A Categorization of Power Measurement and Power Consumption Models in the Telco Cloud

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RESEARCH

A Categorization of Power Measurement and Power Consumption Models in the Telco Cloud

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Abstract

This article surveys the literature, over the period 2010-2020, on measurement of power consumption and relevant power models of virtual entities as they apply to the telco cloud. Hardware power meters are incapable of measuring power consumption of individual virtual entities co-hosted on a physical machine. Thus, software power meters are inevitable, yet their development is difficult. Indeed, there is no direct approach to measurement and, therefore, modeling through proxies of power consumption must be used. In this survey, we present trends, fallacies and pitfalls. Notably, we identify limitations of the widely-used linear models and the progression towards Artificial Intelligence / Machine Learning techniques as a means of dealing with the seven major dimensions of variability: workload type; computer virtualization agents; system architecture and resources; concurrent, co-hosted virtualized entities; approaches towards attribution of power consumption to virtual entities; frequency; and temperature.

Keywords: Virtualization; power consumption; power models; power meters; energy-aware algorithms

1 Introduction

Accuracy in power and energy *measurements* is necessary to devise energy- and/or power-efficient operations. It is also essential for billing in multi-tenant environments, so that the Infrastructure Provider (IPr) can charge customers the fair amount for the resources (including energy) they consume. Precise measurement of a virtual entity's (VE, i.e. virtual machine (VMs) or container) power consumption is difficult, since host power meter measurements cannot be related directly to it. Moreover, power consumption of a VE varies with its hosting machine. Therefore, for VEs, accurate measurement is predicated upon

¹precise **modelling** of energy- and/or power consumption. Before proceeding to the scope¹
²of our survey, we pose three salient questions that frame our work.²

³ ⁴1.1 Why should energy consumption be a topic of interest?⁴

⁵Energy efficiency in the Internet (and in computing and telecommunication networks in⁵
⁶general) has become a significant problem, which has received increasing attention since⁶
⁷the early years 2000 (see, e.g., [1] [2] [3] and references therein), starting from cloud com-⁷
⁸puting infrastructures, and then extending to mobile and fixed networks. Indeed, it has been⁸
⁹shown that the smaller data centres, within which telecommunications points of presence⁹
¹⁰(PoPs) may be classified, represent around 95% of the United States' data center energy¹⁰
¹¹use [4]. Furthermore, this use is comparatively inefficient when compared with that of the¹¹
¹²hyperscale server farms (the remaining 5%).¹²

¹³ ¹⁴1.2 What is the underlying cause?¹⁴

¹⁵Traffic growth is one of the causes of increased energy consumption. Table 1 shows the¹⁵
¹⁶consistency with which Cisco's Visual Networking Index (VNI) has been predicting heavy¹⁶
¹⁷growth in traffic exchanged over the access network by both businesses and consumers¹⁷
¹⁸with:¹⁸

- ¹⁹1 endpoints over managed networks and¹⁹
- ²⁰2 endpoints over unmanaged networks ("Internet traffic").²⁰

²¹Note that the figures refer to compound annual growth rate (CAGR); they do **not** refer to²¹
²²the percentage share of total traffic. The key observation lies in the realization that, year²²
²³after year, significant (heavy, in the case of mobile data) growth is persistently predicted.²³

²⁴Table 1: Compound Annual Growth Rate (CAGR) reported in Cisco's VNI over four con-²⁴
²⁵secutive years²⁵

²⁶ Period	Fixed Internet Traffic	Managed IP Traffic	Mobile Data	²⁶
²⁷ 2014-2019 [5]	23	13	57	²⁷
2015-2020 [6]	21	11	53	
²⁸ 2016-2021 [7]	23	13	46	²⁸
2017-2022 [8]	26	11	46	

³⁰This is corroborated by several other researchers, with perspectives varying from traffic³⁰
³¹at the access segment to traffic in transit between Internet Service Providers (ISPs) [9] [10]³¹
³²[11]. Cisco [5] and Sandvine [12][13] identify "video traffic" and "real-time entertainment"³²
³³as the drivers of this growth. The latest edition of Sandvine's Global Internet Phenomena³³

¹report [14] dedicates its executive summary exclusively to video traffic; the report shows¹
²video as consuming 60% of downstream traffic, a further 2% increase over 2018. Alcatel-²
³Lucent Bell Labs [10] observed that growth in the metro-core due to video traffic exceeds³
⁴growth in video traffic crossing the long-haul core. Indeed, it is widely recognized that⁴
⁵video is the prime driver of this growth in traffic and attendant energy consumption and⁵
⁶research has been addressing this problem [15–26].⁶

⁸1.3 How is energy consumption being tackled?⁸

⁹From these works, development of cache architectures emerges as an important approach⁹
¹⁰to controlling energy consumption, but other mechanisms exist and yet more are emerg-¹⁰
¹¹ing within the general thrust towards “future networks” (ITU-T Y.3001 [27]). Networks¹¹
¹²are evolving into flexible and programmable “softwarized” virtualized infrastructures, and¹²
¹³strongly integrated paradigms as in 5G [28, 29] rewrite the research agenda. We may now¹³
¹⁴distinguish between radical and reformist approaches. Reformist approaches seek to im-¹⁴
¹⁵prove the caching of content and are characterized by investigation of the reduction of the¹⁵
¹⁶length of the path between source and destination of IP traffic. Radical approaches employ¹⁶
¹⁷the dynamic and reactive control afforded by the softwarized, virtualized infrastructures.¹⁷
¹⁸Radical methods are enabled by standardized architectures (e.g. [30]) that equip the control¹⁸
¹⁹plane with uniform interfaces that exploit extant and emerging green capabilities. Signif-¹⁹
²⁰icant difference may exist in the techniques to be applied to achieve a trade-off between²⁰
²¹energy and performance, with respect to “legacy” infrastructures.²¹

²²Indeed, *the impact of virtualization technologies on power consumption in public*²²
²³*telecommunication networks (PTNs) is still unclear*. There is a general belief that Net-²³
²⁴work Functions Virtualization (NFV) should result in reduced energy consumption, owing²⁴
²⁵to consolidation of resources and increased flexibility in turning unused hardware (HW) on²⁵
²⁶and off as needed. However: it is also true that “the massive introduction of general-purpose²⁶
²⁷HW enabled by NFV would tend to increase power requests with respect to specialized²⁷
²⁸HW solutions” [28]. Therefore, there is a need to operate power-aware management and²⁸
²⁹control mechanisms in these environments. At the same time, it is necessary to limit the²⁹
³⁰complexity of these mechanisms and the level of human intervention therein, to keep Op-³⁰
³¹erational Expenditures (OPEX) within reasonable limits. One approach to understanding³¹
³²the impact consists of comparative analyses of implementations of infrastructure, with and³²
³³without virtualization. This approach is taken in [31], where the evolved packet core (EPC)³³

¹is studied. This work shows that the virtualized implementation is indeed less energy effi-¹
²cient. Unfortunately, the scope of virtualization and containerization within the converged²
³wireless and wireline infrastructure is very broad and consideration of a single "use-case"³
⁴[32] cannot be generalized to an overall statement. We therefore note that the scope for our⁴
⁵survey needs an operational context and suggest one next. 5

⁶1.4 The scope of this survey 6

⁷1.4.1 Operational context 7

⁸We suggest that the "**telco cloud**" is our context. "Telco cloud" is an evolving notion that⁹
¹⁰evokes a number of common terms in attempts to describe it. Virtualization, software-¹⁰
¹¹defined networking (SDN), automation and orchestration are four such terms. Other promi-¹¹
¹²nent terms are edge computing, containerization, microservices and resilient infrastructure¹²
¹³[33]. To avoid reducing the telco cloud to a melting pot of terms requires three key obser-¹³
¹⁴ventions that organize them into a coherent image. 14

¹⁵1 The telco cloud is, fundamentally, a **hybrid cloud**: 15

- ¹⁶(a) self-sourced virtualization and containerization and 16
- ¹⁷(b) out-sourced (public cloud) containerization. 17

¹⁸The complementary collaboration of the PTN operator's (PTNO) network, compute¹⁸
¹⁹and storage infrastructure, with that of global providers of infrastructure and appli-¹⁹
²⁰cations, is manifested well in [34]. A distributed cloud infrastructure operates at net-²⁰
²¹work (transport and interconnect) junctions. It includes (cloud) infrastructure owned²¹
²²and operated by the PTNO, by public cloud providers, and by enterprises which con-²²
²³sume their joint service. 23

²⁴2 Secondly, the telco cloud serves both internal and external clients [33]. 24

- ²⁵(a) Internal use can suggestively be referred to as the **IT Cloud** [35]. This consists²⁵
²⁶of applications specific to PTNOs: operational support systems (OSS) and busi-²⁶
²⁷ness support systems (BSS), as well as more general applications, like customer²⁷
²⁸relationship management (CRM). 28
- ²⁹(b) External uses are growing organically on the basis of use cases seeded by ETSI²⁹
³⁰[32] and the 5GPPP [36]. 30

³¹3 **The service-based architecture (SBA) of the 5G Core** is a good fit with **cloud-**³¹
³²**native computing. Containerization** is distinctively central to cloud-native comput-³²
³³ing [37][38]. The Cloud Native Computing Foundation explicitly identifies contain-³³

ers as components of the approach to the concept of cloud native computing [39].¹

There is a clear drive towards use of containers in lieu of virtual machines as the²
operating environment for network functions [37], and the 5G Core's SBA provides³
a clear scope for employing containers.⁴

The VEs in context may be deployed in:⁵

1 **datacenters**: the real estate referred to here consists of points of presence (PoPs) such⁶
as metro-core PoPs at the near edge;⁷

2 **softwarized and virtualized networks**: here, we refer to points of presence such as⁸
central offices (COs) and sites even deeper into the edge such as remote radio head⁹
(RRH) sites and roadside cabinets.¹⁰

1.4.2 Model scope¹³

We survey **predictive** energy and power models, as well as measurements that facilitate¹⁴
qualitative and/or quantitative prediction, of consumption by individual VEs relevant to the¹⁵
telco cloud. A simple interpretation of the rationale that drove our selection is that we have¹⁶
sought works that **measure real-time power consumption by VEs** and/or **model real-time**¹⁷
power consumption by VEs. The object of measurements and modelling is strictly the VE.¹⁸

Nonetheless, the devil is in the details and so the details of this simple rationale must¹⁹
be worked out. One important, finer point regards the VEs themselves. There are software²⁰
technologies, which we shall elaborate upon in later sections, which are **functionally criti-**²¹
cal to VEs. Works that measure, and/or model, such technologies' power consumption are²²
in scope. Justification of this claim on scope is not hard. Since power consumption is a²³
scalar quantity, reduction of power consumption of a component of a VE translates into²⁴
reduction of power consumption by the VE. In fairness, the translation is not direct (1:1).²⁵
A generalization of Amdahl's law comes to mind: that improvement in a component, mea-²⁶
surable by some metric, is attenuated by the ratio of that component's use (measurable by²⁷
that metric) to the system's (the VE's) use (measurable by the same metric). However, we²⁸
can safely summarize the finer point we alluded to at the start of this paragraph, as follows.²⁹
Research that studies measurement and modelling of power consumption by a component³⁰
of a VE is in scope. We clarify this by example. For instance, we would³¹

1 **Include** the Data Plane Development Kit (DPDK) [40], as it serves the critical func-³²
tion of networking (VEs that serve as virtual network functions (VNFs));³³

¹ 2 **Include** a comparative study that measures power consumption by a VE using two¹
² different implementations of input/output virtualization technology, say: SR-IOV²
³ (single-root IO virtualization) and paravirtualization;³

⁴ 3 **Exclude** a comparative study that measures power consumption by various network⁴
⁵ adapter (or network interface card (NIC)) architectures, **unless** it reveals the impact⁵
⁶ of these architectures on VEs' power consumption.⁶

⁷ Further detail emerges from the "real-time" requirement. This term is a reflection of the⁷
⁸ need for **application agnosticism**. Power meters that follow from such measurements and⁸
⁹ models may be used regardless of whether instantaneous or statistical readings of power⁹
¹⁰ are required. Studies (on measurements and models) meet this requirement by satisfying¹⁰
¹¹ the following criteria.¹¹

- ¹² 1 Predictors¹²
¹³ (a) must be of fine temporal granularity;¹³
¹⁴ (b) must be updated with the regularity of the temporal granularity;¹⁴
¹⁵ (c) must enable prediction of power consumption at the same temporal granularity.¹⁵
- ¹⁶ 2 Workload: Only resource-specific constraints are considered (e.g. processor-intensive).¹⁶
¹⁷ In particular, models must not constrain the stochasticity of the workload.¹⁷

¹⁸ Our last detail regards workload. We observe, in section 4.4.1, that the universal power¹⁸
¹⁹ model is a fallacy and the principal reason is that interaction between workload and ar-¹⁹
²⁰ chitecture cannot be pinned down indefinitely. This does not mean that modelling is a²⁰
²¹ fruitless endeavour. It simply means that validity constraints must be placed on the model²¹
²² in terms of workload and architecture. Therefore, we do not exclude modelling and mea-²²
²³ surement because of its workload-scope or architectural scope. We do, however, observe²³
²⁴ that such models are pitfalls for those who apply them without knowledge of such limits²⁴
²⁵ (section 4.3.3).²⁵

²⁶ We now proceed to present some recent, related surveys, highlighting their methodology²⁶
²⁷ and analytical approach. Against this background, we summarize the novelty of this survey.²⁷

²⁸ 1.5 Related surveys²⁸

²⁹ In recent years, a lot of research work has been done for modeling power for servers in data²⁹
³⁰ centers and cloud environment in general. Several surveys in this regard cover different³⁰
³¹ aspects of modeling and energy efficiency approaches for servers and virtual entities.³¹

¹ An analysis of power models from micro- to macro-level is presented in [41]. This survey¹
² covers different aspects and levels of both hardware- and software-centric modeling tech-²
³ niques. Researchers studied the models based on the computing resources (CPU, mem-³
⁴ ory, storage and I/O), system architecture (such as single or multiple cores), availability⁴
⁵ of Graphics Processing Units (GPUs), system/network components, operating system and⁵
⁶ virtualization environments. They categorize the existing models at different layers mov-⁶
⁷ ing from architecture level modeling to the level of power models for whole data centers.⁷
⁸ However, the survey did not focus greatly on power modeling techniques that consider the⁸
⁹ effect of different virtual entities. ⁹

¹⁰ According to the categorization in [41], power models depend on different organizational¹⁰
¹¹ context including power consumed by system components, running applications, and/or¹¹
¹² execution strategy of processes. These metrics, however, can derive additive component-¹²
¹³ based, regression-based or machine-learning-based power models. Additive models usu-¹³
¹⁴ ally present an aggregated view of server power consumption, which could be based on¹⁴
¹⁵ different resources (such as cpu, ram, I/O, disk), or disaggregate static and dynamic power¹⁵
¹⁶ consumption of the server. Regression based models are mostly based on the relation of¹⁶
¹⁷ power to the dynamic evolution of some measured system parameters. Power modeling¹⁷
¹⁸ using machine learning techniques is an advanced research area which can be further clas-¹⁸
¹⁹ sified as supervised, unsupervised, reinforcement and evolutionary learning. Furthermore,¹⁹
²⁰ at a much higher level, such as that of data center environments as a whole, power models²⁰
²¹ for group of servers, datacenter networks, conditioning and cooling systems were studied.²¹
²² The survey also analyzed the modeling methods at operating system (OS) and virtualiza-²²
²³ tion level, and for data-intensive, communication-intensive, and general applications. At²³
²⁴ the end, the researchers compare the power models against their complexity, effectiveness,²⁴
²⁵ application and use-cases. ²⁵

²⁶ The survey carried out in [42], analyzes the power models based on their modeling ap-²⁶
²⁷ proaches. According to it, power modeling methods can be divided into two main themes;²⁷
²⁸ analytical models and formula-learned models. In the former, parameters affecting the sys-²⁸
²⁹ tem power are known to the researcher; however, the weight for each parameter needs to²⁹
³⁰ be determined. On the contrary, in high-level formula-learned or machine learning based³⁰
³¹ modeling, no prior knowledge of the system is required and the model is developed from³¹
³² scratch using the provided data set. The survey further describes the commonly used ma-³²
³³ chine learning techniques, and later focuses on the use and effectiveness of neural networks³³

¹in power modeling. According to this survey, the approach to model power for any server¹
²may vary in several aspects. These different characteristics are summarized as i) *degree of*²
³*autonomy*, i.e. to which level the power model is dependent on external hardware, ii) *level*³
⁴*of granularity*, which describes the depth of logical (core, thread, etc.) or physical (de-⁴
⁵vice specific, system level, etc.) level to which the model can precisely estimate the power,⁵
⁶iii) *methodology*, describing the selection of method, which could be simulation, analytical⁶
⁷modeling or data-training, iv) *simplicity*, which can be assessed by the number of variables,⁷
⁸method selection and models' computing overhead, v) *portability*, as most of the models⁸
⁹developed are effective for some specific architecture, workload, or environment, and their⁹
¹⁰generalization is still a question, vi) *accuracy*, which defines the measurement accuracy or¹⁰
¹¹estimation precision of power for any model, and vii) *power meter* (as most studies use¹¹
¹²external power meters as a ground truth for their modeling, their accuracy is also a major¹²
¹³concern for developing a more efficient model).¹³

¹⁴ The survey in [43] adopts a slightly different approach of analysis and evaluates the¹⁴
¹⁵selected existing power modeling techniques in a unified environment. The comparative¹⁵
¹⁶analysis has been performed for 24 different software power models and measurement¹⁶
¹⁷methods with 9 different benchmarks under a single experimental environment. It evalu-¹⁷
¹⁸ates the existing software power measurement techniques and models for different applica-¹⁸
¹⁹tions, benchmarks, system configuration, server architecture and for their estimation errors.¹⁹
²⁰According to [43], most of the software-based power models use system performance met-²⁰
²¹rics provided by the operating system, or performance monitoring counters provided by²¹
²²hardware sub-systems of the server. Software power models considered in this study are²²
²³categorized in three types as single variable CPU-based, multi-variable CPU-based, and²³
²⁴single-variable throughput-based. The result of this unified experimental setup shows that²⁴
²⁵power models based on support vector machine (SVM) and interpolation techniques shows²⁵
²⁶the least error for different resource-intensive applications, whereas lasso regression with²⁶
²⁷30 variables was found to be the worst power model with the highest error. Also the mod-²⁷
²⁸eling techniques are mainly divided into two categories; linear and non-linear, where each²⁸
²⁹category is further classified based on its derivation from mathematical modeling or ma-²⁹
³⁰chine learning techniques.³⁰

³¹ Another survey [44], with a more limited scope, focuses on the power modeling of servers³¹
³²in the cloud while considering complexity of virtualization environment, heterogeneity and³²
³³workload complexity. It presents the usability, applicability and limitations of the studied³³

approaches, and also presents the analysis of traditional existing and emerging modeling techniques. It reviews the existing power modeling methods at three stages: data acquisition methods, power consumption models and power modeling methods for servers, VMs and containers. According to this study, the collection of data for power models could be based on: a) instruments such as external power meters, b) dedicated acquisition systems which are generally customized products by developers for a specific hardware, c) simulation based, and d) software monitoring tools. The latter constitute a widely used method that is based on system indicators and sensors. For the second stage, i.e. the power modeling, either hardware-centric, virtualization-centric or application centric power modeling schemes can be used. Each type has its own drawback and usability; hence, the domain is still an open research area for further generalization and measurement precision. The selection of method which is considered as third step of the modeling in [44] is characterized as power modeling based on: a) empirical parameterization, b) function regression, c) machine learning, and d) evolutionary algorithms. The survey, after analyzing different power models, concluded that functional regression and machine learning methods yield high accuracy when provided with large enough data sets and clear power behavior of servers. This survey is more similar to the present one; however, we distinguish further by providing statistical analysis of existing approaches, used tools, methods and measurement metrics. Also, our survey focuses on modeling of power for individual virtual entities and on the effect of the virtualization environment on server and network functions power behavior.

In general, the surveys mentioned above present the literature of server models irrespectively of the operational environment. One of the major trends, not only in data centers but also in networking is the presence of virtual entities and the adoption of virtualization environments. In this respect, this survey concentrates on power models of virtualized entities, and focuses mainly on components and parameters that could affect their power consumption. It further provides a statistical analysis of included research works with respect to their data acquisition methods, measurement tools and modeling methods, to give researchers a bird's-eye view of the existing literature through which one can identify the approaches carried out in different studies.

1.6 Intended audience

Our intended audience is the prospective researcher, seeking to understand the *dynamics* of research into predictive modelling, and supporting measurements, of power consump-

tion by individual VEs relevant to the telco cloud. Dynamics are characterized through a¹
 thorough frequency analysis, which we develop through application of a novel method that²
 is unique in its ability to *parse* research literature.³

Through the visual aids we provide, and our observations through cross-cutting *themes*,⁴
 a prospective researcher obtains a thorough characterization of the problems, approaches,⁵
 developments, formal methods and tools that have proven useful in the proceedings of⁶
 previous research.⁷

1.7 Organization of this survey

The survey is organized as follows.

1 In [45], we describe our method: a problem-approach-development (PAD) triad,¹²
 which, to the best of our knowledge, we are the first to use, to identify research¹³
 dynamics. We have delegated description of the method to a separate paper, to re-¹⁴
 solve the difficulty of elaborating fully on the method without distracting attention¹⁵
 from the results which we have obtained and which we document separately in this¹⁶
 review.¹⁷

2 Section 2 identifies and describes those interests that have given rise to research in¹⁸
 our scope.¹⁹

3 Section 3 presents the detailed results.²⁰

4 Section 4 is our analysis of the results. There, we give a qualitative assessment²¹
 through themes which emerged as we organized the data. We have classified these²²
 themes as “state of the art”, “fallacies” and “pitfalls”, to suggest guidance and warn-²³
 ings which we were able to glean from others’ experiences.²⁴

5 Section 5: we conclude by attempting to encapsulate the insights we have gained²⁵
 through this work.²⁶

We complement this paper with:

- 1 an online repository, that carries our raw data (see section 7.2.2),²⁸
- 2 an appendix (section 6), which describes and classifies applications that depend upon²⁹
 accurate models of power consumption by virtual entities to execute their function³⁰
 effectively, and³¹
- 3 another appendix (section 7), where we describe and compare tools and methods³²
 employed by researchers in their pursuit of developments within their field of study.³³

¹2 Research Domains (interest categories)

²We observe a (limited) number of interests which give rise to research within our scope.

³These are:

- ⁴1 predictive models of real-time power consumption;
- ⁵2 power/energy efficient computer and network system integration, and
- ⁶3 high-performance, power-efficient packet I/O frameworks.

⁷It is important to note that interests are *latent*: they are not usually explicitly stated within
⁸RUs. Researchers' interests - what *motivated* them to go through the pains of research - are
⁹deduced through knowledge of the underlying field and comparison with other RUs from
¹⁰a high level. This is particularly difficult with such a cross-cutting interest like energy con-
¹¹sumption; researchers may have very diverse complementary disciplines (the discipline
¹²which they are studying for energy consumption). There is a real risk of subjectivity in
¹³parsing, although this is mitigated by group review (as we have done) and experience. No-
¹⁴tably, group review helps to sort out myopias and fixations: it is indispensable to levelling
¹⁵the sharper quirks of individuals' subjectivity.

