead during the test. As for the power overhead, it only amounted to a 5% increase in the same test.

Finally, we compared the results of N^3 with the publicly available power models and models of which the MAPE was reported in the literature. Table 7 shows the accuracy of these models compared to the power model presented in this paper.

While we are pleased that our model performed better than or on par with established works, it is also worth noting that some of these profilers have higher levels of granularity than our model does. Furthermore, some works, like *PowerBooster*, have not been updated for several years.

6. Conclusion

Given the great importance of estimating power consumption in embedded systems and smartphones, the literature has seen a great deal of research devoted to this subject. In this paper, we have presented, through an in-depth study of the literature, a generic methodology for building power profilers by adapting the profiling process to their context of use. The method is streamlined into a set of manageable steps, explaining the design choices to be made through each of them, starting with the goal of building the profiler. Then, we presented a compilation of profilers and models found in the literature and categorized them according to the steps explained in the proposed methodology.

Figure 11: Online N^3 Power estimation against the measurements for the development board.

Table 7: Comparison of the accuracy of several power models and profilers.

Profiler / Model	MAPE (%)	Source	Year
N^3	2.88	Measured	2019
<i>Snapdragon Profiler</i>	4.8	Measured	2018
<i>Trepm</i>	5.5	Measured	2018
Yoon et al. [31]	5.1	[31]	2017
<i>PETra</i>	4	[33]	2017
Walker et al. [35]	3.8	[35]	2017
Djedidi et al. [19]	4.4	[19]	2017
Kim et al. [32]	2.9	[32]	2015
<i>eLens</i>	~ 10	[77]	2013
Kim et al. [80]	3.8 \sim 7.2	[80]	2012
<i>Power Doctor</i>	10	[74]	2012
<i>eProf</i>	10	[74]	2011
<i>Sesame</i>	5	[29]	2011
<i>PowerBooter</i>	4.1 / 24	[28]/Measured	2010/2018

The proposed methodology is then applied in this work to build a new accurate profiler, based on a NARX neural network model, and used as a monitoring tool to detect anomalies in power consumption. In the results section, the proposed model has been implemented and validated with outstanding results—best in its class—that highlight how the accuracy reported in the literature is improved while maintaining low power and computational overhead.

Thus, N^3 is a profiler capable of generating accurate online power estimation for mobile and embedded devices, making it the optimal tool for power monitoring and debugging, and using the power profile to detect anomalies in the system. Finally, thanks to its accuracy and performance, N^3 has been implemented in an online monitoring framework for safety-critical avionic systems [18].

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