¹⁶We use this section to separate interest categories from the others (P, A and D), for two
¹⁷reasons:

- ¹⁸1 to avoid repeating essentially the same three interest categories with every RU ana-
¹⁹lyzed, and
- ²⁰2 to avoid cluttering the remaining, more objective data with data that is always subject-
²¹to the suspicion of subjectivity.

²²We close this introduction to the section on research domains with an important clari-
²³fication. The research domains *are not our scope*: they encompass it. Our scope remains
²⁴research on measurement of power consumption by VEs and models which predict their
²⁵power consumption.

²⁶2.1 Research domain # 1: Models of power consumption

²⁷Table 2 shows a list of the techniques we have detected for building power models. We
²⁸follow up on this table with a brief historical perspective of the development of these tech-
²⁹niques to meet the demands of the scope of VEs.

³⁰*Cycle-accurate simulators* like SimplePower [46] and Wattch [47] extended application
³¹of low-level simulation to estimation of power consumption in processors. The cost of

Table 2: Power Modeling Techniques

Technique	Scope	Sample references	Remark
Cycle-accurate simulators	Processors, Systems on Chip (SoCs)	[46, 47]	Gate/Register-transfer level simulation
System-software instrumentation modeling	Computer systems, Processors, SoCs	[48, 49] [50]	Similar to "top-down"
Functional Level Power Analysis	Computer systems, Processors, SoCs	[51, 52] [53, 54]	Similar to "bottom-up"

low-level simulation is complexity, rendering this technique (i.e. simulating dynamics at register-transfer or gate level) unsuited to real-time estimation of power consumption. *System-software instrumentation modeling* is referred to in [55] and [41] as the "top-down" method. It is "architecture agnostic" [55] and uses system software's abstractions of system hardware to count the occurrence of specific events. Such *event counters* are proxies for rates of hardware - and thus power - use. This is the intuitive basis for the use of event counters as predictors of power consumption. We point out that the terms "event counter" and "performance monitoring counter" are largely used synonymously in the literature we have reviewed.

A seminal work in correlation between energy consumption and processor hardware events investigated the latter's use in the scheduling of threads in an energy-aware manager [51]. Later, it was found [56] that the counter value for the number of instructions fetched can be used to estimate the system's power consumption. These two works represent a departure from system-software instrumentation modeling (top-down) as they are predicated upon a knowledge of functional units within the computer system, particularly at the *microarchitectural level*.

This technique was developed into what has come to be known as *functional level power analysis*. A significant advance in prediction of power consumption took place through the use of abstraction of processor operation into a set of functional blocks. Each such block implements a function recognizable at the semantic level of the microarchitecture, e.g. instruction fetch and data fetch. This analytical approach was first referred to as functional level power analysis (FLPA) in [53]. The major components of this approach are still relevant to most of the modeling work which we have surveyed, i.e.:

1	1	knowledge of microarchitecture	1
2	2	knowledge of interaction of program code and architecture	2
3	3	workloads that isolate specific resources.	3

Another name given to this technique [41, 55] is "bottom-up", in recognition that a power model is being synthesized out of a low-level knowledge of the hardware being modelled.

Adoption and adaptation of the application of FLPA to virtualized environments has been explicitly acknowledged in [54]. Given the widespread interest in [51–53] (these RUs have high citation counts), it is likely that the origin of the development of modeling work in power consumption in virtualized environments may be traced back to these works, which deal with:

- functional level power analysis [52, 53] and
power consumption – hardware event correlation [51], respectively.

¹⁴We observe that this domain's practitioners are biased strongly towards these two bases as ¹⁵their analytical premises. 15

18	2.2 Research domain # 2: Power/energy - efficient computer and network system	18
19	integration	19

Several works are concerned with measurement of power consumption in virtualized environments but stop well short of striving for predictive models [57–63]. These works seem to stem from an interest in obtaining causal relationships between, on the one hand, some aspect of implementation of computer and network systems, and on the other hand, power/energy consumption/efficiency. A wide variety of aspects can be found: non-uniform memory access (NUMA) and simultaneous multi-threading (SMT) [57], scaling execution over multiple processor cores [58], virtualization technology [59], virtualization genre [60], data plane [62] and network functions [63].

Research of this kind might also stem from a perceived opportunity to break new research ground and harvest the low-hanging fruit of an unexplored research space. The term "profiling", as used in [58], is indeed an apt description of research activities rooted in this common interest. However, even if this were the case, IT discipline skills exhibited in such research is suggestive of an interest in computer and network system integration. We propose this as the common root.

¹2.3 Research domain # 3: Power-efficient, high-performance packet I/O frameworks ¹

²General-purpose network I/O has been implemented in stacks of software modules operat-²
³ing in the kernel of general-purpose operating systems. To date, these network I/O kernel³
⁴stacks are incapable of transmitting and receiving at 10Gb/s line rates [64]. Higher per-⁴
⁵formance packet I/O frameworks have been developed, e.g. SR-IOV, DDIO (Data Direct⁵
⁶I/O), DPDK and, more recently, AF_XDP (Address Family eXpress Data Path). Exploita-⁶
⁷tion of SR-IOV's VFs for high performance is hardware-dependent; this dependency ren-⁷
⁸ders SR-IOV problematic to the vision of cloud-native computing: running *anywhere* [65]⁸
⁹@52:01 ^[1]. This hardware-dependence contrasts with DPDK and AF_XDP, which are less⁹
¹⁰restrictive in hardware specification. DPDK's cost might be power consumption [62–64]¹⁰
¹¹(depending on its usage, as discussed in section 4.3.2) and AF_XDP's power-performance¹¹
¹²tradeoff is still comparatively unknown. ¹²

¹³High-performance packet I/O's centrality to the success of NFV seems likely to turn it ¹³
¹⁴into a rich source for future research. In addition, the pressing need to control operational ¹⁴
¹⁵expenditure should maintain interest in power efficiency. The conjunction of these two ¹⁵
¹⁶interests is the noteworthy research domain of *power-efficient, high-performance packet* ¹⁶
¹⁷*I/O frameworks*. ¹⁷

¹⁹**3 Survey results: a Digest of Challenges, Approaches and** ¹⁹ ²⁰**Developments** ²⁰ ²¹ ²¹

²²3.1 A taxonomy of the problem space ²²

²³As our parsing efforts proceeded, we observed that the scope of this survey is relatively²³
²⁴narrow and the problems in our set are not fully independent of one another. Rather, the²⁴
²⁵problems diverge from one another only as *aspects* (we could also say that they are *deriva-*²⁵
²⁶*tives*) of the core challenge of modeling the power consumption of virtualized entities.²⁶
²⁷Each RU is rooted in this core challenge, but the derivative problems (our P-categories and²⁷
²⁸their members) addressed differ from one RU to another. Fig. 1 is an illustration of a sim-²⁸
²⁹ple organization of the challenges which have been tackled in the literature and shows their²⁹
³⁰frequency of presence in RUs. The organization gives prominence to how challenges have³⁰
³¹been perceived: ³¹

³²^[1]We use the @ symbol since a video is being cited and the content cited here may be found ³²
³³by seeking the time indicated. ³³

1 one group regards the concern with obtaining an understanding of the dependency¹
 2 of power consumption on some genre of artifacts. Categories P1,2 and P9 - 11 are in²
 3 this group. 3

4 2 the other regards the concern with how to predict power consumption. Categories P3⁴
 5 - 8 and P12 are in this group. 5

⁶Category P13 regards a very recent development of the problem space and works classified⁶
⁷here present both dependency and modeling concerns. 7

⁸We now proceed to describe the categories in more detail. Each description is preceded⁸
⁹by a list of references to works that tackle a challenge in the problem category. 9
 10 10

11 3.1.1 P1: Host system hardware architecture perspective: dependency of VE power 11 12 consumption on host system architecture 12

¹³[57, 58, 63, 66]. Problem category P1 addresses the impact of specific architectural at-¹³
¹⁴tributes of the host system on power consumption of VEs. On the one hand are the major¹⁴
¹⁵attributes of architecture and system-level design. On the other hand are the changes in¹⁵
¹⁶power consumption (the behavior) as major features are adjusted, inserted or removed.¹⁶
¹⁷Insertions and removals are coarse configurative actions such as enabling or disabling; ad-¹⁷
¹⁸justments consist of progressive modifications such as adding increments of a resource.¹⁸
¹⁹Examples of features which have been tackled include multiple processor cores, processor¹⁹
²⁰frequency scaling, NUMA and hardware threads (e.g. Intel Hyper-Threading). 20

²¹For network functions, the importance of knowledge about the power efficiency of²¹
²²NUMA and multiple-core architectures has the added relevance of these architectures'²²
²³relationship to *determinism* [65] @19:00, @25:25. We dwell further on the underlying²³
²⁴premise of *hard partitioning* in our consideration of the impact of the high-performance²⁴
²⁵data plane on power efficiency (section 4.3.2). 25

²⁶Research that investigates the dependency of power consumption on architecture is ex-²⁶
²⁷ploratory, charting work. It attempts to provide a framework for detailed modeling through²⁷
²⁸the discovery of broad relationships. Problems in this category arise with developments²⁸
²⁹in architecture and system-level design. For example, while [58] is a comparatively old²⁹
³⁰work that tackles architecture, [57] is newer and finds scope for research in system soft-³⁰
³¹ware's exploitation of NUMA. One recent, highly significant scope is that of the use of³¹
³²domain-specific architectures (DSAs). Researchers are exploring specialized hardware in³²
³³the quest for improvement of the energy-performance-cost ratio, and will investigate en-³³

ergy efficiency in the process of their research. As domain-specific cores are mixed with¹
general-purpose cores, many architectures will be investigated from each of the three pin-²
nings: energy consumption, performance and cost.³

A particularly relevant set of DSAs regards real-time packet processing by computer⁴
systems hosting NFs at intermediate nodes (INs) at the network edge. Concern lies with⁵
expediting the common tasks, such as sending/receiving packets and processing headers.⁶
SR-IOV is a good example (see, for example [67], and its inclusion in [63]), but software-⁷
only solutions, such as poll-mode drivers, may also help to cut through the many middle-⁸
men characteristic of general-purpose operating systems [62, 63]. Introduced to serve the⁹
perspective of performance, it is now necessary to understand their impact on power effi-¹⁰
ciency. Therefrom, it is necessary to understand how to **control** their power consumption.¹¹

We suggest that “profiling”, the term chosen in [58] and [68], is a helpful descriptor of¹²
this kind of research. Just as a profile produces an external boundary within which to fill¹³
detail, so does this kind of research provide a framework through which modeling work is¹⁴
facilitated and within which modeling work provides details of power consumption rela-¹⁵
tionships.¹⁶

3.1.2 P2: System perspective: impact of alternative virtualization genres and¹⁸ virtualization platforms on VE power consumption¹⁹

[59, 60]. Here, a behavior that consumes power is investigated across different **implementa-**²⁰
tions of a **system concept**. We have observed investigation of two different system concepts:²¹
(a) virtualization genres and (b) virtualization platforms. There are three members of the²²
virtualization genre group: containers, para-virtualization and hardware-assisted virtualiza-²³
tion. In the virtualization platform group, examples include Xen, Hyper-V, Kernel Virtual²⁴
Machine (KVM [69]), Docker and Linux Containers (LXC).²⁵

Research questions (**problems**) typical of category P2 seek to control scope of experi-²⁶
mentation through exercise of specific resources, e.g. per-host networking using emulated²⁷
switches (software switches)[59, 60], processor-bound and memory-intensive processing²⁸
[59].²⁹

We consider genres and platforms as sub-categories of the same overarching problem³⁰
category. Namely, this is system-level exploration that attempts to establish generalizations³¹
about an uncharted space. Like problems in category P1, new problems in this category³²
arise with fresh alternative virtualization genres and platforms. However, here the scope³³

¹of investigation is broader than with works classified under P1. Unlike P1, where specific¹
²architectural aspects (e.g. NUMA, hardware threads) are explored, the perspective taken²
³here is concern with the impact of a choice of implementation of a system. ³

⁴53.1.3 P3: Estimation of power consumption of (virtualization-) host system ⁵

⁶[70–82]. Measurement of a single server’s power consumption through the use of an exter-⁶
⁷nal power meter is a trivial task. However, at the scale of cloud datacenters, it is a logistical⁷
⁸burden. In addition, travel to the datacenter’s site may be burdensome. Furthermore, ser-⁸
⁹vice availability would be reduced by the process of attaching a physical power meter to⁹
¹⁰the hardware in the virtualization platform, e.g. between the server’s power inlet and the¹⁰
¹¹outlet in the racking cabinet’s power distribution unit (PDU) (naturally, availability would¹¹
¹²only be affected in cases that do not integrate (management and) measurement facilities¹²
¹³within the PDU). ¹³

¹⁴The alternative is deployment of software power meters. In the scope of this survey, the¹⁴
¹⁵cases we consider are meters that attempt to predict host power consumption on *the basis*¹⁵
¹⁶*of activity in the VE*. This challenge is tackled, for example, in [52, 71–73, 75, 80]. These¹⁶
¹⁷works then proceed to tackle the problem of attribution of system power to the guest VEs.¹⁷
¹⁸Indeed, inclusion within scope of both challenges (modeling power consumption of VEs¹⁸
¹⁹and that of the host system power) seems to significantly enhance the usefulness of such¹⁹
²⁰research, with relatively less effort. ²⁰

²¹Host power consumption may be predicted in terms of VE resource utilization, or in²¹
²²terms of *a simple characterization of the VEs’ workload*. Use of simple workload char-²²
²³acterization as predictor requires knowledge of workload parameters like number of pro-²³
²⁴cesses, number of threads, web interactions per second and network interface utilization.²⁴
²⁵Enokido’s and Takizawa’s work [80, 81, 83] is noteworthy in its consistency in modeling in²⁵
²⁶these terms but other variants of this approach have been found, as (a) web interactions per²⁶
²⁷second [78] and (b) number of running VMs [79] of processor- and/or network-intensive²⁷
²⁸workloads. ²⁸

²⁹To contrast: works like [70, 84–88] are not included within this category – notwithstand-²⁹
³⁰ing their development of models for prediction of host system power consumption. In these³⁰
³¹works, host system models were developed as part of the scope of the challenge of mod-³¹
³²eling virtualized entities. Therefrom, the challenge of system power attribution (problem³²
³³category P8) was tackled to proceed to guests’ power models. ³³

¹3.1.4 P4: *Dependency of power model on workload* 1

²[60, 75, 80–83, 87–91]. This category regards the perceived dependency of a VE’s power 2
³consumption model on the tasks it is processing. While it is intuitive to expect power con- 3
⁴sumption to depend on workload, it seems far less intuitive to expect the model to depend 4
⁵on workload. If this dependency is detected, the problem of model formation must un- 5
⁶dertake this aspect of investigation. Two different, major approaches towards achieving 6
⁷**adaptability** of model to workload have been observed. 7

⁸
⁹1 **Adaptation during run-time:** The selected mode of instrumentation may not be 8
¹⁰suited to a generalizable, closed form relationship between inputs and power con- 9
¹¹sumption. In this case, model parameters must be re-trained online. This approach is 10
¹²therefore of the operating-time, or run-time, kind. 11

¹³2 **Off-line adaptation:** A larger set of inputs may need to be identified to comprehen- 12
¹⁴sively characterize variation of power consumption with workload. This approach is 13
¹⁵therefore of the design-time, or off-line, kind. 14

¹⁶We conclude this part with a note about two descriptors of workload: homogeneous and 15
¹⁷specific. The term “homogeneous” is encountered in literature to refer to the case where 16
¹⁸host system deployments within scope are subjected to a single workload. The term seems 17
¹⁹to originate in warehouse scale computing (WSC). Conclusions drawn from this kind of 18
²⁰workload have drawn criticism as the results, while significant by virtue of the mass of 19
²¹WSC, are not generalizable. The term “specific” identifies a single application; for ex- 20
²²ample, a member of the Standard Performance Evaluation Corporation (SPEC) CPU2006 21
²³suite [92]. This term is used to indicate that models tested under such a workload are 22
²⁴application-dependent and are valid only within a limited range of the this dimension of 23
²⁵variability (“workload”, see section 4.1.1). 24

²⁷3.1.5 P5: *Dependency of VE’s power consumption and model on VE’s resource* 26 ²⁸*configuration (heterogeneity)* 27

²⁹[75, 85, 90] This category regards the perceived dependency of a VE’s power consumption 28
³⁰and/or the dependency of its power consumption model on (a) the physical host’s resource 29
³¹configuration and (b) the individual VE’s resource allocation. Research here is concerned 30
³²with a very practical problem: the impact on power consumption of the differences between 31
³³hosting machines/containers (case (a)) and the differences between virtual machines (case 32
33

¹(b)). We have observed that occurrences of research that undertake the challenge tackle it¹
²as an adjoint to another focus, not as the research's primary objective. ²

³ 1 **Physical host configuration** Host machines in a cloud datacenter may be expected to³
⁴come in a limited variety of models, principally related to resource capacities such as⁴
⁵the number of processor packages per server, cores per processor package, amount⁵
⁶of RAM per server, spread in storage device sizes, etc. Processor power consumption⁶
⁷is notably variable, even within a single family of processors. Indeed, specialization⁷
⁸in optimized power consumption within a family is part of the study carried out in⁸
⁹[31] within the context of an edge cluster for use in NFV. As a VE migrates from one⁹
¹⁰processor within a family to a processor of different specialization, the model will¹⁰
¹¹differ. ¹¹

¹² 2 **Individual VE's resource allocation** The power consumed by a VE varies with al-¹²
¹³location of resources to (i.e. in use by) a VE, which can be dynamically varied,¹³
¹⁴the number of virtual cores assigned to a VE being a notable example; see, e.g.¹⁴
¹⁵[70, 74, 84–86]. Moreover, VEs are commonly offered in sizes, e.g. small, medium¹⁵
¹⁶and large, where allocation varies within all the major resource categories, demand-¹⁶
¹⁷ing prediction of power consumption matched to the size of the purchased VE. ¹⁷

¹⁸3.1.6 P6: Impact of temperature and/or frequency on models that predict VEs' power ¹⁸ ¹⁹consumption ¹⁹

²⁰[73, 93, 94]. This category regards the challenge of inclusion of processor package tem-²⁰
²¹perature in **models** of power consumption. Works that tackle this challenge are concerned²¹
²²with detailed models of power consumption. Here, interest lies in obtaining models that²²
²³incorporate dependence on hyper-parametric attributes like temperature. ²³
²⁴
²⁴

²⁵3.1.7 P7: Loading the VE's resources and measuring resource use ²⁵

²⁶[60, 64, 70–72, 74, 75, 78, 81–83, 85, 87–91, 93–98]. This category regards use of com-²⁶
²⁷puting resources and measurement of such use by VEs. Interest stems from the role of²⁷
²⁸resources as predictors in modeling. The researcher is firstly concerned with **loading**, or²⁸
²⁹effecting use of resources. What means **within the operating context of the VE**, can be²⁹
³⁰used to load a resource? Should it be loaded in isolation (using synthetic loads) or should³⁰
³¹it be loaded using representative (realistic) workloads? Once these problems have been ad-³¹
³²dressed, the concern with **measurement** of resource use arises. The problem here consists³²
³³of identifying the means that quantify resource use made by the loading. ³³

3.1.8 P8: Attribution of host system power consumption to individual VEs

[70–72, 74, 75, 85, 87–89, 91, 93, 94, 96, 98]. Since host system power *is* directly measurable (e.g. at the wall outlet, or through voltage rail in-line resistors), such empirical evidence can be used as ground truth and compared with power consumption inferred through modeling. Thus, the problem presents itself: how can this consumption be attributed to the host's individual guests (the VEs)? Attribution of host system power to individual VEs is a fundamental problem in proceeding from the directly measurable (host system power consumption) to the indirectly measurable (individual VEs' power consumption). Within the host system, the physical consumers identified in the literature are the following.

1 Idle (static) power consumption

- (a) Power consumption while idle is not attributable to any VE at all, as this consumption arises out of electronic behavior of semiconductor material, not of computation, communication or storage.
- (b) Nonetheless, this power consumption must be accounted for and different approaches have been followed. For example: the physical machine's idle power is attributed to individual VEs in fractions equal to the ratio of each VE's virtual CPUs (vCPUs) count to the total complement of vCPUs active on the physical machine [70, 84–86].

2 Active (dynamic) power consumption is required to process a workload

- (a) The active component can be linked to a particular VE.
- (b) This includes active power consumption in peripherals, e.g. NIC and mass storage device.

3 Overhead, for example:

- (a) operation of heat dissipating units (fans) to prevent thermal runaway, and
- (b) losses in the power supply.

A “top” (host) – “down” (guest) approach to attribution has been observed.

1 Decide on what host system power consumption is within the scope of the study and how to divide it. The problem of attribution of the above three causes may be summarized as follows:

- (a) Is idle power attributed to the VEs or is it attributed to the host/a privileged guest?
- (b) Is consumption by peripherals within scope? How will this be attributed?

(c) Are overheads modeled or is correlation with other sources of power consumption going to account for them?

2 Select a set of performance metrics that are correlated to a VE's power consumption.

3 Select a model that maps a VE's performance metrics to its power consumption.

4 This fourth consideration is tackled only by those researchers who investigate the *adaptability* of the attribution obtained through steps 1,2 and 3. Does the obtained attribution adapt well to concurrent, co-hosted VEs? That is: if concurrent, co-hosted VEs were to be investigated, would the division, metrics and model still result in accurate prediction?

3.1.9 P9: Implementation of virtual I/O; P10: Implementation of network functions; P11: Implementation of software Layer 2 (L2) data plane switching

[62, 63, 66]. These three categories are introduced together, since elements from the respective categories are commonly implemented *as a set* for the purpose of realization of virtualization of network functions. Here, researchers seek comparative statements and/or broad correlations (e.g. independent, positive, negative) between workload (often in terms of packet rate and size) and power consumption, across implementations of the same type. As was observed for categories P1 and P2, researchers seek a profile of the power characteristics of implementations. It may be helpful to repeat that by "profile", we understand that characteristics sought here are not of the detailed form of closed-form expressions.

Examples of elements from the respective categories are:

- Virtual I/O (P10): virtio [99] and DPDK poll-mode drivers (PMDs) [100]
- Network functions (P11): Bro (now Zeek) [101] and Snort [102]
- Software layer 2 data plane switching (P12): Open Virtual Switch (OvS) [103] and VALE [104].

Problems in each of these three categories merit separate classification as they have been tackled separately in the literature. For example, in [62], a number of components are investigated: three different implementations of software virtual switch (P12), two different I/O virtualization devices and two different implementations of the same network function (intrusion detection system (IDS)). In [66], power consumption by packet transmission under DPDK is investigated under the condition of enforcement of (a) the network adapter's affinity to NUMA nodes and (b) DPDK process pinning to processor cores.

¹3.1.10 P12: Investigation of processor green capabilities ¹

²[57, 64, 73, 80, 93–95, 97, 105]. Works in this category investigate low-power-idle (LPI)²
³and adaptive rate (AR) operation of a processor as a means of reducing power consump-³
⁴tion. The challenge is broad enough to permit a sub-categorization into (a) those works⁴
⁵that investigate the influence of frequency as a power-model parameter [93, 94] and (b)⁵
⁶other works that address improved, real-time governance of LPI and/or AR [64, 95, 105]⁶
⁷to minimize the power consumed to process a load. ⁷

⁹3.1.11 P13: Improvement of power efficiency of high-performance IO virtualization ⁹ ¹⁰frameworks ¹⁰

¹¹A separate classification was set up for [64] as this work represents an evolution of those¹¹
¹²classified under P9. This work extends beyond profiling and suggests use of low-power-¹²
¹³instructions as the means to balance performance and power efficiency. ¹³

¹⁵3.2 A taxonomy of characteristics of application of the scientific method ¹⁵

¹⁶Fig. 2 illustrates the taxonomy we use to structure the approaches detected in research¹⁶
¹⁷work. Line thickness and percentage values represent the utility (see [45, subsection 7.5])¹⁷
¹⁸of the specific approach. We now proceed to describe the categories within the context of¹⁸
¹⁹the taxonomy. Each approach-category's description is preceded by a list of references to¹⁹
²⁰works, each one of which uses a component within that category's set. ²⁰

²²3.2.1 Analytical foundations ²²

²³This group of categories regards the theory and hypotheses that comprise the essential²³
²⁴abstractions at the basis of scientific research. ²⁴

²⁶A1: Power attribution principle [62, 63, 70–72, 74, 75, 82, 85, 87–89, 91, 93, 94, 96,²⁶
²⁷98]. When **system** power is measured, whether at the wall outlet or at one or more of²⁷
²⁸the power supply's output lines, there is the problem of attributing the measurement to²⁸
²⁹the logical divisions (VEs) of the host computer system. Attribution of system power to²⁹
³⁰modeled entities starts with a decision on which power consumption is within scope (see³⁰
³¹section 3.1.8). Next, power in scope is attributed to (burdened on) one or more entity.³¹
³²For example: will idle power consumption be attributed to the host system or will it be³²
³³attributed to the VEs? ³³

¹A2: *Modeling bias* [64, 70–77, 85, 87–89, 91, 93, 95–97, 105]. Researchers approach the¹
²problem of developing a model under some bias which conditions their final outcome. This²
³bias is manifest in researchers' selection of a particular type of regression to apply to their³
⁴data. We note that this same observation is carried in [106].⁴

⁵We delegate our observations on researchers' methods to section 7.2.2. Here, on the other⁵
⁶hand, our purpose is solely to draw attention to what we have observed as researchers'⁶
⁷modus operandi without analyzing their choice of approach.⁷

⁸
⁹A3: *Green operating principles* [64, 95, 105]. Works in this category weave radical (i.e.9
¹⁰from the grass roots) approaches to power efficiency into their developments. For example¹⁰
¹¹instead of conventional scheduling, *run-to-completion* [107] is exploited to obtain dedi-¹¹
¹²cated (or, at least, very sparsely shared) resources for the processing of packets. This ap-¹²
¹³proach is further nuanced by real-time control of adaptive rates and sleep depth. In one¹³
¹⁴particular case [64], the novel concept of a low-power instruction instead of transitions¹⁴
¹⁵to/from low-power idle (sleep) states is used.¹⁵

¹⁶
¹⁷A4: *Physical analysis* [73]. This category regards approaches rooted in physical proper-¹⁷
¹⁸ties of (semiconductor) material in the consumption of energy. For example, [52] regards¹⁸
¹⁹a unique study that implicitly applied Dennard's law in the process of obtaining weights¹⁹
²⁰that scale a processor sub-unit's contribution to power consumption. In [108], the physical²⁰
²¹cause of power consumption in metal-oxide-semiconductor (MOS) material is examined²¹
²²and used as the basis for modeling equations.²²

²³
²⁴A5: *Identification and use of metrics of energy efficiency* [57, 58, 78, 97]. The relationship²⁴
²⁵between system architecture and power consumption can be investigated through identifi-²⁵
²⁶cation of relevant metrics of energy efficiency. For example, an easily recognizable metric,²⁶
²⁷albeit rather broad in possible interpretations, is the J/b (joule/bit). Use of such metrics²⁷
²⁸encourages joint consideration of function and power consumption.²⁸

²⁹3.2.2 *Experiment design*²⁹

³⁰The practical, hands-on aspects of the empirical process are the product of a (probably³⁰
³¹cyclical) design phase, concerned with a number of stewarding activities pertinent to test³¹
³²subjects and ancillary objects in the testing scenario, instrumentation, inputs and outputs.³²

³³The activities include selection, configuration, interconnection, initiation, observation and³³

termination. We have identified several examples of such activities within our research¹ scope and grouped them under **resource provision** (categories A6, A7), **workload selection**² (A8 - A9) and **data collection** (A10 - A13). We describe these categories next.³

A6: *Managed resource provision* [57–60, 62, 63, 66, 73, 79–81, 85, 93–95]. This concerns the provision of resource capacity either to a specific VE (the guest system) or to the physical entity (the host system) hosting the VEs. Within the empirical process, the techniques in this category provide the means to observe the effect on power consumption of managed changes in resource provision. Examples include (manual) pre-configuration of:

- frequency of operation of processor cores [57, 63, 93];
- core affinity [59, 66] and hardware-thread affinity [81];
- network interface data rate capacity capping [79].

These techniques are executed as part of the process of setting up experimentation, *before* operations start. This qualification is necessary to distinguish from such approaches as may change the operating, run-time context.

A7: *Controlled resource provision* [64, 90, 95, 97]. Provision of resources may change during the running of an experiment (rather than before it starts). Approaches in this category include the automated adjustment of:

- 1 processor frequency (also known as performance state, or P-state) [64, 90, 95, 97]
- 2 depth of processor sleep (also known as as low-power-idle-state, or C-state) [95]
- 3 number of hardware threads [90]
- 4 time spent running a low-power instruction [64]

These techniques are approaches to solving the problem of full-throttle operation. Without guided operation of adjustments like those listed above, operation of the processor may quite reasonably be likened to a multi-assembly-line manufacturing plant that operates line machinery whether there are goods to produce or not.

A8: *Resource-specific workload*, A9: *Representative workloads* These two categories regard the **workload selection** stage, within experiment design in the scientific method. The workload comprises the **inputs** referred to earlier (section 3.2.2). In Table 6, we identify **workload type** as one of the seven dimensions of variability of power models. The influence of workload type on the model obtained is evident in the attention paid by researchers to selection of workload type. We can distinguish two broad categories of type.

¹ **Resource-specific workloads** (category A8) [57–60, 62, 63, 66, 72–74, 76, 77, 79, 80, 82,¹
² 83, 87–89, 96, 98] are applied to investigate the impact of utilization of specific resources²
³ on power consumption. Such **synthetic** workloads are applied to a machine (whether virtual³
⁴ or physical) to reduce (as much as possible) the scope of power-consuming resources to a⁴
⁵ targeted set. Resource-specific workloads are most commonly used in exploratory work, to⁵
⁶ gain an understanding of the behavior of a resource’s power consumption. We refer to this⁶
⁷ approach as resource-specific workloads, or synthetic workloads, or resource isolation.⁷

⁸ **Representative workloads** (i.e. representative of **real use**) (category A9) [60, 63, 64, 70,⁸
⁹ 71, 73, 75, 78, 81, 82, 85, 87, 90, 91, 93–97] may be used complementary with, or alterna-⁹
¹⁰ tive to, resource-specific (synthetic) workloads. A notable complementary use is made in¹⁰
¹¹ the testing (post-training) phase of model development, when representative workloads are¹¹
¹² used to validate a model (obtained using synthetic workloads). They may also be used in an¹²
¹³ entirely alternative approach to synthetic loading, to support development of applica-¹³
¹⁴ tion agnostic models. Representative workloads lead to training data that incorporates variation¹⁴
¹⁵ in utilization of more than one resource at a time; hence providing at least limited applica-¹⁵
¹⁶ tion agnosticism.¹⁶

¹⁷

¹⁸ A10: Resource instrumentation (microarchitecture and system software), A11: Load in-¹⁸
¹⁹ strumentation: direct characterization, & measurement of workload, A12: Direct power¹⁹
²⁰ measurement, A13: Hardware instrumentation of predictors These four categories regard²⁰
²¹ the **data collection** stage, within experiment design in the scientific method. Previous cate-²¹
²² gories (section 3.2.2) regard selection of workload type. Approaches described here regard²²
²³ measuring **how much** of a resource is being used, or workload is being applied. Categories²³
²⁴ A10, A11 and A13 regard instrumentation of those variables considered (by the researchers²⁴
²⁵ concerned) to be reliable predictors of power consumption.²⁵

²⁶ **Category A10** [58, 60, 63, 64, 70–72, 74–77, 82, 85, 87–91, 93–98] includes approaches²⁶
²⁷ that measure resource use. These measurements are then used to predict power consump-²⁷
²⁸ tion. We make a somewhat weak distinction, for reasons we shall refer to, between in-²⁸
²⁹ strumentation of microarchitecture and instrumentation by system software. The former²⁹
³⁰ regards parts of the processor interface that address the processor’s infrastructure for mon-³⁰
³¹ itoring: event counters (e.g. instructions retired, last-level-cache (LLC) misses, translation³¹
³² lookaside buffer misses) and, more recently power counters (e.g. Intel’s Running Aver-³²
³³ age Power Limit (RAPL) [109]). On the other hand, system software’s instrumentation³³

¹is carried out through intermediary system software and includes, most notably, proces-
²sor utilization. We have seen references to these two categories as “hw counters” and “sw
³counters” respectively [110]. The distinction is weak since system software is increasingly
⁴exposing microarchitecture instrumentation (consider, for example, Linux’s perf tool). This
⁵reduces the need to directly access hardware registers and blurs the separation between
⁶what is abstracted and what is concrete, raw, hardware data. Nonetheless, through our
⁷understanding of the data used, we have been able to separate the approaches into two
⁸sub-categories.

⁹ **Category A13** regards use of hardware sensors to obtain inputs and/or parameters for the
¹⁰power model [64, 73, 93, 94]. These include:

- ¹¹ 1 voltage sensors (processor supply voltage, VDD) ¹¹
- ¹² 2 temperature sensors (processor package and memory temperatures) ¹²
- ¹³ 3 fan speed sensors (processor and chassis fans) ¹³
- ¹⁴ 4 wall-clock time measurement ¹⁴

¹⁵Some of these variables are used in models that predict power consumption while account-
¹⁶ing for the effect of drift of temperature and automated supply voltage adjustment (in dy-
¹⁷namic voltage and frequency scaling – DVFS). ¹⁷

¹⁸ **Category A11** regards use of a simple characterization of workload as predictor of power
¹⁹consumption [58, 62–64, 77, 78, 80, 81, 83, 90, 95, 97]. This is notably different from
²⁰approaches in category A10, which are concerned with resource use as predictor of power
²¹consumption. Other examples (apart from those given earlier) of workload metrics as inputs
²²are “number of processes” [83] (from the same process image, say), “transmission rate”
²³[81] and millions of instructions per second (MIPS) [77]. Characterizations may need to
²⁴be sharper. For example, since packet network traffic arrival is known to often have the
²⁵properties of a Batch Markov Arrival (stochastic) Process (BMAP), this is an operating
²⁶constraint adopted in the approach of several works studying power efficiency of network
²⁷functions [64, 95, 105, 111]. ²⁷

²⁸ **Category A12** refers to the measurement of power consumption, which is most usually
²⁹measured at the wall outlet or at the power supply inlet [57–60, 62, 63, 70–72, 74–77,
³⁰80, 81, 83, 85, 88, 91, 96]. More granular approaches are desirable, and indeed we do
³¹find cases (e.g. [75]) that attempt measurement at the power supply output. The principal
³²drawback of such granular techniques is not construction of intermediary hardware (e.g.
³³riser boards, or line resistors) but the difficulty in attributing power drawn through any ³³

¹single dc voltage output (or group thereof) to particular consumers. With the advent of¹
²RAPL and certain guarantees on its accuracy, the need for direct power measurement has²
³been, at least partially, avoided. ³

⁵3.2.3 *Model validation* ⁵

⁶Model validation is a multi-faceted endeavor and this is reflected in the approaches we have⁶
⁷detected. The approaches range across the candidates that would typically be considered:⁷
⁸simulation (A14) [64], use of test data (A15) [70, 75–77, 89, 97] and corroboration through⁸
⁹experimentation (A16) [64, 95]. We skip elaborating on these categories as they are either⁹
¹⁰self-evident (A15) or because they are too rarely used to permit general commentary. How-¹⁰
¹¹ever, to these three categories we add a fourth (A17), namely: model adaptation technique,¹¹
¹²which we describe below and explain why it fits within this branch of the taxonomy. ¹²

¹⁴*A17: Model adaptation technique* This refers to the approach(es) taken (if any) to de-¹⁴
¹⁵velop an adaptable model or modeling system [70–72, 74, 75, 80–83, 85, 87, 88, 90, 91,¹⁵
¹⁶93, 94, 96, 98]. Here, *adaptability* refers to the fitness for use which the model exhibits¹⁶
¹⁷under change in one or more of the seven dimensions of variability that will be defined¹⁷
¹⁸in detail in Section 4.1.1 below (see table 6). Model adaptability is essential for practical¹⁸
¹⁹virtualization, where changes in, say, the number of co-hosted, concurrent VEs, or in work-¹⁹
²⁰load type are commonplace. Below, we list the major approaches taken towards producing²⁰
²¹adaptable models. Since these approaches emerge in the context of validating a model's ac-²¹
²²curacy under some limited range of the seven-dimensional space of operating conditions,²²
²³we classify this category of approaches as an aspect of model validation. ²³

- ²⁴1 *Adaptation to change in the number of co-hosted, concurrent VEs:* is widely²⁴
²⁵achieved through *time-division multiplexing* of event counters [72, 75, 82, 91, 98],²⁵
²⁶RAPL counters and CPU utilization [74, 85]. This approach enables use of such met-²⁶
²⁷rics as predictors of dynamic (active) power consumption, by apportioning counts to²⁷
²⁸VEs in accordance with the time during which the VEs were active. ²⁸
- ²⁹2 *Adaptation to uncorrelated causes of power consumption:* might be achieved²⁹
³⁰through *additional predictors* [94], to follow causes of power consumption that do³⁰
³¹not correlate well with counters within the current set. This case reflects itself as³¹
³²poor accuracy in predicted power consumption. Although counter-based models are³²
³³reported to fit a variety of processor- and memory-intensive workloads well, it may³³

be necessary to account for unanticipated activity through the approach of adding¹
previously unused counters.²

3 It may not be possible to fit a single model with parameters known *a priori* to the³
whole range of inputs within the scope of study. The commonality here is that no⁴
single representation of power can be obtained, notwithstanding the diversity of pre-⁵
dictors employed in this pursuit. The following adaptive techniques have been found⁶
in the literature.⁷

(a) **Dataset partitioning**, where the dataset is of the form $\{(\{\mathbf{predictors}\}, \mathbf{response})\}$,⁸
is used in [89] to match the best model out of a set of models to current, actual⁹
operation. An individual model in the set is associated with a single node in a¹⁰
decision tree and the node is selected according to features pertinent to current,¹¹
actual operation. A simpler, but conceptually similar, approach is taken in [71].¹²
A number of models are devised and model-selection features are limited to¹³
the number of active VMs and a coarse grading of CPU utilization.¹⁴

(b) **Modeling on demand** is the term we use to succinctly refer to the fourth adap-¹⁵
tation class of techniques.¹⁶

i. One early example of this approach is found in [87], where the depen-¹⁷
dence of the model on workload has been addressed through *online train-*¹⁸
ing, whenever prediction accuracy of extant models falls out of a range of¹⁹
tolerance. The rationale adopted is that if model adaptation to such an "un-²⁰
seen" case is limited to parametric tuning, then a modeling system might²¹
be able to construct a model while VEs are in operation.²²

ii. A broader perspective is found in [90]. An automated system for pro-²³
filing containerized applications is described and demonstrated. Con-²⁴
tainerized applications are profiled from three perspectives: computing re-²⁵
sources consumed, energy consumed and performance. In this case, the²⁶
rationale is that energy consumption can be optimized by determination²⁷
of a frequency-and-hardware-threads host configuration that meets per-²⁸
formance requirements. Thus: starting from central functional require-²⁹
ments (performance requirements), operating conditions are determined³⁰
that minimize energy consumption. This approach is capable of meet-³¹
ing the challenges posed by heterogeneous host hardware and application³²
(workload) diversity, at the cost of analytical modeling. Indeed, charac-³³

teristic curves can be derived but causes underlying observed behaviours¹
 remain unaddressed.²

3.3 A taxonomy of developments⁴

Developments fall cleanly into one of two groups: (a) models of power consumption and (b)⁵
 observations on dependencies of power consumption. The first group (D1-D10) includes⁶
 developments that **predict power consumption** over a sub-space of the seven-dimensional⁷
 space of operating conditions. The second group (D11 - D18) includes developments that⁸
 are oriented towards the **correlation of power consumption** with aspects of system integra-⁹
 tion. As the taxonomy is rather broad, we present it in three parts:¹⁰

- 1 Fig. 3: top-level fork into models and dependencies.¹¹
- 2 Fig. 4: the taxonomy of models.¹²
- 3 Fig. 5: the taxonomy of dependencies.¹³

3.3.1 Models of power consumption¹⁴

Models of host system power consumption: D1: Linear regression models; D2: Non-linear¹⁵
regression models; D3: Machine-learnt models and D4: Models of local mass storage¹⁶

These four categories regard developments in host system power models, under the condi-¹⁷
 tion where workload is processed by VEs. This contrasts with the scope of developments¹⁸
 referred to under categories D5, D6 and D7, where power consumption by a VE is mod-¹⁹
 eled. Such models are interesting from the perspective of analyses of **sets of hosted VEs**²⁰
 that seek to identify operating conditions of optimal host power efficiency. As predictors,²¹
 such analyses use instrumentation that measures resources used by the VEs.²²

Categories D1, D2 and D3 all predict power consumption in terms of resource use but²³
 differ in the type of model produced.²⁴

- D1 regards models of power consumption through linear combinations of scalar pre-²⁵
 dictors [70–72, 82, 87]. The scalar predictors are resource usage metrics.²⁶
- D2 regards polynomial or simple mathematical powers of resource use (the scalar²⁷
 predictors) [70, 73, 74, 88, 93].²⁸
- D3 regards models that employ machine learning (e.g. Gaussian Mixture, Support²⁹
 Vector Machine, Neural Networks) [75, 89, 91]³⁰

Category D4 regards models of power consumed by mass storage local to the host sys-³¹
 tem [98]. These models attempt to predict power consumption in terms of activity metrics³²
 such as total amount of time spent in a known state (in terms of power consumption, e.g.³³

¹active/idle), rate of data exchange (MB/s or input/output operations per second) and mode¹
²of operation (sequential/random and read/write). In the context of the approximations ob-²
³served in the development of these models, their accuracy cannot be fairly assessed without³
⁴implementation. Our choice of a separate category for this device is not as arbitrary as the⁴
⁵first glance might suggest. Few works extend into meaningful consideration of I/O. As edge⁵
⁶computing takes shape, the share of power consumption attributed to I/O devices can fairly⁶
⁷be expected to increase. 7

⁸
⁹
¹⁰*Adaptable VE models: D5, D6 and D7* Developments within these categories consist of¹⁰
¹¹*adaptable* models of the virtualized entity's power consumption and have two important¹¹
¹²characteristics in common. 12

¹³ 1 They are *adaptable* in the seventh dimension of adaptability (see Table 6): within the¹³
¹⁴scope of the employed workload, these models can predict power consumption by¹⁴
¹⁵multiple concurrent, co-hosted (active on a single host system) VEs. 15

¹⁶ 2 The predictors are the measured amount of used computing resources. 16

¹⁷ Models can be distinguished by the predictors they use, workloads employed and mod-¹⁷
¹⁸eling approach: 18

¹⁹ 1 predictors (of VE power consumption) are obtained from system software's instru-¹⁹
²⁰mentation, e.g. CPU utilization (see section 3.2.2), and from microarchitecture in-²⁰
²¹strumentation, e.g. LLC misses (see section 3.2.2); 21

²² 2 workloads used to obtain the model (this restricts the range of workloads within²²
²³which the model is valid) may be: 23

²⁴ (a) specific workloads: the most restrictive, as they relate to a particular test load; 24

²⁵ (b) synthetic workloads: less restrictive than specific but limited to exercise of one²⁵
²⁶resource, typically the CPU; 26

²⁷ (c) combinational workloads: still less restrictive, involving the exercise of a num-²⁷
²⁸ber of resources of the host system (e.g., SPEC CPU benchmarks may be both²⁸
²⁹processor and memory intensive); 29

³⁰ (d) representative workloads (e.g. TPC-W [112]) produce models that are readily³⁰
³¹associated with use cases. 31

³² 3 modeling approach may be: 32

³³ (a) category D5: linear regression [71, 72, 82, 85, 87, 93, 94, 96, 98]; 33

(b) category D6: power (integer and non-integer powers), exponential and logarithmic regressions [74, 79, 88];

(c) category D7: machine-learned (combinations of resource use) [75, 91].

Models of power consumption that use workload profile as predictors: D8 and D9 Categories D8 and D9 group developments from (two) sets of RUs that predict power consumption of hosts and/or VEs through (measurement of) some characteristic of the submitted workload. This contrasts with RUs in categories D1 - D7, where prediction is obtained through (measurement of) some computing resource (processor and/or memory and/or I/O). Most developments in this category are obtained through abstraction of hardware by one or more model parameters that express power consumption under case-specific conditions of operation. Some of these abstractions are identified in the descriptions of these two categories.

Developments in D8 [64, 76–81, 83, 90, 95, 97, 105] use:

- 1 processing load (number of processes, millions of instructions per second (MIPS), etc.) pertaining to a specific application, as predictors of *host system* power [76–80, 83];
- 2 packets per second, through an intrusion detection system implemented in a VNF [97];
- 3 transcoded frames per second, through a transcoder implemented in a containerized network function (CNF), and inferred images per second, also in a CNF [90];
- 4 average network transmission rate, as a predictor of host system power [81]
- 5 statistics of a Batch Markov Arrival Process (BMAP) (packet traffic) as a means of prediction of power consumption by a VNF [95, 105]

Hardware is abstracted through measurement of power consumption at some operating point, or change in power consumption over some operating range. Examples follow.

- 1 In [78], where energy efficiency of web interactions is studied, the operating point is an entire VM running the TPC-W benchmark [112].
- 2 In [80, 83], the operating points are the host's power consumption when (a) idle, (b) one core is active (processing load) and (c) maximum, with all cores active. Furthermore, use is made of the step increment in consumption corresponding to the activation of each additional core. Cores are activated when they are utilized by VEs.

- 3 In [81], the operating point is the power consumption when the host is not transmit-¹
ting. An affine relationship with the host's transmission rate (transmissions originate²
on hosted VEs) is found. ³
 - 4 In [77], an operating range is used: the increase in power consumption that corre-⁴
sponds to an increase in MIPS on the VEs. ⁵
 - 5 In [95], the operating point is the power consumption when a VE running on a single⁶
processor core is switching packets at the maximum rate for a given performance⁷
state. ⁸
 - 6 In [97], fifty-four (54) different features of network traffic are input to an artificial⁹
neural network that selects the operating frequency that optimizes power consump-¹⁰
tion. ¹¹
- With one exception, none of the works in the above list uncovers the hood to peer at the
processor's internals (to obtain predictors of power consumption). The exception is [95];
yet even in this case, the performance monitoring counters are not used as direct predictors
of power consumption, but to obtain (a) the timing information necessary for a queueing
model and (b) the operating state (ACPI (Advanced Configuration and Power Interface
[113]) P- and C-states).
- Developments in D9 [64] are set within the models branch of the taxonomy. These devel-
opments may be considered as useful observations on the operation of processors' green
capabilities. Examples of these observations (all from [64]) include:
- 1 low-power-instructions might be a better candidate than low-power-idle to save²²
power under higher link utilization ²³
 - 2 operation in full ACPI P-state, operation with low-power-instructions on idle detec-²⁴
tion and operation with low-power-idle on idle detection are in (a) ascending order²⁵
of latency to return to active processing and (b) in descending order of power con-²⁶
sumption ²⁷
 - 3 80% is a processor utilization threshold below which low packet latency is guaran-²⁸
teed under BMAP traffic arrival ²⁹
- By "green capabilities", we refer to a broader range of microarchitectural aspects than
the by-now-conventional adaptive rate and low-power-idle operation. While these latter
two remain at the centre of attention, there is also the means of low-power-instructions
[64] that has been successfully employed to improve power efficiency.

Notwithstanding the origin of these observations in modelling work, it may be argued¹ that they might also be classified within the dependencies branch of the taxonomy. We² have chosen the models branch, but as further studies add to the body of knowledge on³ how to operate processor green capabilities, this category's position in the taxonomy might⁴ need to be changed.⁵

D10: Relative accuracy of modeling approaches [73, 75, 76, 89] Developments presented⁷ under category D10 are comparisons of the relative accuracy of alternative modeling meth-⁸ ods with respect to conventional polynomial (including linear), power, exponential and⁹ logarithmic regression. These developments have been found within works that show mod-¹⁰ els classified under category D9. The purpose is to qualify and quantify improvements of¹¹ machine-learned models with respect to conventional regression models.¹²

3.3.2 Dependencies of power consumption¹⁴

This parent node of the taxonomy is divided into two child nodes that are not strictly mu-¹⁵ tually exclusive. For example, the software data plane is considered in works under D15.¹⁶ Clearly, the software data plane is a logical artifact and might be included within a child¹⁷ node of "physical and logical artifacts", or directly thereunder as a leaf node (i.e. as a cate-¹⁸ gory). The choice of separation of D15 - D18 and inclusion under parent node "networking¹⁹ workloads" was taken for two principal reasons. Firstly, the recurrence of investigation of²⁰ power consumption's dependency on networking workload merits attention through sep-²¹ aration. Secondly, as this survey caters for an audience with an interest in softwarized²² networking, an emphasis on power dependency on networking workload seems justified.²³

D11: Knowledge about dependency of power consumption on specific hardware; D12: de-²⁴ pendency of power consumption on architecture; D13: dependency of power consumption²⁵ on resource provisioning and D14: dependency of power consumption on virtualization²⁶ genre & technology Categories D11 - D14 are grouped into a set of works that obtain the²⁷ sense of the correlation (positive/negative/none) between power consumption and some²⁸ genre of artifacts: specific hardware types (D11), computer architecture (D12), resources²⁹ provided (D13) and virtualization genre and technology (D14).³⁰

Category D12 groups works that relate to observations on the impact of architectural³¹ features on power consumption [57, 58, 80, 83, 88]. While these observations are useful,³² they are generally too coarse to be directly applicable to real-time power control. Their³³

¹use emerges from guidance which they provide in the development of power models. For¹
²example, it was observed that when the number of threads that fully occupy a core's time²
³(active 100%) exceeds the number of logical cores in the system, the energy efficiency³
⁴(measured, in this case, in hash/J, a computational metric of energy efficiency) decreases⁴
⁵[57]. Evidently, this is good guidance; equally evidently, it is not a directly applicable⁵
⁶development. 6

⁷ Categories D11, D13 and D14 relate closely to (various aspects of) implementation, and⁷
⁸as such are of particular interest to the *system integrator*. Data of high quality from these⁸
⁹developments inform and guide the tasks of gathering components into systems that meet⁹
¹⁰the non-functional requirements obtained from concern with energy and power efficiency. 10

¹¹ Category D11 gathers observations about the dependency of power consumption on spe-¹¹
¹²cific processor hardware [58, 82, 88]. We have observed that these developments are gath-¹²
¹³ered as a by-product of the process of research; they are rather incidental. Like any imple-¹³
¹⁴mentation, their usefulness is limited to the lifetime of the concerned device(s). 14

¹⁵ Category D13 [85] includes developments that regard the specific resource configuration¹⁵
¹⁶of: 16

- ¹⁷ 1 the instantiating host, i.e. the relationship between a VE's power consumption and¹⁷
¹⁸the specific resources of its host hardware specifics such as the number of cores and¹⁸
¹⁹amount of memory carried by the host instance; 19
- ²⁰ 2 the guest VE, i.e. the variation of a VE's power consumption with its resource as-²⁰
²¹signment, on the same host. 21

²² Category D14 gathers observations about the dependency of power consumption on in-²²
²³stances of virtualization genre and technology [59, 60]. Developments in this category are²³
²⁴less incidental than those in category D2 and are obtained with the focused intention of²⁴
²⁵tackling challenges relating power consumption of implementations. These developments²⁵
²⁶relate to a less diversified group of implementations. For example, there are fewer virtu-²⁶
²⁷alization platforms than processors to choose from. Direct use of these developments is²⁷
²⁸mostly limited to the specific implementations concerned; however, some generalizable²⁸
²⁹conclusions exist. For instance, it was observed that both hardware-assisted virtualization²⁹
³⁰and paravirtualization are less efficient (in the specific empirical setup) than non-virtualized³⁰
³¹operation in the use of processor caches [60]. This empirical evidence favours the hypothe-³¹
³²sis that cache hit ratios suffer due to the greater thread rotation in virtualized and container-³²
³³ized environments. 33

¹*D15, D16, D17 and D18: Knowledge about dependency on power consumption while pro-*

²*cessing a networking workload* Development categories D15, D16, D17 and D18 are²

³grouped here as their central characterization is knowledge about the behavior of power³

⁴consumption by VEs while processing a networking workload. ⁴

⁵ Categories D15, D16 and D17 reflect the challenges described in P11, P9 and P10, re-⁵

⁶spectively. Category D15 regards contributions to knowledge about the power consump-⁶

⁷tion of software data planes [62, 63]; D16 regards virtualization of network I/O [62, 66],⁷

⁸and D17 is about network functions [62, 63, 97]. Thus, in [66], the power efficiency of⁸

⁹DPDK PMDs is demonstrated with respect to Netmap drivers, for packet transmission.⁹

¹⁰This development is balanced by [63], where the power efficiency of transmission through¹⁰

¹¹a DPDK-enhanced Open vSwitch is shown to be worse (@500-byte Maximum Transfer¹¹

¹²Unit (MTU)) than that of the unenhanced Open vSwitch. In each of these categories, ef-¹²

¹³forts are made to allocate burden through isolation of power consumption and attribution¹³

¹⁴to the sub-system (data plane/virtualized IO/network function) under study. ¹⁴

¹⁵ Category D18's developments differ from those of D15 - 17, because they cut across these¹⁵

¹⁶categories' sub-system boundaries [60, 78]. For example, in [78], the energy efficiency¹⁶

¹⁷of web transactions executed on co-located VMs is found to be highest in the operating¹⁷

¹⁸condition of processor-core over-subscription (more VMs than cores). In [60], it is shown¹⁸

¹⁹that power consumed by packet delivery to a VM through a software packet switch is¹⁹

²⁰much higher than that required for delivery in a non-virtualized environment. In both these²⁰

²¹papers, the object of interest incorporates virtualization of network I/O *and* the data plane.²¹

²²In [78], the object of interest further encompasses the network function (a web service and²²

²³accompanying application and database components). ²³

²⁴ All four categories are of keen interest to the system integrator. Emphasis is on the com-²⁴

²⁵ponents in the integrator's set of building blocks, specifically on the behavior of power²⁵

²⁶consumption of various implementations, and types thereof (in the scope of the categories).²⁶

²⁷ ²⁷

²⁸3.4 P-A dyads graphics ²⁸

²⁹ Over the following pages, we present a comprehensive set of graphics (Figs. 6 and 11 ²⁹

³⁰to 22) that illustrate the approaches detected to tackle specific challenges (reference num-³⁰

³¹bers for pertinent RUs appear in the shape tags). For example, consider Fig. 6. The graphic³¹

³²shows the component approaches applied to discover "the impact of specific architectural³²

³³attributes of the host system on power consumption of VEs" (see P1 in section 3.1.1). The ³³

¹presence of approach categories A1, A5, A6, A8 and A10 - A12 does not mean that *ev-*¹
²*ery RU* tackling this challenge uses a component from *all* of the approach categories. It²
³does, however, mean that every RU tackling P1 uses a subset of the approaches shown. We³
⁴proceed by giving examples (relevant to P1), with references. ⁴

⁵ 1 ***Managed resource provision (A6)***: Prior to running experiments, researchers set the⁵
⁶ conditions for the experiment through this approach [57, 58, 63, 66]. ⁶

⁷ 2 ***Resource-specific workload (A8)***: This may be used to stress the component imple-⁷
⁸ menting the architectural attribute under test [57, 58, 63, 66]. ⁸

⁹ 3 ***Simple workload characterization and instrumentation (A11)***: The workload must⁹
¹⁰ be characterized by some parameter that serves to measure its demand for power¹⁰
¹¹ [58, 63]. ¹¹

¹² 4 ***Resource instrumentation (A10)***: This is an alternative to use of workload profiling¹²
¹³ (A11) as predictor of power consumption. Rather than use, say, number of threads,¹³
¹⁴ or transmit bandwidth (for networking workloads) as predictors, this approach uses¹⁴
¹⁵ resource instrumentation [58, 63]. ¹⁵

¹⁶ 5 ***Identification of metric of energy efficiency (A5)***: In certain cases [57, 58], energy or¹⁶
¹⁷ power efficiency is investigated, rather than energy or power consumption. In these¹⁷
¹⁸ cases, the researchers identify and use a relevant metric of efficiency, rather than¹⁸
¹⁹ metrics of consumption (watts or joules). ¹⁹

²⁰ On any of the dyad graphics, the approaches shown (inside the approach categories) in-²⁰
²¹ clude only those which are used by at least one RU that tackles the challenge category that²¹
²² is the root of the dyads. We delegate a repository with a full tabulation of all approaches in²²
²³ any approach category. Similarly, all individual developments within a category are dele-²³
²⁴ gated to the same repository. See section 7.2.2 for the details. ²⁴

²⁵ ²⁵

²⁶3.5 Causality DAG ²⁶

²⁷ The Causality Directed Acyclic Graph (DAG) in Fig. 7 shows a bird's eye-view of the²⁷
²⁸ proceedings of research in scope. ²⁸

²⁹ ²⁹

³⁰3.6 Triads Graphic ³⁰

³¹ Fig. 8 shows the triads graphic. To improve readability, we limit illustration to the triads³¹
³² that are in the top twenty percentile of a list ordered according to thickness. These triads³²
³³ comprise 49.2% of the total number of compiled triads. ³³

¹3.7 Statistics 1

²Bar charts that illustrate the category metrics described in [45, section 7] are presented²
³below. 3

⁴ 1 Challenges: Fig. 9 4

- ⁵ (a) frequency of occurrence in the set of all RUs; 5
- ⁶ (b) frequency of occurrence in the set of all challenges in all RUs; 6
- ⁷ (c) frequency of occurrence, weighted by approach diversity, in the set of all chal-⁷
⁸ lenges in all RUs. 8

⁹ 2 Approaches: Fig. 10 9

- ¹⁰ (a) frequency of occurrence in the set of all approaches in all RUs; 10
- ¹¹ (b) frequency of occurrence in the set of all triads in all RUs. 11

¹² 3 Developments: frequency of occurrence in the set of all developments in all RUs: ??¹²

¹³To improve legibility, the x-axis labels show category numbers only. The codes ("terse,"¹³
¹⁴dense representations of a verbose articulation of a concept", see [45, section 3.1] linked to¹⁴
¹⁵the numbers are shown in Table 3, Table 4 and Table 5. In Table 3, we also show questions¹⁵
¹⁶that help to clarify articulation of the challenge posed. 16

¹⁷ *3.7.1 Other results* 17

¹⁸Average number of challenges tackled per RU, $\frac{R_{P_k}}{F_{P_k}} = 2.6$. 18

¹⁹4 Analysis Through Themes 19

²⁰The themes presented in this section are the product of a thematic analysis undertaken
²¹according to the method described in [45] and summarized in [45, section 10.2]. We first
²²present an overview through a graphic (Fig. 23) that groups the themes and then proceed
²³to an exposition of the themes within the sub-sections. 23

²⁴4.1 State of the art 24

²⁵4.1.1 Seven dimensions of variability 25

²⁶Through our collation and resolution of the derivatives of the core challenge in this research
²⁷space, we observe seven dimensions of variability in modeling power consumption by a
²⁸virtual entity. Comparison with the power consumption of physical machines throws the
²⁹core challenge into sharper relief. With physical machines: 29

- ³⁰• power consumption can be measured directly; 30
- ³¹• the foundational dependence on virtualizing agent is ontologically foreign and 31

Table 3: Challenge category codes and representative challenge questions

CAT#	CODE	PROBLEM
P1	Architecture of VEs and PMs - profiling power consumption	What is the impact of specific major architectural features of computer hardware on the power consumption of VEs?
P2	Virtualization genre, platform	Is it possible to meaningfully rationalize the behaviour of VE power consumption across different implementations of systems for virtualization?
P3	Estimation of power consumption of virtualization-host system	Can host system power consumption be predicted on the basis of VE activity?
P4	Workload-adaptable power models	Can workload-adaptable power models be developed?
P5	Resource heterogeneity	How do a VE's power consumption and power model vary with resource configuration (heterogeneous VEs)?
P6	Influence of temperature on power-model	How does temperature of operation affect VEs' power models?
P7	Resource use and measurement in VEs	How can load be targeted at specific VE resources? How can the actual resource consumption be measured?
P8	Host system power attribution	How can the measured power consumption of a host to be attributed to the hosted VEs?
P9	IO Virtualization	What is the impact of specific major implementations of IO virtualization on the power consumption of VEs?
P10	Network functions	Which particular implementation of a network function is most power or energy efficient?
P11	Software L2 data plane switching	What is the impact of specific major implementations of software layer 2 data plane switching on the power consumption of VEs?
P12	Investigation of processor green capabilities	How can we model operation under real-time exploitation of processor green capabilities?
P13	Improvement of power efficiency of high-performance IO virtualization frameworks	How can we improve the power efficiency of high performance packet IO frameworks?

- the activity of other physical machines (that do not send or receive workload) is irrelevant.

The seven dimensions of variability are shown in Table 6. It is not surprising that the problems we have seen researchers tackle are closely aligned with these dimensions. The research space is precisely about the need to obtain an understanding of the impact that these variables have on power consumption. The scope of models we found in the RUs covers only a subspace of the seven-dimensional space but the extent is not usually stated. We

Table 4: Approach category codes

CAT#	CODE
A1	Power attribution principle
A2	Modeling bias
A3	Green operating principles
A4	Physical analysis
A5	Identification and use of metrics of energy efficiency
A6	Managed resource provision (setup time)
A7	Controlled resource provision (operation time)
A8	Resource-specific workloads
A9	Workloads representative of real use
A10	Computing resource instrumentation
A11	Workload characterization and instrumentation
A12	Direct power measurement
A13	Hardware instrumentation of predictors
A14	Simulation
A15	Use test data in post-training phase
A16	Corroboration through experimentation
A17	Model adaptation technique

Table 5: Development category codes

CAT#	CODE
D1	Host models->linear regressions: predictors=computing resources
D2	Host models->non-linear regressions: predictors=computing resources
D3	Host models->machine-learn: inputs=computing resources
D4	Host models->mass storage energy consumption
D5	Adaptable VE models->linear regressions: predictors=computing resources
D6	Adaptable VE models->power, exponential and log regressions: predictors=computing resources
D7	Adaptable VE models->machine-learn: inputs=computing resources
D8	Host/VE models of power consumption->predictors=workload characteristics
D9	Host/VE models of power consumption->observations on operation of processor green capabilities
D10	Relative accuracy of modeling approaches
D11	Power's dependencies->physical and logical artifacts->component implementation
D12	Power's dependencies->physical and logical artifacts->architecture
D13	Power's dependencies->physical and logical artifacts->IT system implementation->dependence on resource provision
D14	Power's dependencies->physical and logical artifacts->IT system implementation->dependence on virtualization/containerization genre and technology
D15	Power's dependencies->networking workloads->software L2 data plane switching
D16	Power's dependencies->networking workloads->in I/O virtualization
D17	Power's dependencies->networking workloads->in VNFs
D18	Power's dependencies->networking workloads->in general networking

touch upon this issue briefly in section 4.3.3 (research without context) and section 4.4.1 (universal power model).

Table 6: Seven dimensions of variability

DIMENSION	PROBLEM CATEGORY
1. Workload type	P4, P7
2. Virtualization agent	P2, P9, P11, P13
3. Host (resources and architecture)	P1, P3
4. Temperature	P6
5. Power attribution	P8
6. Co-hosted, concurrent VEs	P8, P5
7. Frequency	P12, P13

4.1.2 Adaptable Models

We observe three conditions which must be met for an automated modeling system to obtain a model of VE power consumption. The first, fundamental condition is common to all successful research into modeling of VE power consumption.

1 Resources utilized by the VE (whether measured through architectural or microarchitectural instrumentation) must be strongly correlated to power consumption by the VE as well as power consumption in host system overheads. If the overheads are uncorrelated to the VE's activity, or weakly so, then any significant power overhead must be modelled through separate consideration of its driving causes, e.g. temperature [93]. Furthermore, in order that modeling may apply across a diversity of operating contexts, two other conditions must hold.

2 Any change in the parameters of correlation must be dynamically learnt and the model adjusted.

3 Any change in operating context that invalidates parameters of correlation, must be of finite duration. An indefinite transient precludes the formation of a model.

Two of the seven dimensions are commonly investigated in evaluation of modeling systems: workload type and co-hosted, concurrent VEs. We suggest that a modeling system may be labelled adaptable if, minimally, it meets the above three conditions under these two dimensions, i.e. (a) operations of variable workload type per VE, and (b) a variable number of concurrent, co-hosted VEs. Before proceeding to refer to evaluations observed in the RUs, it is useful to draw attention here to the need for a modeling system, rather than simply a model, in the estimation of power consumption. Dynamic adjustments are effected through the intervention of such a system, which adjusts model parameters to the operating context.

¹*Workload type* Different types of workload correspond to different use of resources;¹
²hence, behavior of power consumption also differs. Several researchers [63, 87, 88] stud-²
³ied the effect of changing workload type either by categorizing the workload itself or by³
⁴categorizing the resources consumed by a specific kind of workload. Research studies [87]⁴
⁵and [88] characterized the use of CPU utilization for workloads, which is known to have⁵
⁶a workload-type dependent relationship with power consumption [75]. Thus, in both [87]⁶
⁷and [88], the need arises to re-train on change of workload type (second condition). Also,⁷
⁸note the observation in both [87] and [88] about the duration of re-training for refined mod-⁸
⁹els (third condition). In [63], energy consumption for multimedia applications is studied,⁹
¹⁰which identifies the use of forwarding engines for different data-planes as one major cause¹⁰
¹¹of increase in power consumption. 11

¹² On the other hand, each one of [75, 82, 91, 93, 94] is capable of adapting to different¹²
¹³workload types without re-training. All predictors here are event counters. However, events¹³
¹⁴are not necessarily linear predictors of power consumption across all workload types. In¹⁴
¹⁵[96], it was found that the model parameters of a linear regression of event counters onto¹⁵
¹⁶power consumption are workload specific. Given the contrast with the other works cited¹⁶
¹⁷above, it seems that the root cause is the selection of events for prediction. 17

¹⁸ 18
¹⁹*Concurrent operation* In [74], a non-linear model of the dynamic power of a multi-¹⁹
²⁰(virtual)-core VM is obtained. The dynamic power p_{vm} is expressed in terms of the average²⁰
²¹utilization (u_v) which n virtual cores impose on a total of N physical cores: 21

$$p_{vm}(u_v, n) = \alpha \left(\frac{n}{N} \right)^\beta u_v^\beta \quad (1)$$

²² 22
²³ 23
²⁴ Parameters α and β are determined through linear regression of the logarithmic form. The²⁴
²⁵relationship was successfully tested under the operating context of one VM and three VMs.²⁵
²⁶The model is limited to processor-intensive workloads; indeed, this is not surprising, since²⁶
²⁷the predictor is (virtual) processor utilization. However, a conclusion can be drawn: the²⁷
²⁸accuracy of the model in predicting the dynamic power of an individual VM is independent²⁸
²⁹of concurrent operation of other VMs (albeit for a limited range of workload types). 29

³⁰ In [87], it is shown that estimation based on processor utilization can accurately predict³⁰
³¹the power consumption of multiple concurrent VEs. The prerequisite is that a model for that³¹
³²VE's workload type has been learnt. The conclusion to be drawn here is the same as that³²
³³drawn for [74]: that the prediction accuracy for individual VEs is independent of concurrent 33

operation. Furthermore, the range of workload types has expanded to a broader range. With regard to results obtained in [96], the conclusion is yet again the same: individual prediction accuracy (albeit workload-type-dependent) is independent of concurrent operation.

Independence of workload type is manifestly claimed in [75, 82, 91, 93]. Furthermore, the first three of these have been evaluated under multiple concurrent VEs. It is noteworthy, therefore, that not only is the modeling system adaptable, but it also produces a model that is itself adaptable without the need for real-time adjustment. In [91], evaluation is restricted to a single VE; therefore, this modeling system does not meet our conditions of adaptability.

We therefore conclude that limited adaptability (defined as independence of workload type and number of concurrent, co-hosted VEs) has been achieved. From surveyed RUs, we conclude that presently, the limits of adaptability are the following.

- 1 Workload type: Power consumption of processor-intensive, memory-intensive, disk-intensive workloads and mixes thereof, has been modeled by a single modeling system in an automated manner.
- 2 Co-hosted, concurrent VEs have been modeled up to but not exceeding over-commitment of processor physical cores.

Caution has been exercised in claiming these limits. For example, while commitment of logical cores (e.g. Intel Hyper-Threading logical cores) has been investigated, we have found no evidence that power consumption has been modeled in a manner that automatically adapts to a transition of consumption from physical to logical cores.

4.1.3 Lack of use of metrics of energy efficiency and standards to address this deficiency

We note several experiments, e.g. [59, 60, 81, 83, 114–116] that target power consumption but less than 12% of the RUs in our corpus approach the problem in terms of some energy efficiency metric [57, 58, 78, 97]. It is necessary to move beyond measurements of how much power was consumed, to measurements of how much power was consumed to carry out a specific task. This change in approach facilitates comparison between research works. More importantly, it directly addresses the question about cost of operation of infrastructure.

This approach requires identification of a unit of comparison that transcends the boundaries of disparate systems that deliver this unit. This unit of comparison is referred to in the Life Cycle Assessment (LCA) framework (ISO 14040) [117] as the functional unit. A definition specific to telecommunications equipment is given in [118] : the functional

¹unit is defined as “a performance representation of the system under analysis”. Since this¹
²definition is too broad to serve as a standard, units specific to a variety of classes of equip-²
³ment are defined too [118]. In our corpus, two approaches we have seen are hash/J [57] and³
⁴J/Web Interaction [78]. The functional units in these cases are performance of one crypto-⁴
⁵hash and one web interaction, respectively. Another is to define a functional unit specific⁵
⁶to a digital service delivered over a telecommunications network, e.g. ten minutes’ time of⁶
⁷browsing [119]. Note that L.1310 [[118], p.4] recognizes both metrics where energy is in⁷
⁸the numerator [78] as well as those where it is in the denominator [57]. Guidance is avail-⁸
⁹able: energy efficiency measurement for several NFV components has been standardized,⁹
¹⁰as well as measurement standards for servers, switches and virtualization systems [120].¹⁰

¹²4.1.4 Trends¹²

¹³Here, we present trends which we have identified through our collation of problems, ap-¹³
¹⁴proaches and developments. This sub-sub-section is divided into four parts: section 4.1.4¹⁴
¹⁵regards trends in tackled problems; section 4.1.4 in complexity of tackled problems; sec-¹⁵
¹⁶tion 4.1.4 in approaches and section 4.1.4 in developments. Within each part, trends are¹⁶
¹⁷numbered using Arabic numerals, to differentiate cleanly between them.¹⁷

¹⁹Challenges¹⁹

- ²⁰ 1 The causality DAG (Fig. 7) shows that the research space can be characterized suc-²⁰
²¹cinctly: note the thickness of the links originating at P7 (VE resource use and mea-²¹
²²surement) and P8 (how to attribute host system power to VEs).²²
- ²³ (a) The graphic in Fig. 1 and the bar chart in Fig. 9 show that the challenge-²³
²⁴category tackled most frequently ($R_{P_7} = 25.3\%$) is how to load the VE’s re-²⁴
²⁵sources and measure the loading (P7). P7 also has the most frequent presence²⁵
²⁶in RUs: $F_{P_7} = 65.7\%$ (see Fig. 9).²⁶
- ²⁷ (b) The accurate specification and measurement of load is essential to model for-²⁷
²⁸mation. These measurements provide the aggregated (i.e. indiscriminate of²⁸
²⁹which VE is consuming) predictors – the input side of the model. Disaggregat-²⁹
³⁰ing the predictors and attributing measured power consumption to the individ-³⁰
³¹ual VEs (the output side of the model) constitutes the second most frequently-³¹
³²tackled challenge ($R_{P_8} = 16.5\%$). P8 also has the second most frequent pres-³²
³³ence in RUs: $F_{P_8} = 42.9\%$.³³

- (c) In the following, the vector (P,A,D,weight) will be used to indicate a path¹
(P,A,D) and the number of triads (weight) through the path.²
- i. 34.2% of triads collected regard P7 and P8 respectively.³
 - ii. The triads graphic (Fig. 8) shows that efforts rooted in these two chal-⁴
enges converge on a common objective: building adaptable models of⁵
VEs' power consumption, notably using regressions to linear combina-⁶
tions of computing resource predictors.⁷
 - iii. The set of triads leading to linear regressions consists of (7,10,5,20),⁸
(8,17,5,13), (7,9,5,12), (8,1,5,10), (8,2,5,8), (7,8,5,6), (8,12,5,4), (7,6,5,3)⁹
and these account for 11.3%.¹⁰
- 2 The third most frequently-tackled challenge is that of estimation of virtualization-¹¹
host-system power consumption ($R_{P_3} = 15.4\%$). This category might be overlooked¹²
in a first inspection of the research space, as it might seem futile to attempt to estimate¹³
a power consumption which can be measured. However: in practice, the logistical¹⁴
challenge of measurement of horizontally-scaled system deployments seems to be¹⁵
well known and several works have been undertaken to develop software meters.¹⁶
- 3 Several significant links originate on P1 (profiling power consumption's dependency¹⁷
on architecture). The DAG (Fig. 7) indicates that approaches to tackling P1 are¹⁸
spread across a mixture of managing resource provision, use of synthetic (resource-¹⁹
specific) workloads and prediction using system software's instrumentation.²⁰
- 4 Another large group of links originates on P3 (estimation of host system power con-²¹
sumption). The DAG (Fig. 7) indicates that a primary concern in tackling P3 is²²
the type of model to select. The most common choices are linear and non-linear;²³
machine-learning techniques are the least common of the three. The thickness of the²⁴
triad (3,2,10,11) (D10: relative accuracy of formal approaches), indicates that there²⁵
is already significant interest in whether the advanced models are worth the effort to²⁶
develop them and computational resources required to operate them.²⁷
- 5 While $F_{P_7} = 65.7\%$ (loading VEs and measuring their use of resources), only 8.6%²⁸
($F_{P_{7.2}} = 8.6\%$) of all RUs investigate loading containers and measuring their use of²⁹
resources. With virtual dataplane devices, the figure is even lower: $F_{P_{7.3}} = 2.9\%$.³⁰
This imbalance suggests that there is much room left for research into modeling³¹
power consumption by containers and dataplane devices.³²

¹*Challenge complexity* In [45, section 7.3], we suggest that diversity of approaches is a¹
²metric of the complexity of a challenge. We note (see Fig. 9) that challenge complexity²
³(W_{P_k}) generally follows the frequency with which a particular challenge-category is tack-³
⁴led. That is: the more frequently the challenge is addressed, the more diverse are the ap-⁴
⁵proaches applied to it. This can be verified by noting that the heights of both sets of bars in⁵
⁶the chart (superimposed on the same graphic) follow roughly the same pattern. However,⁶
⁷some categories do stand out. For example: 7

- 8
⁹ 1 P6 regards the influence of temperature on the power model. Approach diversity is 8
¹⁰ poor here because only the use of additional instrumentation can be attributed to this 10
¹¹ challenge. Model bias might be attributed to this challenge too but largely, model 11
¹² bias is determined by other challenges within the scope of the RU. 12
- ¹³ 2 While host system power attribution (P8) has the second highest research interest 13
¹⁴ (and frequency of occurrence, F_{P_k}), the number of approaches taken to solve this 14
¹⁵ challenge is relatively small. 15
- ¹⁶ 3 On the other hand, power consumption's dependencies are tackled by a dispropor- 16
¹⁷ tionately large number of approaches. This is not surprising, as the objects of study 17
¹⁸ (architecture, virtualization platform, virtualization genre) are multi-faceted and de- 18
¹⁹ pendencies can be investigated through a variety of approaches. 19

²⁰
²¹
²²*Approaches* Our approach utility metric, U_{A_k} (see [45, section 7.5] and Fig. 10), seems to 22
²³be a useful one. It communicates clearly what we have observed in our surveying. Below, 23
²⁴we draw attention to saliencies perceived during surveying and confirmed by the metrics. 24

- ²⁵ 1 Instrumentation of consumption of computing resources (A10 - which includes mi- 25
²⁶ croarchitectural instrumentation and that abstracted by system software) is repeat- 26
²⁷ edly adopted ($U_{A_{10}} = 15.5\%$, $R_{A_{10}} = 15.7\%$) in empirical work in this field. It is 27
²⁸ also the most utilized of all approaches. In comparison, workload instrumentation 28
²⁹ accounts for 8.2% utilization ($R_{A_{11}} = 5.2\%$). 29
- ³⁰ 2 Resource-specific workloads (A8) are the more utilized approach to loading VEs 30
³¹ (14.3% of all triads). This approach category is the second most utilized. Workloads 31
³² representative of real use (A9) account for 9.0% of all triads. The corresponding 32
³³ frequency of occurrence figures (R_{A_k}) are 13.4% and 10.0% respectively. 33

Two other high-utility approaches are (a) modeling bias (A2, with $U_{A_2} = 11.9\%$, $R_{A_2} = 11.6\%$) and (b) the managed provision of resources (A6, with $U_{A_6} = 10.2\%$, $R_{A_6} = 10.8\%$). Use of representative workloads (A9) follows at $U_{A_9} = 9.0\%$, $R_{A_9} = 10.1\%$.

A comparison of the patterns of bar height distribution for U_{A_k} and R_{A_k} reveals that some categories stand out.

(a) While A12 (direct power measurement) is not as frequent as the other software-based forms of instrumentation, this approach has a utility that sticks out of the pattern (see Fig. 10). The reason is that most, if not all, developments obtained in an RU that includes this approach depend on the directly measured power.

(b) Similarly, while workload characterization and instrumentation (A11) is employed with a frequency that is about one-third that of its alternative (i.e. computing resource instrumentation, A10), it has a far better utility-to-frequency ratio than A10. The triads graphic (Fig. 8) indicates that one important cause of this high utility is that software-L2-data-plane switches and (virtual) network functions are investigated primarily using measurement of workload (and not measurement of computing resources consumed to process a workload).

Developments

55.6% of all identified developments are obtained in modelling power consumption. The remaining 44.4% regard how power consumption depends on implementations. Implementations investigated (for their impact on power consumption) range from entire virtualization platforms (e.g. KVM) to components (e.g. processors).

The most frequent ($R_{D_{12}} = 14.5\%$) category of developments is that which regards observations on dependency of power consumption on architecture. The cause of this high frequency is that developments in the study of architecture establish directional (negative, positive, neutral) correlations rather than predictive forms. For example, in a single RU [80], all of the following developments emerge:

- (a) D12.08: VM power consumption increases linearly with vCPU frequency of operation when the vCPU is operating at 100% utilization;
- (b) D12.09: Virtualization-host-system power consumption increases linearly with the number of physical cores operating at 100% utilization;
- (c) D12.1: Virtualization-host-system power consumption increases with the number of VMs active on the same core

1 3 Amongst developments of models, the most common category (D8) is of the type¹
2 where power consumption (host or VE) is predicted in terms of workload character-²
3 istics ($R_{D_8} = 12.0\%$). The next most common category regards prediction of power³
4 consumption as a linear function of computing resources ($R_{D_5} = 8.5\%$). Machine-⁴
5 learnt models of VE power consumption comprise the second least frequent category,⁵
6 with $R_{D_7} = 1.7\%$ 6

7 4 Despite the frequency of developments in category D10 (see Fig. 4), few works⁷
8 [73, 75, 76, 89, 91] compare accuracy of model types. Models have largely been⁸
9 treated as a means to an end, with little investigation of their relative accuracy and⁹
10 range of validity (in the seven dimensions of variability). This may be a reflection¹⁰
11 of researchers' interests. As the popularity of methods from the body of knowledge¹¹
12 of data science increases, works (e.g. [76]) that span a broader range of model types¹²
13 may be expected to increase in concert. 13

14 5 Adaptable, non-linear VE models (D2) occupy a modest 4.3%. Such a distribution¹⁴
15 adds weight to the observation that this research space is ripe for exploration using¹⁵
16 advanced modeling techniques. Indeed, one attraction for data scientists is the rel-¹⁶
17 ative ease with which data can be collected. However, polynomial and other types¹⁷
18 of regression to closed-form are problematic as suspicion of over-fitting increases¹⁸
19 with the order of the polynomial. For example, in [88], a sixth-order polynomial is¹⁹
20 suggested to model the relationship between processor utilization and power con-²⁰
21 sumption by a host. In section 7.2.2, we compare formal methods at some length and²¹
22 suggest that it is time for future research to use the more sophisticated techniques. 22

24 4.1.5 Three levels of abstraction 24

25 We note that existing power models may be classified into one of three levels of abstraction. 25

26 In ascending order of abstraction, these are: 26

- 27 1 Microarchitecture and architecture 27
- 28 2 Simple characterization of workload 28
- 29 3 Complex characterization of workload 29

30 The meaning of “abstraction” specific to our use here is perhaps most easily grasped by 30
31 referring to the variables used as model inputs. In all cases, the variables are some measure 31
32 of load. At the lowest level, inputs that quantify operation of processor sub-units are used 32
33 (event counters and event timers). The highest level uses inputs that quantify the demand 33

¹for a telecommunications system or service. Clearly, the latter inputs are far more detached¹
²from the underlying, concrete implementation than the former.²

³ Many power models use hardware resource consumption to estimate the power consumed³
⁴by virtual components. A study was conducted in [116], to evaluate the available power⁴
⁵models for processors, VMs and servers. According to this survey, most of the power mod-⁵
⁶els for virtual machines use physical machine counters to estimate the corresponding re-⁶
⁷source utilization by the virtual components. We offer further insight on this matter. We⁷
⁸concur in the observation that much current research is concerned with modeling power⁸
⁹consumption of virtual machines. The approach may succinctly be described as estimates⁹
¹⁰obtained from models trained out of either architectural or microarchitectural instrumen-¹⁰
¹¹tation data. We distinguish between architecture and microarchitecture using the classical¹¹
¹²interpretation [[121], p.17]. Now, the term “architecture” is severely overloaded and its in-¹²
¹³terpretation can easily differ from that which we wish to exploit. In the following descrip-¹³
¹⁴tion of the levels of abstraction, we use the alternative “system software’s instrumentation”¹⁴
¹⁵to convey the same meaning as “architectural instrumentation” with less ambiguity.¹⁵

¹⁶ Microarchitectural instrumentation: This is the lowest level of instrumentation. Power¹⁶
¹⁷consumption is expressed in terms of variables that are defined at sub-CPU and sub-¹⁷
¹⁸subsystem levels. The granularity of this level holds the greatest potential for accuracy, but¹⁸
¹⁹the rate of change of observed variables has deterred several researchers from pursuing this¹⁹
²⁰approach to instrumentation, citing concerns about communicational and computational²⁰
²¹overhead. This concern has been dismissed by three groups of researchers [52, 98, 109],²¹
²²who have indicated that acceptable accuracy can be achieved with negligible overheads.²²
²³Given the proliferation of works based on this approach, the availability of high-level lan-²³
²⁴guage code that facilitates use and the potential for capture of physical behaviors, then our²⁴
²⁵general recommendation is a preference to investigate use of microarchitecture instrumen-²⁵
²⁶tation.²⁶

²⁷ System software’s instrumentation: This regards a class of instrumentation that has mean-²⁷
²⁸ing across the spectrum of computer systems. The input variables, such as CPU or network²⁸
²⁹interface utilization, are produced by some digest (function) of intermediary system soft-²⁹
³⁰ware. For example, an operating system’s (OS) measurement of core utilization can roughly³⁰
³¹be described as the core’s duty cycle on behalf of the OS. This is significantly removed from³¹
³²knowledge of activity within the core. While models at this level are more abstract, they³²
³³are still low-level, especially when compared with the other levels.³³

¹ A less frequently encountered abstraction is used by Enokido, Takizawa and various oth-¹
²ers with whom they have co-published. They use simple characterization of workload e.g.²
³[81, 83, 122]. These models describe power consumption in terms of fundamental de-³
⁴scriptors of workload, e.g. number of processes and transmit/receive data rate. The least⁴
⁵granular model uses a complex characterization of workload [31, 123]. The objective here⁵
⁶is to quickly proceed to a good estimate of the power or energy required to produce the⁶
⁷workload. This kind of model has no use in real-time control but it is useful for macro-⁷
⁸scopic comparisons, i.e. comparisons between two disparate systems for provision of a⁸
⁹service. Possibly, the disparity is paradigmatic; for example: classical vs virtualized im-⁹
¹⁰plementations. Thus in [31], the implied (system) metric is the amount of power required¹⁰
¹¹to deliver 1 million packets per second of throughput through an evolved packet-core's¹¹
¹²(EPC) serving gateway (SGW). In [123–125] the objective is to minimize the amount of¹²
¹³consumed power by virtualizing baseband processing functions, evolved packet core, cus-¹³
¹⁴tomers premises equipment, and radio access network functions. 14

15

15

¹⁶4.1.6 Service determinism: a criterion particular to the telco cloud 16

¹⁷The NFV data plane demands determinism [107, 126], [65] @25:45 ¹². Strictly, *service*¹⁷
¹⁸*determinism* is sought, since the packet arrival process is generally unconstrained. The root¹⁸
¹⁹cause of this need is to correctly size equipment resources to meet load demands, whether¹⁹
²⁰throughput, latency or jitter. This need is intense, as it impinges on a PTNO's obligations,²⁰
²¹specified in legally-binding service-level agreements (SLAs). 21

²² Service determinism has been approached through augmentation of GP hardware, with²²
²³domain-specific architectures (DSAs, which we first referred to in 3.1.1). Hardware-centric²³
²⁴DSAs for the NFV data plane are constructed out of elements (or systems thereof) that can²⁴
²⁵be divided into three groups. 25

²⁶ 1 ***IO system architecture***: This group comprises the abstraction, *directly at a periph-*²⁶
²⁷***eral interface***, of functionality that facilitates virtualization of hardware, e.g. SR-²⁷
²⁸IOV (used in PCI - Peripheral Component Interconnect) and N-port ID virtualization²⁸
²⁹(Fibre Channel). 29

³⁰ 2 ***Processor architecture***: This comprises architectural change that facilitates parti-³⁰
³¹tioning of processor resources, such as multi-core processors and NUMA. 31

³²^[2]We use the @ symbol since a video is being cited and the content cited here may be found 32
³³by seeking the time indicated. 33

¹ 3 **Co-processing:** Compression and decompression, encryption and decryption, and¹
² packet header processing are examples of high-volume tasks that can be offloaded to²
³ co-processing subsystems. Examples include Intel QuickAssist Technology (QAT)³
⁴ and TCP Offload Engine (TOE).⁴

⁵ We further observe a set of approaches that are complementary to DSAs in the quest for⁵
⁶ determinism. These include:⁶

⁷ 1 **Large memory pages:** exploitation of the facility to organize virtual memory into⁷
⁸ larger pages than the GP 4 KiB;⁸

⁹ 2 **Userspace programming:** diversion of control of hardware resources away from the⁹
¹⁰ multi-service kernel, to single-common-use user space programs, e.g. DPDK and¹⁰
¹¹ AF_XDP.¹¹

¹² Notably, resource partitioning (second hardware-centric approach), combined with userspace¹²
¹³ programming (second complementary approach), realize the run-to-completion scheduling¹³
¹⁴ model [107].¹⁴

¹⁵ **The cost of current realizations of service determinism.** The (aforementioned) combi-¹⁵
¹⁶ nation of core partitioning and userspace programming has been widely adopted through¹⁶
¹⁷ Intel's popularization of DPDK, via Intel's open source liaison efforts. The multi-core pro-¹⁷
¹⁸ cessor enables service determinism through an approach that is anathema to the principles¹⁸
¹⁹ of multiprogramming: dedication of hardware to a specific task.¹⁹

²¹ 4.1.7 Direct or indirect measurement of power consumption in virtualized environments?²¹

²² We observe that most research in modeling power consumption seeks to obviate the need²²
²³ for direct measurement through indirect measurement, namely: of resource use which has²³
²⁴ a discoverable relationship with power consumption by the entity hosting the resources.²⁴

²⁵ Modeling, here, has the objective of indirect measurement of a variable that is not directly²⁵
²⁶ accessible (power consumption by VEs), through others which have convenient and re-²⁶
²⁷ liable instrumentation. The accessible variables are referred to as (power) proxies. The²⁷
²⁸ RAPL interface provides a unique approach to measurement as it directly addresses power²⁸
²⁹ consumption. However, notwithstanding appearances of direct measurement, RAPL is ac-²⁹
³⁰ tually based on a software model that uses performance-monitoring counters (PMCs) as³⁰
³¹ predictor variables to measure power consumption. It is available in processors starting³¹
³² from the Sandy Bridge microarchitecture. RAPL measures the power consumption of dif-³²
³³ ferent physical domains, where each domain consists of either cores, sockets, caches, or³³

¹GPU. We briefly denote its accuracy through references to research that has investigated¹
²them.²

³
⁴ 1 A study was conducted to find the advantages and drawbacks of using RAPL [109].⁴
⁵ Different Intel's architectures such as Sandy Bridge, Haswell and Skylake were used⁵
⁶ in the experiments to analyze RAPL's accuracy and overhead. Data collected were⁶
⁷ modeled using a linear model and a Generalized Additive Model (GAM). Accuracy⁷
⁸ of predicted results was compared with the measured power consumption from a⁸
⁹ precise external hardware power meter where RAPL based models show 1.8-4.3% of⁹
¹⁰ error for the various architectures. Prediction accuracy of RAPL-based power models¹⁰
¹¹ was also compared with those based on OS counters, where OS-based models show¹¹
¹² a higher error of 5-16%. Also, the performance overhead (in terms of time) of using¹²
¹³ RAPL was studied at different sampling frequencies and for different application¹³
¹⁴ runs. Results show that even with high sampling frequency of 1100Hz, RAPL incurs¹⁴
¹⁵ overhead of not more than 2%. Some limitations of using RAPL include: poor driver¹⁵
¹⁶ support to read energy counters, overflow of registers due to their 32-bit size and¹⁶
¹⁷ measurement of energy consumed by individual cores.¹⁷

¹⁸ 2 Another study to analyze the precision of RAPL is presented in [127], where only¹⁸
¹⁹ the dynamic change in power consumption is observed. WattsUp Pro, an external¹⁹
²⁰ power measurement unit, is used as a reference for power measurement values. Intel²⁰
²¹ Haswell and Skylake servers were used in the experiments to run different appli-²¹
²² cations and to find the reliability of RAPL with the help of external power meters.²²
²³ However, in this research work, only two power domain packages (power consump-²³
²⁴ tion of whole socket and DRAM domain of RAPL) were observed. Applications²⁴
²⁵ such as dense matrix multiplication and 2D Fast Fourier Transform were used for²⁵
²⁶ server power profiling. Results show that the power measurement error varies with²⁶
²⁷ changing application and its workload size. For different applications the average²⁷
²⁸ measurement error using RAPL was in the range of 13-73% considering WattsUp²⁸
²⁹ power meter as the ground truth. It was concluded that with the modern multi-core²⁹
³⁰ parallel processing and resource contention for shared resources, there is a complex³⁰
³¹ non-linear relation between performance, workload size and energy consumption.³¹
³² Hence it is difficult to attain low error percentage for power measurement using on-³²
³³ chip sensors.³³

¹4.2 Research gaps ¹

²With interest focused on the telco cloud, three significant challenges remain unaddressed,²
³while a fourth requires further attention: ³

- ⁴ 1 modeling of containers' power consumption; ⁴
- ⁵ 2 the effect of overcommitment on power efficiency; ⁵
- ⁶ 3 investigation and classification of DPDK applications and ⁶
- ⁷ 4 the fourth challenge, which is starting to receive some attention (as seen in [64, 95,⁷
⁸ 97, 105]), regards modeling of power consumption by virtualized I/O. ⁸

⁹ Note that our treatment of research gaps does not address improvements in approaches. ⁹

¹⁰We have already indicated, in section 4.1.4, that more adaptable modeling methods are ¹⁰
¹¹required to tackle the dimensionality of the field (see section 4.1.1). Indeed, a treatment of ¹¹
¹²adaptable models is undertaken in section 7.2.2. Similarly, we do not include lack of use of ¹²
¹³metrics of energy efficiency (section 4.1.3) with research gaps, as it is a deficiency in the ¹³
¹⁴approaches, not a challenge in itself. Rather, here, our attention focuses on where the more ¹⁴
¹⁵pressing challenges lie for development of the telco cloud. ¹⁵

¹⁶ ¹⁶
¹⁷*Modeling of containers' power consumption* Few works [90, 93, 94] tackle containers ¹⁷
¹⁸from the perspective of their power consumption. Yet VMs are no longer the destination for ¹⁸
¹⁹the telco cloud (see, for example, [37] and [128]@10:30). Containers have replaced virtual ¹⁹
²⁰machines as the base for deployment of virtual network functions. In [90], the approach(-²⁰
²¹set) taken is to: ²¹

- ²² 1 use representative workloads e.g. HEVC (High Efficiency Video Coding) transcod-²²
²³ing and machine learning image classification, and ²³
- ²⁴ 2 customization of the set of low-level instruments used to correlate power and energy²⁴
²⁵consumption with workload characteristic. ²⁵

²⁶This work develops a profiling tool: it provides guidance that is specific to application and ²⁶
²⁷both the hardware and software aspects of the containing platform. "[P]olicy" for "tradeoff" ²⁷
²⁸between energy, power and application performance" is the cited objective. Given the high-²⁸
²⁹dimensionality of the core challenge, this approach-set to modelling and measurement of ²⁹
³⁰power consumption may well be more coherent with the European Telecommunications ³⁰
³¹Standards Institute's (ETSI) Management and Orchestration (MANO) standard. Such in-³¹
³²formation would then be included in the infrastructure-resource-requirements meta-data ³²
³³descriptors in the VNF package [129]. ³³

¹*The effect of overcommitment on power efficiency* **Overcommitment** consists of the allo-¹
²cation of more capacity of some compute resource to VEs, than is physically installed. The²
³concept is very similar to oversubscription of telecommunications capacity to subscribers,³
⁴such as when the arithmetic sum of capacities of access links exceeds the aggregating⁴
⁵device's backhauling capacity to a central office/local exchange. In this context, overcom-⁵
⁶mitment principally concerns processing cycles and memory space. ⁶

⁷ As with oversubscription, there is an optimization problem to solve. One problem of in-⁷
⁸terest to this survey's scope is understanding the relationship (say, ratio) of committed vir-⁸
⁹tual resources to installed physical resources that optimizes total cost of ownership (TCO)⁹
¹⁰of cloud infrastructure: ¹⁰

- ¹¹ • on the one hand, the facility to overcommit has a direct impact on the density of¹¹
¹² packing of VEs (number of concurrently active VEs) on a virtualization-host-system,¹²
¹³ thereby reducing the TCO. ¹³

¹⁴ on the other hand, overcommitment may reduce the power efficiency of a workload. ¹⁴

¹⁵ Had this challenge been tackled in any depth, or at least in any breadth, it would have¹⁵
¹⁶merited a category of its own. Currently, however, we are only aware of a single study [78]¹⁶
¹⁷that tackled this challenge. Results obtained strongly justify overcommitment of processor¹⁷
¹⁸cores to vCPUs, for the case of transaction web service workloads, with the increase in¹⁸
¹⁹throughput (measured in web interactions per second, or WIPS) increasing at a faster rate¹⁹
²⁰than power consumption. This behavior proceeds well into overcommitment ratios of pro-²⁰
²¹cessor cores to vCPUs equal to 3 (three). Overcommitment of physical to VM memory is²¹
²²not investigated. ²²

²⁴*Investigation and classification of DPDK applications* In section 4.3.2, we address the²⁴
²⁵relationship between DPDK and power consumption. In the course of a public discussion²⁵
²⁶in the forum offered by the North American Network Operators' Group (NANOG)[130],²⁶
²⁷there emerged a need for clarity on DPDK's association with inefficiency in power con-²⁷
²⁸sumption. Interest was particularly expressed in knowledge of a classification of extant²⁸
²⁹DPDK applications according to their power consumption, and contribution to the code²⁹
³⁰base to improve power-hungry applications. ³⁰

³¹*Modeling of power consumption by virtualized I/O* Power consumption of network I/O³¹
³²has been investigated to some extent as this is central to the feasibility of network func-³²
³³tions decoupled from hardware. Yet while software and hardware solutions are already³³

¹available (see section 4.3.2), they require frequency and idling control (see section 3.2.2)¹
²targeted to their specific operating conditions. Notably, naive DPDK runs the processor²
³core at its maximum power consumption, regardless of load. Exploitation of adaptive-rate³
⁴(AR) processing and low-power idle (LPI) should provide a means to save power while⁴
⁵processing high networking loads. However, effective control of these means is still elu-⁵
⁶sive. Despite both using Xeon Haswell microarchitectures, [95] and [64] reach opposite⁶
⁷conclusions about the feasibility of processor core C-states. The former [95] finds LPI an⁷
⁸effective means of reducing power consumption of packet forwarding (with limitation on⁸
⁹latency) while the latter [64] finds it ineffective, preferring use of the *pause* instruction.⁹
¹⁰ Furthermore: in [111], performance state transitions (P-state) are found to impose a high¹⁰
¹¹transition latency, while in [64], P-state regulation is the preferred approach. There is scope¹¹
¹²for research in the dynamic adaptation of the processor's operating state to save power.¹²

¹⁴4.3 Pitfalls¹⁴

¹⁵4.3.1 Power consumption does not in general increase linearly with processor utilization¹⁵

¹⁶Notwithstanding advances made in identifying operating contexts that manifest sub-linear¹⁶
¹⁷power-utilization relationship [75, 82] recent publications [70, 131–138] persist in using¹⁷
¹⁸the linear model without acknowledging its limitations. The model is simple to use and has¹⁸
¹⁹some foundations in research [49]. It has three premises, described here with regard to the¹⁹
²⁰operation of Microsoft Windows:²⁰

- ²¹1 When Windows has no threads to run on a logical core, it schedules the idle thread²¹
²²[139].²²
- ²³2 The idle thread keeps the processor in a low-power state [140]. The specific state²³
²⁴depends on the processor's green capabilities.²⁴
- ²⁵3 In the complement (non-idle time), the processor issues instructions at a constant²⁵
²⁶rate.²⁶

²⁷This simple model has limitations [[141], p. 6/12] [[75], p. 808]. It fails to take into ac-²⁷
²⁸count diverse processor operating contexts, some of which are coming to bear on current²⁸
²⁹use cases. Specifically, the third premise is true only to the extent to which instructions are²⁹
³⁰being fetched and data are being loaded from/stored to instruction and data cache, respec-³⁰
³¹tively. Consider the context of 90% and greater hit ratios. At such cache hit ratios, the rate³¹
³²of instruction issue is expected to be narrowly distributed about its mean. By contrast: the³²
³³lower the hit ratio at the cache level before main memory, the lower the fraction of non-³³

¹idle time at which power consumption saturates. This saturation is strikingly illustrated in¹
²[[75], Fig. 1]. Variation of power consumption due to execution of tests from the SPEC²
³CPU2000 benchmark suite is shown. The power consumption diverges at 25% CPU uti-³
⁴lization and the consumption of the processor-bound test (mesa) is greater than that of the⁴
⁵memory-bound test (mcf) by a factor of about 2.6. ⁵

⁶ Another good (albeit overly broad) illustration of this pitfall is given in [[142], Fig. 5].⁶
⁷Data on power consumption and CPU utilization under a standardized benchmark is plotted⁷
⁸for four different physical server models. None of the relationships is linear. Neither is there⁸
⁹a single, common behavior. ⁹

¹⁰ Researchers align themselves into two groups in regard to CPU utilization. One group¹⁰
¹¹favors (operating-)system metrics (of which CPU utilization is one metric) and the other¹¹
¹²favors event counters (microarchitectural instrumentation). The arguments posed by each¹²
¹³group against the other's approach can be summarized as follows. The "system metrics"¹³
¹⁴group claims that the "event counters" group's work is (a) not portable (at least across mi-¹⁴
¹⁵croarchitecture families) and (b) cannot be exercised without low-level access to the host¹⁵
¹⁶(thereby, this approach cannot be exploited by user-level privileges) (see, e.g., [50], p.121¹⁶
¹⁷and [87], p.43). The "event counters" group claims that CPU utilization is a workload-¹⁷
¹⁸dependent predictor (see, e.g., [72], p.1380) and therefore cannot be used without re-¹⁸
¹⁹training the model. Indeed, this modification to the "system-counters" approach is em-¹⁹
²⁰ployed in [88] (section 3.2, "Runtime phase"), where, it is stated that "[b]ecause of changes²⁰
²¹of VM's internal applications ... parameters must [be] recalculated automatically". Given²¹
²²these arguments, it seems that the system metrics group argument is weak: both system²²
²³metrics and event counters require re-training if hardware is changed but system metrics²³
²⁴lack the granularity to discriminate between workloads (cf. [75], Fig.1). This means that²⁴
²⁵CPU utilization can only be used as the sole predictor if it is re-trained with change in²⁵
²⁶workload. We deal with this problem, which we have termed the fallacy of the universal²⁶
²⁷model, in section 4.4.1. ²⁷

²⁸ As regards use of hardware threads (Intel® Hyper-Threading), we have observed that²⁸
²⁹various works concur on the operating context under which a linear relationship is subject²⁹
³⁰to the lowest error. This includes at least the following two conditions. ³⁰

- ³¹ 1 The processor cores are increasing their instruction issue rate in proportion to the³¹
³²fraction of time they spend busy [75]. This implies that instruction and data cache hit³²
³³ratios are high. This is simply the third premise. ³³

1 2 Only one logical core is active per physical core at any given time [75, 76, 82].¹

2 Expressed alternatively, actual utilization must lie below half maximum utilization.²

3 The underlying cause is that activation of the second logical core employs fewer³

4 organizational units of the processor than activation of the first logical core. ⁴

5 The first condition is particularly problematic, as cache miss ratios are likely to be much⁵

6 higher in the context of virtualized environments. In such environments, the number of⁶

7 runnable threads is the sum of runnable threads controlled by independent operating sys-⁷

8 tems. Evidently, this is higher than the expected number of runnable threads on a single⁸

9 server instance. ⁹

10 Other evidence of this “utilization trap” is not hard to find. In [70], the compute resource¹⁰

11 is stressed using cputlimit and stress-ng. The “cputlimit” utility runs a specified process¹¹

12 image, then pauses and resumes it until a certain percentage utilization is reached [137].¹²

13 The repetitive execution of a single process is highly likely to create conditions for very¹³

14 high instruction- and data-cache hit ratios. Such favorable hit ratios skew results towards¹⁴

15 the linear relationship between CPU utilization and power consumption. ¹⁵

16 ¹⁶

17 4.3.2 DPDK is not intrinsically inefficient in power consumption ¹⁷

18 Before proceeding to our exposition of this pitfall, we distinguish between data, control¹⁸

19 and management planes. “Data plane” is a term used to refer to the infrastructural means¹⁹

20 that provide the capacity for exchange of customer (or subscriber, or end-user) data. It is²⁰

21 complemented by a control plane, which refers to those means that facilitate the dynamic²¹

22 setup, maintenance and tear-down of a functional data plane. Another complementary part²²

23 is the management plane. This includes the infrastructural means for a network operator to²³

24 configure and monitor the control plane and the data plane, as well as intervene to correct²⁴

25 faults arising in either plane. Simpler networks may have no control plane. ²⁵

26 Research on power efficiency in DPDK applications [62–64, 66] has portrayed DPDK as²⁶

27 power inefficient. In one particular case [63] (p. 43), it is claimed that “we found that a poll²⁷

28 mode driver (PMD) thread accounted for approximately 99.7 percent CPU occupancy (a²⁸

29 full core utilization).” The implication that seems to emerge here is that the PMD itself is²⁹

30 driving this power consumption. ³⁰

31 This portrayal is problematic at best and incorrect at worst. The referenced investigations³¹

32 of DPDK have indicated a very low power efficiency [62–64, 66], but they do not clearly³²

33 distinguish between responsibility of the DPDK API and the application using it (the API).³³

¹A recent, public thread [130] has emphasized the responsibility of the application devel-
²oper in the avoidance of the naïve, "default approach" of busy polling. Such an approach²
³would, indeed, poll network IO hardware continuously [63] p. 44, truly fitting the epithet³
⁴"spinning-hot" [65] @26:23 [31]. However, a broader (in the sense of including industrial⁴
⁵correspondents) investigation [130] suggests that:

- ⁶ • contrary to claims in [63], it is the driving behaviour of OvS that is inefficient in⁶
⁷ power consumption, and⁷
- ⁸ • there are simpler, technical means of throttling a polling loop, including, say the use⁸
⁹ of program code to interleave ACPI C1 states with polls according to traffic demands.⁹

¹⁰ These latter observations cast doubt on the claim that automated frequency control is¹⁰
¹¹outside the scope of current frequency governors, since "the OS won't be able to distinguish¹¹
¹²whether it's under a heavy load" [63], p. 45. On the other hand, savings through NUMA¹²
¹³awareness [66], (where transmit/receive port, memory and processor core are kept within¹³
¹⁴the same NUMA node), is affirmed in [130].¹⁴

¹⁶4.3.3 *Research on power models without power-relevant context*¹⁶

¹⁷This pitfall traps readers who attempt to draw conclusions from published research which¹⁷
¹⁸lacks a clear specification of context relevant to power consumption. The pitfall is best¹⁸
¹⁹illustrated through examples.¹⁹

²⁰ 1 ***Failure to emphasize context: idle power consumption vs frequency.*** Dependence²⁰
²¹of idle power consumption on clock frequency is context-sensitive. In [58], it is ex-²¹
²²plicitly stated "idle power consumption remains constant, regardless of the CPU fre-²²
²³quency ... across the whole frequency range" (1.6 – 2.6 GHz). The CPU is an Intel²³
²⁴Xeon E5620. In [94] and [93], a quadratic relationship between idle power consump-²⁴
²⁵tion and frequency is observed. Here, the CPU is an Intel Core i5 Haswell. In these²⁵
²⁶two instances, emphasizing the restricted scope of findings would suffice to spare a²⁶
²⁷reader from excessively broad inferences.²⁷

²⁸ 2 ***Failure to emphasize context: idle power consumption vs hardware and software***²⁸
²⁹***specification.*** Enokido's and Takizawa's work [83] derives a power consumption²⁹
³⁰model for a server while VMs run computation-bound processes. The servers used³⁰
³¹run on Intel Core i5-3230M processors. These processors are used in the mobile³¹

³²^[31]We use the @ symbol since a video is being cited and the content cited here may be found³²
³³by seeking the time indicated.³³

device market [143]. They are capable of low-power idle states [144]. CentOS 6.5¹ uses a tickles kernel [145]. Combined, these facts, relevant to the context of power² consumption, provide a plausible explanation for the observed increment in power³ (denoted, in [83], by $\min C_i$), when a core in a package is activated. Again, therefore,⁴ the scope of findings is likely to be restricted.⁵

3 ***Failure to fully define context: Configuration of power-relevant parameters.*** An-⁶ other example regards [146]. No reference is made to whether Hyper-Threading is⁷ enabled. This is essential to understanding how the ESXi vCPUs are created. Nei-⁸ ther is any information given about how the vCPUs are related to physical (or logical)⁹ cores. Nor are we told how virtual network interfaces and switching are set up. ESXi¹⁰ version 5 offers both paravirtualization (“vmxnet”) and emulation (“e1000”) to im-¹¹ plement virtual network interfaces. The impact on energy consumption of selecting a¹² virtual network interface implemented by emulation can be expected to be high [60].¹³

¹⁴The examples cited illustrate the importance for a researcher into power models to qualify¹⁴ his/her results ***with a well-defined physical context***. Research into power models involves¹⁵ hard components and a diligent characterization thereof is essential to the acceptance of¹⁶ work as scientific research.¹⁷

¹⁹4.3.4 *Benchmarks may skew power consumption according to their organizational*¹⁹ ²⁰*dependencies*²⁰

²¹In section 4.3.1, it was seen that both “cpulimit” and “stress-ng” do not produce generally²¹ representative measurement of power consumption. This observation is not limited to mea-²² surement of power consumption. Use of kernels, toy programs and synthetic benchmarks²³ to measure performance has been identified as unrepresentative [[121], p. 40] of general²⁴ performance. Benchmarks are standardized workload generators that are used for compar-²⁵ ison of computer systems for a specific class of application. Unless this application class²⁶ is a good representative of the application of the computer system in productive use, the²⁷ power consumption measured under test is not a reliable predictor of that obtained during²⁸ productive use. It is necessary to plan test workload generators in advance and state the lim-²⁹ its of validity of results. In [78], TPC-W is used, which is a transactional web benchmark³⁰ that can simulate the business oriented online web-servers. The MySQL++Java version of³¹ TPC-W benchmark, suitable for cloud applications, is used to generate the online traffic,³² where three different traffic profiles based on browsing, purchasing and ordering of books³³

¹are generated. The throughput measure for these servers are observed through the metric¹

²Web Interactions Per Second (WIPS).²

³

⁴

⁵4.3.5 *Processor organization significantly impacts power consumption*⁵

⁶We illustrate this point with a wide-ranging example [147], which compares the Intel Xeon⁶

⁷X5670 and AMD Opteron 2435.⁷

⁸ 1 Different idle loops (using no operation, pause, repetition, etc.) were tested to see⁸

⁹ their effect on power consumption of both systems. It was observed that the Intel⁹

¹⁰ Xeon has a loop stream detector, which disables the processor's features like fetch¹⁰

¹¹ and decode. On the other hand, the AMD processor has no hint to process these loops¹¹

¹² efficiently; hence, it consumed more power than the Intel processor.¹²

¹³ 2 A processor consumes different amounts of power depending upon the instruction¹³

¹⁴ (such as load, addition, multiplication, etc.) and the level in the memory hierarchy¹⁴

¹⁵ which is accessed by the instruction.¹⁵

¹⁶ (a) For the Xeon, data throughput of all instructions from a particular memory¹⁶

¹⁷ hierarchy level is almost the same but there is a difference in their power con-¹⁷

¹⁸ sumption. The 'load' operation consumes the lowest power compared to other¹⁸

¹⁹ instructions, and this holds true for all memory hierarchy levels. The reason is¹⁹

²⁰ that the 'load' instruction just needs to load the content on the processor regis-²⁰

²¹ ters whereas 'add' and 'mul' operations are more computation demanding.²¹

²² (b) However, the AMD processor's behavior is the opposite. When the 'load' op-²²

²³ eration accesses L1 cache, it achieves almost one-and-a-half times the data²³

²⁴ throughput of other operations and hence also consumes more power. This²⁴

²⁵ difference in resource utilization is due to the different microarchitecture of²⁵

²⁶ AMD processors, where the 'load' instruction is handled by many floating-²⁶

²⁷ point pipelines. Other instructions just use a single pipeline for their opera-²⁷

²⁸ tions. Moreover, AMD processors have an exclusive cache level design, which²⁸

²⁹ requires write-back when evicting data among different cache levels. Since In-²⁹

³⁰ tel's inclusive cache design does not require this function, it consumes less³⁰

³¹ power. Within higher memory hierarchy levels (L2 or L3 or main memory), the³¹

³² AMD's computation ('add' and 'mul') and data transfer operations ('load') de-³²

³³ liver roughly the same data throughput and consume roughly the same power.³³

¹4.3.6 Isolation of VE for power modeling and measurement

²Isolation of any VE from its hardware counter parts can not be done completely [[148](#)]; thus,
³the assumption of measuring power consumption of an individual virtual entity irrespec-
⁴tive of the hardware on which it is implemented is an illusion. The virtual infrastructure
⁵is composed of several components at both hardware and software level, where the effect
⁶of underlying hardware, OS and VNF technology can significantly impact the power con-
⁷sumption. Hence, isolation as well as modeling of power consumption for an individual
⁸virtual component is difficult to obtain.

¹⁰4.4 Fallacies

¹¹4.4.1 A universal power model

¹²We have suggested that the core challenge in modeling power consumption by VEs lies in
¹³the number of dimensions of variability. This has been demonstrated throughout this survey,
¹⁴where a number of generalizations have been addressed. Summarizing, the literature shows
¹⁵that:

- ¹⁶1 host power consumption does not generally have a linear relationship with processor
¹⁷utilization;
- ¹⁸2 CPU-intensive workloads that repeatedly execute the same code skew power con-
¹⁹sumption results;
- ²⁰3 network-intensive workloads are power- and time-consuming because they employ
²¹emulations of network switches, but the root cause (emulation in the hypervisor soft-
²²ware switch) disappears with SR-IOV [[149](#)], p. 5;
- ²³4 host saturation must be taken into account in predicting VEs' power consumption;
- ²⁴5 processor utilization (an architectural attribute) is insufficient to predict host power
²⁵consumption and microarchitectural attributes, such as LLC misses, are necessary to
²⁶predict host power consumption even for the same level of processor utilization.

²⁷This list, while not exhaustive, amply illustrates that the several dimensions of variability
²⁸are significant in determination of VE power consumption. A model claiming to determine
²⁹power consumption as a function of fewer variables than the dimensions we have pointed
³⁰out must be accompanied by a scoping region that limits its use. While a precise scope
³¹may be an unrealistic demand, it is essential that guidance be given about conditions of use
³²of the model. We now illustrate this point by using two examples from the corpus. Khan
³³[[57](#)], p. 51] compares energy efficiency (hash/J) obtained by scheduling process threads

¹on additional cores, with that obtained by scheduling them on hardware threads on active¹
²cores (through Intel Hyper-Threading). He shows that the former is greater than the lat-²
³ter. In apparent contrast, Enokido and Takizawa [[81], p. 279] show that for a given data³
⁴transmission rate through the uplink of a software virtual switch, greater energy efficiency⁴
⁵(W/bps) is obtained by operating an additional hardware thread on an active core (through⁵
⁶Intel Hyper-Threading), than operating an otherwise idle core. An important difference lies⁶
⁷in the task's processing "intensity", i.e. the rate of supply of instructions. While Khan's⁷
⁸operations are tightly bound to the processor (cryptographic hashing), Enokido's and Tak-⁸
⁹izawa's operations are distributed over the processor and network input/output. Without⁹
¹⁰delving into detail, it is realistic to hypothesize that the average instructions per second¹⁰
¹¹demand are far lower in the networking application, since transmission of a large file¹¹
¹²(as is the case here) does not take place in one processing burst. Operating time is divided¹²
¹³between the processor and the media channel. In such a scenario, the added capacity of the¹³
¹⁴same-core hardware thread suffices. 14

¹⁵ At the time of writing, the scope of validity (where the scope is a sub-space of the seven-¹⁵
¹⁶dimensional space (section 4.1.1)) is typically only implicit. Notably, in [87], a "refined¹⁶
¹⁷model" is used as a means of accurate prediction of power consumption by virtual ma-¹⁷
¹⁸chines while running very specific benchmarks. It is also noteworthy that the authors con-¹⁸
¹⁹template a type of onboarding process wherein "new" VM entrants to a cloud are modelled¹⁹
²⁰as a prerequisite to their inclusion in the power-prediction system. Indeed, such a process is²⁰
²¹already intrinsic to management and orchestration of virtual network functions. Just as the²¹
²²virtual deployment unit (VDU) nodes (in virtual network function descriptors (VNFDs))²²
²³store VM properties describing computer system resource demands, so can the descriptor²³
²⁴template be extended to provide properties regarding power consumption demands. This²⁴
²⁵"onboarding" is necessary since the selected predictors and modeling do not cover a suffi-²⁵
²⁶ciently broad range of workload types, and a specific model must be learnt online, i.e. – on²⁶
²⁷the fly. 27

²⁸ On the other hand, we propose that a comprehensive power model for existing imple-²⁸
²⁹mentations is possible. We suggest three conditions. 29

- ³⁰ 1 Every resource that consumes power must own a counter that registers its usage, or 30
³¹ lack thereof, during a specific clock cycle. 31
- ³² 2 Usage of a specific resource during a specific clock cycle must consume a constant 32
³³ amount of energy. This has the following corollaries. 33

- 1 (a) Energy consumption by the specific resource is a linear function of the number¹
- 2 of clock cycles for which the resource is active. 2
- 3 (b) Power consumption of a system can be expressed as a linear combination of³
- 4 the total set of such resources. 4
- 5 (c) The amount of energy consumption by a specific resource during a specific⁵
- 6 clock cycle must be independent of usage of other resources during any other⁶
- 7 clock cycle. 7
- 8 3 Usage of the specific resource must be convertible to its power consumption, i.e. the⁸
- 9 power consumption must be observable. 9

10 In particular, if the second condition holds true, then a whole processor core cannot be an¹⁰
 11 atomic resource. 11

13 5 Conclusion 13

14 Energy efficiency of computer and telecommunications systems has become a major con-¹⁴
 15 cern over the last two decades, involving both equipment and networks. As regards the¹⁵
 16 computing world, the advent of datacenters and the cloud has played a major role in raising¹⁶
 17 awareness toward the issue of energy consumption (see, e.g., [41, 150, 151]). The attention¹⁷
 18 of Telecom operators in this respect has been directed not only to the wireless segment¹⁸
 19 [152], but also to the fixed network, starting with the “traditional” IP networking equip-¹⁹
 20 ment of special-purpose routing and switching devices [1, 153]. The main motivations be-²⁰
 21 hind both cloud and network operators have been the reduction of OPEX, but also the²¹
 22 increasing attention toward a “green” approach to the industrial evolution. 22

23 Having reached a maximum by the end of the first decade of the years 2000, the attention²³
 24 on the theme has been slightly decreasing with the advent of network virtualization and²⁴
 25 softwarization brought forth by SDN, NFV, and the advent of 5G (with some notable ex-²⁵
 26 ceptions, like [95, 154, 155], among others). As we noted in the Introduction, the reason can²⁶
 27 be attributed to the belief that the increased flexibility and the consolidation of resources²⁷
 28 made possible by virtualized networking components (see, e.g., [156–158]) would have²⁸
 29 sufficed not only to compensate the increased energy consumption caused by the adoption²⁹
 30 of general-purpose hardware, but also to curb it in general. We noticed that this is not the³⁰
 31 case. However, as noted in [159], the interest in energy efficiency is rising again with the³¹
 32 evolution toward the 6th generation mobile network (6G), where the very ambitious goal³²
 33 of 1Tbit/J is being set. Moreover, network operators are looking with increasing interest to³³

¹the business opportunities offered not only by network softwarization and by the stricter in-¹
²tegration between the mobile and fixed segment, but also by the deployment of computing²
³capabilities in the network edge brought forth by Mobile Edge Computing (MEC).³

⁴ These considerations have led us to address specifically modelling and measurement of⁴
⁵power consumption in virtualized computing and networking environments and to concen-⁵
⁶trate the scope of our investigation to what is more pertinent to the Telco cloud. In doing⁶
⁷this, we have decided to adopt the IPAD method of thematic analysis, in order to attempt to⁷
⁸produce a quantitative categorization of the multi-faceted research aspects that are scattered⁸
⁹in the literature. One of our main reasons for the adoption of this methodology is grounded⁹
¹⁰in the additional complexity that lies in the analysis of the energy consumption caused by¹⁰
¹¹VEs that act in telecommunication systems, with respect to those acting in the computing¹¹
¹²world. On one hand, it is true that, as softwarization advances in networking and telecom-¹²
¹³munication systems, their characteristics become closer to computer systems' ones; on the¹³
¹⁴other hand, the nature of teletraffic and the distributed essence of networking add complex-¹⁴
¹⁵ity to the functionality and interaction of processing units that have to perform the spatial¹⁵
¹⁶transport of information or to deal with both transport and in-network computation.¹⁶

¹⁷ Among the themes that our survey has brought us to identify, besides the review of the¹⁷
¹⁸state of the art that has led to our taxonomy and the related statistics, we have tried to high-¹⁸
¹⁹light the main research domains, along with pitfalls, possible gaps and fallacies. As regards¹⁹
²⁰the first, we have pointed out three major interests addressed in the literature within the²⁰
²¹scope of our investigation: i) predictive models of real-time power consumption, ii) inte-²¹
²²gration of computing and networking systems with emphasis on energy efficiency and iii)²²
²³high-performance, power-efficient packet I/O frameworks. All problem categories we iden-²³
²⁴tified within these broader domains touch one or more of a set of seven main variables that²⁴
²⁵may affect power consumption by virtual entities and the ensuing model representations:²⁵
²⁶workload type, characteristics of the virtualization agent (VM or container), host machine²⁶
²⁷resources and architecture, temperature, operating frequency, attribution of a fraction of²⁷
²⁸consumed power to individual VEs, and mutual influence of concurrent VEs.²⁸

²⁹ Among the major pitfalls that could be noted from our thematic analysis, we highlight²⁹
³⁰here the often unacknowledged limitations of the widely used linear models, the failure³⁰
³¹to precisely identify the physical context in some experimental research, the influence of³¹
³²synthetic workload generators on measurements, and the sometimes overlooked relevance³²
³³of processor organization on power consumption measurements. We have also pointed out³³

¹the unavoidable need to precisely identify the scope and limitations of models and the¹
²fallacy of the quest for a “universal” power model.²

³
⁴ Evolution of the research space on power consumption in virtualized the environments⁴
⁵composing the Telco cloud now suggests directions for further development of power mod-⁵
⁶els:⁶

- ⁷
⁸ • Division of the problem into (a) a modeling concern: (i) what components to include,⁸
⁹ (ii) what workload(s) to consider, (iii) what state factors (temperature, frequency,⁹
¹⁰ performance & idle states) to choose to be accounted for.¹⁰
- ¹¹ • Division of the approach into (a) microarchitectural instrumentation, based on inti-¹¹
¹²mate knowledge of the microarchitecture and the memory system; (b) granular attri-¹²
¹³bution based on time-division multiplexing; (c) model selection (we have suggested¹³
¹⁴some guidance in section [7.2.2](#)¹⁴
- ¹⁵ • Development of parameterized models, subject to continuing (if not continuous) op-¹⁵
¹⁶timization of the parameters under machine learning.¹⁶
- ¹⁷ • Among high-performance packet I/O frameworks, a classification of applications¹⁷
¹⁸that use DPDK APIs in order to assess their power consumption and correct usage¹⁸
¹⁹would be of particular interest, given their diffusion and potential.¹⁹

²⁰ As we mentioned at the beginning of this Section, we believe that the interest in under-²⁰
²¹standing and mitigating power consumption of virtual entities is bound to grow in the near²¹
²²future (and – we may add – especially in the Telco cloud), owing to the increased soft-²²
²³warization process in networking and to the relevance of edge computing in the roadmap²³
²⁴beyond 5G. Attention should be increasingly shifting toward indirect measurement of the²⁴
²⁵power consumption by VEs and the development of prediction models based on the use²⁵
²⁶of Artificial Intelligence / Machine Learning (AI/ML) techniques. As we mentioned in our²⁶
²⁷sub-section on research gaps to be addressed, modelling in particular the power consump-²⁷
²⁸tion of containers (and Metal-as-a-Service approaches, as well), along with that of virtual-²⁸
²⁹ized I/O should play a relevant role. In this vision, we tend to agree with the architectural²⁹
³⁰paradigm referred to as Smart Green Network Concept in the latest version of the Strategic³⁰
³¹Research and Innovation Agenda (SRIA) 2021-27, recently issued by NetWorld2020 [[160](#)],³¹
³²where AI-as-a-Service (AIaaS) occupies a relevant position above a unified controllability³²
³³layer and below a cooperative services layer offered to verticals.³³

6 Appendix - Applications

Interest in measuring and modeling power consumption by virtual machines and containers derives from the relationship which power consumption has with the cost of operations of information and communication technology (ICT) infrastructure. This statement is relevant to infrastructure provision across the scale, whether in Cloud datacenters or virtualized infrastructure running in points of delivery within the access segment of a public telecommunications network (PTN). Operation, administration, maintenance and management (O&M) [17] of ICT infrastructure using guidance from knowledge of power consumption is referred to as power-aware O&M. Power-aware O&M of redundant infrastructure hinges on models of physical infrastructure's power consumption as a function of VM workload (measured in terms of architectural or microarchitectural entities). Therefore, application of modeling and measurement lies in the power-aware O&M of virtualized environments.

Power-aware O&M has the objective of optimization of such O&M. We distinguish between optimization and minimization through service constraints: optimization is the minimization of costs subject to constraints on operations explicitly or implicitly obtained from service-level agreements (SLAs). A well-known example of the impact of SLAs on power consumption regards the use of redundant equipment to meet service availability requirements. Service availability (an important parameter of SLAs) depends critically on the absence of single points of failure (SPOFs). The redundant physical equipment deployed to avoid SPOFs increases power consumption.

Here, we briefly survey research into power awareness of O&M in virtualized environments, where such O&M have significant power consumption that must be measured and modelled. Five concerns emerge:

- 1 Creation, deletion, startup, shutdown, hibernation, resumption and migration operations characterize the dynamicity of virtualized environments. The significance of their overhead in power consumption must be quantified to determine its impact on energy efficiency. In particular, migration's cost is not trivial, although acceptable. [84].
- 2 Furthermore, in order to operate a commercial virtualized environment, heterogeneity in both VMs and hosts must be characterized in models. Primarily, heterogeneity refers to variability in allocation of resource quantities: a virtualized environment supports diverse VM sizes. Secondly, there are also implementation differences in

physical machines and these differences manifest themselves in the power models.¹
This dimension of variability must be included in modeling to support frameworks²
of O&M.³

3 Pay-per-use is one of the key tenets of Cloud Computing. Implementation of this⁴
tenet depends upon the facility to account for resource usage. This facility may be⁵
passed on to the consumer or reserved by the provider for internal cost control. We⁶
observe an evolution of research into comprehensive frameworks capable of automat-⁷
ing the transformation of resource usage into cost.⁸

9 4 Real-time control of power consumption is concerned with scheduling VEs (a) to⁹
minimize consumption or (b) to cap it.¹⁰

11 5 The use of models to reason about macroscopic changes to digital services and/or¹¹
systems is concerned with the exploration of the impact of alternatives in service de-¹²
livery or system implementation. We refer to such applications of models as *macro-*¹³
scopic analyses.¹⁴

15 The first two concerns are part of the broader scope of a Network Function Virtualization¹⁵
Management and Orchestration framework (NFV-MANO) [161] whereas the third concern¹⁶
is part of a Business Support System (BSS). The fourth concern is part of the scope of a¹⁷
Virtual Infrastructure Manager (VIM). The fifth concern is that of strategic management.¹⁸
We divide our review of application research into these three system classes (NFV-MANO¹⁹
– 6.1, VIM – 6.2, BSS – 6.3) and macroscopic analyses (6.4).²⁰

21

22 6.1 Management and Orchestration²²

23 We consider a sample of works that deal with power-aware VM migrations [84, 134, 162,²³
163]. Their approach is divided into two parts. The first part regards basic research, where²⁴
the researchers develop a power model to guide the second part. This latter part may be²⁵
described as an approach to applied research, where the power model(s) is(are) used to²⁶
quantify the impact of migrations on power consumption. In order to present the sample,²⁷
we apply and present a first iteration (see [45, sub-section 4.2] for some clarification of²⁸
what we mean by "iteration" here) of the IPAD protocol on RUs that employ models to²⁹
improve the power or energy efficiency of VM migrations.³⁰

31 In [84]:³¹

32 1 Problem: How does VM migration affect power consumption?³²

33 2 Approach³³

- 1 (a) Basic research 1
- 2 i. Workload Model: Historical data about static and periodic cloud workload²
- 3 patterns was collected and used in an ARIMA model to predict workload.³
- 4 The predicted workload was transformed into a prediction of power con-⁴
- 5 sumption through the linear/polynomial model of power consumption as a⁵
- 6 function of virtual processor utilization. 6
- 7 ii. Power Model: A relationship was obtained, through linear or polynomial⁷
- 8 regression, between the workload (utilization of virtual processors hosted⁸
- 9 by a physical machine), and its power consumption. 9
- 10 (b) Applied research: Applied research: The approach taken is to reduce frequency¹⁰
- 11 of migration. The SLA is respected by bounding server power below a thresh-¹¹
- 12 old. Server power consumption is used since the relationship between workload¹²
- 13 and host power consumption is determined during basic research, and mea-¹³
- 14 surement of host power consumption is less invasive and less demanding than¹⁴
- 15 measurement of several individual VM workloads. 15
- 16 3 Developments 16
- 17 (a) The migration algorithm does not migrate the VM as soon as the high CPU¹⁷
- 18 utilization peak is detected. The algorithm waits for some time and if the high¹⁸
- 19 utilization persists, then the VM is migrated. This facilitates improved energy¹⁹
- 20 efficiency through optimal migration of heterogeneous virtual machines under²⁰
- 21 different workloads. 21
- 22 (b) VMs can be migrated without violating performance terms of the Service-Level²²
- 23 Agreement (SLA) by limiting the server's power consumption below a given²³
- 24 threshold. This framework considers the heterogeneity of virtual machines and²⁴
- 25 predicts the variation in key parameters such as power, performance and migra-²⁵
- 26 tion cost, for different usage and size of the VM. 26
- 27 4 Limitations: The workload prediction model is limited to estimating the precise²⁷
- 28 power cost of periodic workloads; therefore, it might not be useful for a dynamic²⁸
- 29 scenario. 29
- 30 30
- 31 6.1.1 *Orchestration in Datacenters* 31
- 32 Deploying a single service in a single host is fairly simple to manage. However, these³²
- 33 days, in large datacenters and cloud networks, no single server is serving a single appli-³³

cation. Virtualization has opened new ways of service provisioning and application processing on a single server where several users can run a number of different applications, each isolated from the other. Optimal resource management and task scheduling in such scenarios is impractical to achieve using traditional scheduling schemes such as round robin, first come first served, etc. Heuristic or meta-heuristic based optimization models are usually preferred in heterogeneous networks for this purpose. However, in some cases, even these methods can take a significantly long time to find the optimal solution and consequently consume more energy. Considering these issues, many researchers proposed energy-efficient management schemes [164–166] and orchestration tools [167–169] to manage resources effectively. These commercial tools help to manage large networks of clustered applications, multiple datacenters, public and private clouds, etc., and seem to be a robust, energy efficient choice for VM consolidation and load balancing.

We again apply and present a first iteration of the IPAD protocol; in scope here are RUs that employ models to obtain strategies and management schemes.

In [165]:

- 1 Problem: Develop an energy efficient management scheme for a large network with minimum impact on system performance.
- 2 Approach: Cloud application behavior at a given instant is considered. Performance state and power state are adapted to meet the application's demand. Specifically: DVFS and VM consolidation are used in the proposed orchestrator to reduce power consumption.
- 3 Developments
 - (a) developed an energy-efficient cloud orchestrator (e-eco) which opts for an appropriate management scheme;
 - (b) the proposed strategy allows VM consolidation for hosts running at low CPU usage rate when images of VMs are centralized. It is an energy efficient technique as it only requires memory pages to transfer through the network. However, when VM images are only available where they were initialized, it is preferred to reduce the processor's frequency using DVFS to save energy.
 - (c) In comparison to previous studies, e-eco reaches the same energy saving rates with far less impact on the application performance. Performance trade-off between power saving and SLA violation was about 25% and 6%, respectively.

In [164]:

1	1	Problem: Energy efficient orchestration tool for VM consolidation in cloud.	1
2	2	Approach	2
3	(a)	Heuristics and meta-heuristics are applied to obtain algorithms based on	3
4		Greedy Bin Packing (GBP) and Multi-Commodity Flow (MCF) to tackle VM	4
5		placement.	5
6	(b)	Input regarding state of resources (idle/used) is required to tackle consolidation.	6
7	3	Developments	7
8	(a)	An optimal solution for VM placement and its network paths (required band-	8
9		width for consolidation) is found.	9
10	(b)	Different approaches for consolidation categorized as max power saving (ag-	10
11		gressive), balanced load and max performance (less aggressive), are proposed	11
12		based on the power and performance tradeoff.	12
13	(c)	Consolidation strategies are assessed. For example, in critical and latency sen-	13
14		sitive applications, a less-aggressive consolidation approach (i.e. using maxi-	14
15		mum available servers) shows better performance, although energy efficiency	15
16		is compromised to some extent in this case. Aggressive consolidation (i.e. al-	16
17		locate maximum VMs to a single server) saves the maximum energy while	17
18		maintaining the performance when VMs are not fully (100%) utilized.	18
19	(d)	VM consolidation (supported by context information from users) helps in re-	19
20		ducing the power consumption if some idle VMs are present in the system.	20
21		The algorithm groups all idle VMs together and places them on the server with	21
22		lowest power state to reduce power consumption.	22
23			23
24	6.1.2	Real-time control: Schedulers	24
25		In automated virtualized environments, scheduling is a set of activities in the control plane,	25
26		guided by a management policy, that instantiates, monitors, migrates and terminates the	26
27		virtual machines and/or containers which encapsulate the workload. One useful implemen-	27
28		tation of a power-aware scheduler would operate either to minimize a (cost) function of	28
29		power under service constraints or a multi-objective function of power and some key per-	29
30		formance indicator.	30
31		In [170],	31
32	1	Problem: how to schedule dynamically arriving tasks among VM.	32
33	2	Approach	33

- 1 (a) A bias in favor of variants of Round-Robin scheduling is adopted. 1
- 2 (b) Heuristics and meta-heuristics are applied to obtain algorithms based on vari-2
- 3 ants of Round-Robin scheduling. 3
- 4 3 Developments 4
- 5 (a) An algorithm is proposed, that combines classical Round Robin and Weighted5
- 6 Round Robin for scheduling of dynamically arriving tasks among VMs. 6
- 7 (b) Furthermore, Improved Weighted Round Robin (IWRR) is proposed. The static7
- 8 scheduler in IWRR considers the task length, priority, resource capacity (sup-8
- 9 ply) and load (demand) on VMs to allocate a task to an appropriate VM. 9
- 10 (c) To further optimize system performance, a dynamic scheduler monitors the10
- 11 system status. It balances the load among VMs on completion of each task. In11
- 12 this way, unbalanced resource usage that may occur because of poor estimation12
- 13 of task completion time or processing delay can be fixed immediately. 13
- 14 In [91], 14
- 15 1 Problem: how to deal with dynamic load and resource management in virtualized15
- 16 environments. 16
- 17 2 Approach 17
- 18 (a) Model bias favors a discrete state transition model, employing the following18
- 19 state variables: 19
- 20 i. server power state (on/off) 20
- 21 ii. number of VMs 21
- 22 iii. frequency of operation of vCPU 22
- 23 (b) Employs a non-linear power model. 23
- 24 3 Developments: A predictive controller for virtual systems based on a non-linear24
- 25 power model and a discrete state transition model is obtained. The processor is25
- 26 switched among the various states during runtime, to balance the workload among26
- 27 different virtual machines. 27
- 28 4 Limitations: This model is unsuitable for a large state space, as this would make28
- 29 scheduling and design complex. 29
- 30 30
- 31 6.1.3 Real-time control: Server Power Capping 31
- 32 We demonstrate how models are applied to server power capping by parsing one relevant32
- 33 RU using the IPAD review protocol. 33

1	In [162],	1
2	1 Problem: host power capping in a dynamic environment.	2
3	2 Approach	3
4	(a) Power model: employs a model that relates the effect of hyper-threading and	4
5	processor fan speed to VM power consumption.	5
6	(b) Attribution: to attribute fan power consumption fairly among all VMs, each	6
7	VM's share is found using the dynamic power behavior for each virtual ma-	7
8	chine.	8
9	(c) Migration: a host near its power threshold is detected with assigned maximum	9
10	and minimum power of the server. The VM to migrate is chosen by monitoring	10
11	its dynamic power and its effect on server power after migration. The virtual	11
12	machine selected for migration is that with the least dynamic power necessary	12
13	to reduce its host's power consumption below an upper threshold. The VM	13
14	consuming least dynamic power is chosen as this correlates positively with the	14
15	least time to migrate.	15
16	3 Developments	16
17	(a) Modeling: the study found that the varying power consumption of a fan changes	17
18	the power consumption of a server.	18
19	(b) Results show that this power measurement scheme for virtual machines is ac-	19
20	curate enough to support effective server power capping through the use of VM	20
21	migration.	21
22		22
23		23
24	6.2 Billing	24
25	Fair billing of power consumption is enabled by granular tracking of the financial cost of	25
26	power consumption by resources (compute, storage and network) used by a customer. The	26
27	emphasis on usage is purposeful. Even with the earliest accounting method of billing by	27
28	active time, it was recognized that resource allocation does not impinge on an infrastruc-	28
29	ture provider's operating cost until it is active, i.e. in use. At such a level of granularity,	29
30	accounting is indiscriminate of power consumption. With respect to some referential time	30
31	period, whether the resource is active and idle or active and fully utilized, only the active	31
32	status affects the charge imposed on the customer. 'Pay-as-you-go' and even 'pay-as-you-	32
33	use' do not fairly charge users, as these billing models do not consider the workload on the	33

¹processor or consumed resources. These models charge equally for users having similar¹
²VM configuration even if they utilize different CPU percentages. ²

³ For example, consider the case where two users use a similar VM in the cloud but run³
⁴different applications, say, a web server and a CPU-intensive workload, respectively. The⁴
⁵VM running the web server will use around 5% of the CPU whereas the other VM might⁵
⁶use 90% of the CPU resources. ‘Pay-as-you-go’ will charge the same price to both users⁶
⁷despite both having distinct workload profiles and consequently, energy consumption. ⁷

⁸ This is gratingly unjust and calls for remedial action. Indeed, significant effort has been⁸
⁹brought to bear in at least two channels of effort: the academic, wherein modeling and⁹
¹⁰measurement is the primary means to enable a fair billing application, and the industrial,¹⁰
¹¹where, concurrently, efforts to harness academia’s (and industry’s) developments in this¹¹
¹²space are under way in the form of a green abstraction layer for virtualized environments.¹²
¹³A brief review of these two channels follows. ¹³

¹⁴ ¹⁴
¹⁵*Development within academia* We observe firstly several works directed specifically at¹⁵
¹⁶coupling power consumption, virtual resource usage and accounting for costs. Here, the¹⁶
¹⁷intention is not solely to relate virtual resource usage and the ensuing power consumption¹⁷
¹⁸but rather a more ambitious infrastructural combination of measurement and cost into a¹⁸
¹⁹single system. ¹⁹

²⁰ In [171], ²⁰

²¹ 1 Problem: how to move away from fixed billing, based on VM size and duration of²¹
²²usage, to billing cost for service based on CPU/resource usage. ²²

²³ 2 Approach: a cost model named ‘Proportional-Shared Virtual Energy (PSVE)’ is con-²³
²⁴ceived of for VM instances. It is a composite of CPU energy consumption and tradi-²⁴
²⁵tional commodity prices, such as management and operational cost of hypervisor. ²⁵

²⁶ 3 Developments ²⁶

²⁷ (a) Considering the CPU usage knowledge available at hypervisor, a proportional²⁷
²⁸energy-cost sharing model for a VM can be developed. ²⁸

²⁹ (b) The proposed model can also be used to evaluate the efficiency of services²⁹
³⁰by service providers and to develop optimized applications to reduce energy³⁰
³¹consumption. ³¹

³²*Industrial Development/Green Computing* Industrial effort is visible in extension of the ³²

³³European standard for green abstraction of non-virtualized environments [172] to virtual-³³

¹ized environments. This second version of the standard [173] for a green abstraction layer¹
²aims to facilitate the development of software for automation of control and accounting²
³functions. It is tightly integrated into ETSI's group of specifications on management and³
⁴orchestration of virtual functions, e.g. [174], adhering to the architecture described therein.⁴
⁵Along with improving architecture for green computing, use of renewable energy sources⁵
⁶(RES) to operate cloud datacenters is also proposed. Renewable energy generators using⁶
⁷solar panels were installed at datacenters located in different geographical locations [175].⁷
⁸These datacenters have been using a flexible load management tool, EcoMultiCloud [176],⁸
⁹that balances the load considering objectives such as energy cost variation and renewable⁹
¹⁰energy production in the region at a particular time. Performance evaluations show that¹⁰
¹¹use of RES in a distributed datacenter network can save energy cost significantly without¹¹
¹²compromising on performance. 12

13

13

¹⁴6.3 Macroscopic analyses 14

¹⁵Digital services (online news sites, video over-the-top, voice-over-IP as in 4G cellular¹⁵
¹⁶networks) and telecommunications systems (e.g. centralized/cloud radio access network,¹⁶
¹⁷evolved packet core service gateway) are the object of several optimization studies that are¹⁷
¹⁸too broad in scope to afford the computational weight of granular power models of the¹⁸
¹⁹kinds described in the paragraphs of section 3.3.1. These studies estimate power consumed¹⁹
²⁰to meet demand for a service-/system-specific workload. The objective is the investigation²⁰
²¹of the impact of infrastructural alternatives on power consumed to meet the temporally –²¹
²²and possibly geographically – variable load profile. An understanding at a macroscopic²²
²³level is sought of the effect of some change in the composition of the digital service, on the²³
²⁴power consumption. 24

²⁵ The approach towards understanding includes: 25

- ²⁶ • identification of a unit of workload, and 26
- ²⁷ • a temporal (and possibly geographical) profile of the demand (load) for the service 27

²⁸ We have referred to a complex characterization of workload as a means to “quickly pro-²⁸
²⁹ceed to a good estimate of the power or energy required to produce the workload” (sec-²⁹
³⁰tion 4.1.5). Such an approach abstracts real-time operation of a computing or telecommuni-³⁰
³¹cations (sub-) system, by reducing the characterization of the power-performance relation-³¹
³²ship of its major components to a conservative ratio of power consumed to produce a unit 32
³³of workload. Therefore, the aim of such research is not to facilitate real-time energy-aware 33

¹control (through the development of models of real-time, dynamic power consumption)¹
²but to justify the use of an (alternative) architecture, organization or implementation. Two²
³examples are described briefly below. 3

⁴ In [31], the concern regards whether a telecommunications system built around virtual⁴
⁵network functions (VNFs) can readily be claimed more energy efficient than one built⁵
⁶around physical network functions (PNFs). A case study is undertaken with a focus on⁶
⁷the evolved packet core's (EPC) serving gateway (SGW). Part of the modus operandi of⁷
⁸this application of power modeling is explicitly declared in [31]: 8

⁹ 1 a mathematical model, and 9
¹⁰ 2 the energy consumed to meet 10
¹¹ 3 the performance levels demanded of the SGW. 11

¹² The "performance levels demanded" are derived from the workload. Therefore, a profile¹²
¹³of workload is required, to determine the performance of the system components over a¹³
¹⁴temporal (and possibly geographical) range. The conjunction of a temporally unfolding¹⁴
¹⁵workload and power consumed to meet this workload lead to the energy consumption.¹⁵
¹⁶Hence, a figure of merit can be ascribed: the *energy consumed to process the workload* is¹⁶
¹⁷an indicator of energy efficiency. 17

¹⁸ The missing piece in this puzzle is how to "fit" the workload into the investigated (sub-)¹⁸
¹⁹system (this is the first phase) and therefrom, to its power consumption (this is the second¹⁹
²⁰phase). Herein lies the key abstraction inherent to the macroscopic analysis. 20

²¹ 1 Phase 1: the maximum throughput of a server bridges the gap between hardware and²¹
²²workload. 22

²³ 2 Phase 2: transforms a performance level into a power consumption. 23

²⁴We identify this two-phase transformation, from workload to power consumption, as a²⁴
²⁵model in the highest of the three levels of abstraction into which we have classified power²⁵
²⁶models earlier (section 4.1.5). 26

²⁷ In this particular example, the maximum throughput is bound (reasonably, albeit sweep-²⁷
²⁸ingly) to the maximum power consumption of the implementing device. The VNF is im-²⁸
²⁹plemented on a commodity-off-the-shelf (COTS) server. The PNF is implemented as a²⁹
³⁰chassis-bound SGW. 30

³¹ In [123], 31

³² • the telecommunications sub-system is a centralized- (cloud-) radio access network 32
³³(C-RAN); 33

- the workload consists of a volume of baseband signal processing at the virtual baseband unit (vBBU).

The baseband signal processing function is divided into four transmission steps (coding, modulation, mapping and multiple-input-multiple-output processing, followed by a Fast Fourier Transform); there are also the inverse four reception steps.

1 First phase: each step loads a single vBBU with a certain amount of a unit of operation: one million operations per time slot (1 MOPTS). Thus: the computing hardware that performs any one of the four steps, is reduced to a capacity in terms of MOPTS.

2 Second phase (transform performance into a demand for power): transforms the operation of the vBBU to a power consumption that is partly independent of baseband-signal-processing-load (“static”) and partly directly proportional to this load (“dynamic”)

Given these abstractions, and provided that realistic figures can be sourced to represent the second-phase transformation, then the power demands of a load profile can be estimated. Here, the ultimate objective is not the power consumption estimate itself, but a comparison with alternative algorithms for dispatching the steps of baseband signal processing to the vBBUs in a pool.

7 Appendix - The Engineer’s Kit Bag

7.1 Observations on tools

This section presents the researcher with a summary on the usability of different components required for designing a power model. We cover choice of workload and relevant benchmarks, as well as various tools and models frequently used in research studies. Fig. 24 - Fig. 26 show a frequency analysis of the occurrence of these components, extracted from the studies included in this survey. Furthermore, reference to the corresponding research studies can be found in Table 7 - Table 8.

7.1.1 Workload Generators/Benchmarks

Reliability of studies, analyses and models depends heavily on (a) the environment and (b) workload considered. Setting up the environment is simple compared with finding an appropriate workload. A benchmark suite that stresses different aspects of processor (such as computing, memory, and network) in a ratio similar to, and has a computing requirement similar to that of real-time applications in datacenters should be considered.

¹ The Standard Performance Evaluation Corporation (SPEC) provides a number of bench-¹
²marks for different applications and performance evaluation. SPEC CPU benchmarks are²
³industry standards and well accepted in research studies [92]; this is affirmed by our³
⁴frequency analysis (fig. 24). For cloud applications, benchmark suite SPEC Cloud IaaS⁴
⁵[92, 177] stresses resource provisioning, storage, network resources and computation. To⁵
⁶generate a server workload, SPEC Web [178] can be used. An energy efficiency benchmark⁶
⁷for scalable virtual networks, based on SPEC power methodology [177], is also designed⁷
⁸specifically for VNF applications. 8

⁹ Cloud providers and cloud sites are also being evaluated through benchmarks. A re-⁹
¹⁰port [179] shows that the BitCurrent benchmark was used to evaluate nine different cloud¹⁰
¹¹providers. Another study used CloudHarmonics [180] to evaluate 144 different cloud sites.¹¹
¹²In an evaluation of cloud performance models and different cloud benchmark suites on¹²
¹³Amazon EC2 [181], BenchCloud was found to be one of the five widely-used benchmarks.¹³
¹⁴BenchCloud was developed in academia at the University of Southern California (USC).¹⁴
¹⁵It contains a workload from real-time social media applications for big data processing.¹⁵
¹⁶Another benchmark from academia is CloudSuite, developed at EPFL, Lausanne, Switzer-¹⁶
¹⁷land. The workload pattern for CloudSuite is based on media streaming, web services¹⁷
¹⁸and data/graphic analytics. Two industry-based workload patterns generated by Yahoo and¹⁸
¹⁹Transaction Processing Performance Council (TPC) are YCSB and TPC-W, respectively.¹⁹
²⁰TPC-W is a webserver-based benchmark; YCSB is a synthetic workload for cloud ser-²⁰
²¹vice evaluation developed by Yahoo. HiBench is a workload developed specifically to run²¹
²²Hadoop programs in clouds. 22

²³ Selection of a benchmark suite for evaluating modern processors must consider support 23
²⁴for processor features, e.g. multi-core/single core, simultaneous multi-threading (e.g. Intel 24
²⁵Hyper-Threading) and dynamic overclocking (e.g. Intel Turbo Boost), etc. Workload pat- 25
²⁶terns of different benchmarks may also include the facility to select between serial stressing 26
²⁷and parallel stressing. We observe that the analysis of multi-core systems using several in- 27
²⁸stances of serial benchmark suites (e.g. SPEC CPU) is not preferred: such instances will be 28
²⁹treated as multiple applications [182]. This further increases the energy consumption due 29
³⁰to unexpected contention for shared resources. Therefore, parallel benchmark suites such 30
³¹as NPB-MPI, PARSEC, etc., should be used to analyze the performance and energy/power 31
³²consumption of parallel processing. PARSEC is a benchmark which incorporates work- 32
³³loads suited to several different computer classes (e.g. servers, workstations) [93, 94, 182]. 33

¹NBP-MP is derived from NASA real fluid computational applications. It is suitable for tra-¹
²ditional HPC workloads [182]. We present our frequency analysis of occurrence of bench-²
³marks found in the RUs included in this survey, in figs. 24 and 25. ³

⁵7.1.2 Resource Monitoring Tools ⁵

⁶Several methods of monitoring performance are available which either observe parameters ⁷
⁸inside the VE or through its host [187]. Methods that monitor VE performance from outside ⁸
⁹a VE are known as black box methods. These use different software and hardware power ⁹
¹⁰meters to observe performance and resource usage. On the other hand, white box methods ¹⁰
¹¹run a proxy program inside the VE to collect resource utilization data. However, these ¹¹
¹²proxies can impact measurements. This is not considered in many studies. ¹²

¹³The survey in [187] found that black box methods using software meters and hardware ¹³
¹⁴counters are more reliable. Most software meters developed are used to monitor processor ¹⁴
¹⁵computing resources and network traffic which later help in developing the power model ¹⁵
¹⁶for virtual entities [105]. Since these meters run on the object of study they impose some ¹⁶
¹⁷overhead on the system; hence, their own resource consumption must also be considered ¹⁷
¹⁸[116]. Different software tools are designed to track and log microarchitectural registers and ¹⁸
¹⁹counters, to gain knowledge of processor resource consumption. Tools including OProfile ¹⁹
²⁰[188], PERF (ex – Performance Counters for Linux) and sysstat [189], are some examples. ²⁰
²¹They collect data about different processor resources such as cpu usage, cache misses, ²¹
²²memory access, storage and other performance metrics. Several power models have been ²²
²³developed using these tools, with some accounting for the effect of multi-core processors ²³
²⁴in their model. ²⁴

²⁵Considering available literature, Linux perf [190] is a widely-used performance-²⁵
²⁶monitoring tool; this latter observation is confirmed in [191]. ²⁶

²⁷It is integrated in the kernel, thus providing deep insight of system behavior. Fig. 27²⁷
²⁸shows a frequency analysis of occurrence of different tools found in research studies that²⁸
²⁹are part of this survey. PERF is the most widely used (tallest bar in the graph), followed by²⁹
³⁰Oprofile. ³⁰

³¹A new energy and performance monitoring tool 'Containergy' is developed in [90] using ³¹
³²the concept of software containers, that being light weighted incur less overhead. It uses ³²
³³the software containers, control groups, hardware performance counters and DVFS to as- ³³

Table 7: Research studies corresponding to workload and benchmark used

Workload	Bibliography reference	Frequency
Stress	[50, 54, 57, 70, 76, 77, 84, 109, 183]	9
PrimeSearch	[184]	1
LAMP (Linux, Apache, MySQL, and PHP)	[184]	1
RandMem	[142] [71]	2
MemSpeed	[142]	1
gzip	[142]	1
wordcount	[142, 181]	2
Benchmark	Bibliography reference	Frequency
Standard Performance Evaluation Corporation (SPEC)	[47, 52, 56, 72, 75, 87, 92, 106, 131, 132, 142, 177, 177, 185, 186]	14
Princeton Application Repository for Shared-Memory Computers (PARSEC)	[93, 94, 182]	4
NAS Parallel Benchmarks (NAS NBP)	[68, 91, 96, 182]	4
BitCurrent		1
CloudHarmonics		1
BenchCloud	[181]	1
CloudSuite	[133, 135, 181]	3
Yahoo! Cloud Serving Benchmark (YCSB)	[181]	1
Transaction Processing Performance Council - Web Benchmark (TPC-W)	[181]	1
HiBench	[181]	1
Iozone	[68, 96, 142]	3
RuBBoS bulletin board	[60]	1
Apache	[60, 131]	2
Tbench	[60]	1
Multi-core Processor Architecture and Communication (MPAC)	[79]	1
Iometer	[87]	1
NBench (BYTEMARK)	[74, 96]	2
Fhourstone	[74]	1
Dhrystone	[74]	1
Ubench	[74]	1
Snort	[97]	1
TCPReplay	[97]	1
Bonnie++	[91, 96]	2
GCC	[91, 96]	2
CacheBench	[96]	1
Dense Matrix Multiplication	[96]	1
ParFullCMS	[109]	1
Sustainable Memory Bandwidth in High Performance Computers (STREAM)	[109, 184]	2
Mediabench	[54]	1
Embedded Microprocessor Benchmark Consortium (EEMBC)	[54]	1
sysbench	[142]	1

sess the running applications. The effectiveness of the tool is tested using high computing applications such as machine learning for image classification and video transcoding.

Another tool for process-level power monitoring of virtual entities is developed in [192], known as 'BitWatts'. This middleware tool accesses the hardware level RAPL counter for each VM and its running processes. These collected counter values are then transmitted to respective VMs via the fast communication channel VirtioSerial. This fast channel communication reduces the synchronization error and makes the tool useful for real time power monitoring of VM processes.

Moreover, algorithms and languages chosen for designing a software meter also have significant impact on power consumption [183]. This study finds that recursive algorithms are more energy efficient than the iterative ones. Furthermore, a test program was implemented using various programming languages. Implementations of tools in C and C++ are the most energy efficient. Implementations in other languages consumed significantly more energy. Perl consumes the most, followed by OCaml, Python and Prolog. For comparison's sake: the Perl implementation consumed 25516 J in this study, while the most energy-efficient implementation (C++) consumed just 53 J (C implementation: 54.5 J).

Notwithstanding improvements in software power meters, none is as precise as external hardware meters (e.g. Raritan Dominion PX-5367: error +/-1%, precision 0.1 W). Evidently, these meters cannot be applied directly to measurement of virtual entities' power consumption and cannot be used to make quick energy-aware decisions in scheduling, etc. On the other hand, they can be used to validate power models. Hence, whatever power model is developed, validation using external power measurements as the ground truth is important.

7.2 A brief methodology: observations on formal methods

We refer to methodology here in the classical sense: a study of alternative methods used for modeling, with the intention of picking the method most suited to the task at hand. A cross-section through modeling methods found in RUs is presented first (section 7.2.1), followed by our recommendations on model selection (section 7.2.2).

7.2.1 A cross-section of modeling methods detected in RUs

The most common methods used to develop power models are linear models [70–72, 74, 75, 77, 187]. We have confirmed this in the statistics we have compiled (Fig. 26) from research studies included in this survey: linear models are far more numerous than the rest.

Table 8: Research studies corresponding to monitoring tools and modeling methods

Monitoring tools	Bibliography reference	Frequency
iptraf	[79]	1
Zabbix	[50, 84, 85]	3
Joulemeter	[87, 106, 141]	3
cWatt+	[93, 94]	2
Oprofile	[91, 96, 188, 191]	4
PERF	[72, 76, 77, 142, 189–191]	7
Gwatt	[124, 193]	2
Trepp Profiler	[114]	1
Ceilometer	[161]	1
SimplePower	[46]	1
Wattch	[47]	1
ipmitool	[185]	1
top	[142]	1
sysstat	[189]	1
Powerapi	[183]	1
cpustat	[185]	1
Brink/Abyss	[56]	1
iostat	[185]	1
Modeling methods	Bibliography reference	Frequency
Integer linear Programming Formulation (ILP)	[186]	1
Gaussian Mixture Vector Quantization (GMVQ)	[75]	1
Linear Regression (LR)	[49, 50, 54, 56, 70–72, 74–77, 84, 91, 106, 109, 185]	16
Autoregressive Integrated Moving Average (ARIMA)	[50, 70, 84, 86]	4
Polynomial Regression (PR)	[50, 88, 142]	3
Artificial Neural Network (ANN)	[97, 106]	2
Support Vector Recognition (SVR)	[76, 77, 91]	3
Random Forest (RF)	[108]	1
Migration Energy Aware VNF Reconfiguration (MEAVR)	[186]	1
Gaussian Process Recognition (GPR)	[76]	1
New-minimum bin slack (NMBS)	[123]	1
First Fit Decreasing (FFD)	[134]	1
Interquartile Range (IQR)	[134]	1
Generalized Additive Model (GAM)	[109]	1

¹Linear models are the simplest and are acceptable in most cases; they are used by many¹
²researchers. Examples of such methods include Least Squares Estimation (LSE), Lasso,²
³Mantis, etc. 3

⁴However, the statistics also show that some research is seeking alternatives to linear re-
⁵gression as a means of fitting relationships between power and its determinants. Non-linear
⁶models such as Polynomial Regression, Multi-Gaussian Regression and Exponential Re-
⁷gression are also being used [50, 76, 88, 142]. More complex processors show non-linear
⁸behavior when power management is exercised. 8

⁹
¹⁰The following studies used different modeling methods to improve precision of server
¹¹power models. 11

¹²1 **Elman Neural Network.** The dynamic traffic behavior in cloud computing and data-
¹³centers causes heterogeneity in the network, which therefore cannot rely on a power
¹⁴model based on a particular workload. This requires the use of reinforcement learn-
¹⁵ing for continuous improvement of the model with the changing computing and
¹⁶networking environment. One approach uses an Elman Neural Network (ENN) to
¹⁷estimate the power consumed by servers in the cloud [106]. The ENN consists of
¹⁸input, output and state (instead of hidden) layers, where the state layer is a com-
¹⁹bination of several hidden layers with local feedback within these hidden layers.
²⁰This local feedback helps the model to learn the temporal pattern of the dataset for
²¹the specified time interval, which is neglected in other regression methods. Server
²²resources such as CPU utilization, memory and disk usage, and I/O request rate
²³are fed as inputs to model the power consumed. Two hyper-parameters – number
²⁴of neurons in the state layer and setback time of Back Propagation Through Time
²⁵(BPTT) – are optimized for training. When this model was used to estimate power
²⁶consumption for two different servers, it showed better accuracy than other exist-
²⁷ing Artificial Neural Networks (ANN) and regression models. In [42], application
²⁸of artificial neural network (ANN) for power modeling shows enhanced accuracy.
²⁹Neural networks with one and two hidden layers are used. Weights and biases to
³⁰the neurons are assigned uniformly through Nguyen-Widrow algorithm, and training
³¹is performed using Levenberg-Marquardt algorithm which corrects the model based
³²on mean squared error. To reduce the complexity and computation, the number of
³³variables is further reduced using the forward selection method. 33

- 1 2 **Generalized Additive Models.** It is also evident from the literature that servers with¹
2 different configurations and multi-core functionality may possess linear or non-linear²
3 behavior in their power consumption depending on the offered load. Hence, differ-³
4 ent studies suggest both linear and non-linear regression methods to develop a power⁴
5 model for the server. One such study used Simple Linear Regression and Generalized⁵
6 Additive Models (GAM) to estimate the power consumption of the server under dif-⁶
7 ferent load conditions [109]. RAPL counters were used to collect the training data.⁷
8 Later, the accuracy of power estimation for different servers was compared using⁸
9 an external power meter as ground truth. The model was developed for memory-⁹
10 intensive applications, using the memory statistics and power consumption as the¹⁰
11 predicted and response variable, respectively. Since the power profile of the server¹¹
12 had some non-linearity, GAM predicted power of the server more precisely in the¹²
13 non-linear region than the linear model. 13
- 14 3 **Various other machine-learning-based models.** It is challenging to predict real-time¹⁴
15 (runtime), optimal, task scheduling with DVFS and Dynamic Power Management¹⁵
16 (DPM) enabled. Hence, machine learning based models are preferred, as they can be¹⁶
17 trained and adapted. Ordinary Least Squares (OLS), Support Vector Machine (SVM),¹⁷
18 ANNs, Naive Bayes, Multinomial Logistic Regression (MLR) are some of the many¹⁸
19 supervised learning methods that have been used in different environments to opti-¹⁹
20 mize runtime scheduling [194]. Considering the dynamic behavior of servers, differ-²⁰
21 ent reinforcement learning (RL) methods are also being used. Reinforcement learn-²¹
22 ing algorithms such as Q-learning, On-line distributed, Modular Q-learning, Back²²
23 Propagation Neural Networks (BPNN) and Multi-Level RL (MLRL) are mostly used²³
24 to minimize the energy consumption of the server while continuously improving the²⁴
25 model [194]. These reinforcement models have been found effective in power man-²⁵
26 agement of datacenters through consolidation and optimal VM allocation. 26
- 27 4 A new Locally Corrected Multiple Linear Regression (LC-MLR) power model is²⁷
28 proposed in [195], which is an extension to an existing MLR method with additional²⁸
29 error correction. The error correction term is dependent on a linear function of each²⁹
30 resource utilization, obtained using the slope and intercept of the selected resource³⁰
31 interval. The resource interval is the interval between two consecutive points in the³¹
32 dataset which is selected by locating the particular consumed resource at any in-³²
33 stance. In another study [187], researchers apply the tree regression method on the³³

collected datasets which is further improved by feeding new data. The basic idea¹
 is to create a tree by dividing the dataset into different partitions until there is no²
 proper feature found in a newly created partition. Each partition has a set of features³
 (chosen metric such as CPU utilization, LLC cache miss, etc.) and its corresponding⁴
 value. This tree regression model is further optimized through tree pruning, where⁵
 the tree model is tested against new datasets to merge some branches and leaf nodes,⁶
 resulting in enhanced accuracy of the model. ⁷

⁹ 7.2.2 *Selecting a modeling approach* ¹⁰

¹¹Architecture, system deployment, and workload patterns in computing environments are¹¹
¹²so diverse that no one modeling approach and method can be a universal solution for all¹²
¹³circumstances. However, for the selection of a model, diagnostic measures are needed to¹³
¹⁴assess its reliability. ¹⁴

¹⁵ The basic rule of thumb is to select the simplest model and only move to a more complex¹⁵
¹⁶one if the desired accuracy is not met. The dataset itself contains information such as mul-¹⁶
¹⁷ticollinearity, number of outliers, size of dataset, non-linearity, etc. that points towards the¹⁷
¹⁸right choice. The nature of data points, that is whether the input variables are independent¹⁸
¹⁹of each other or not, is one important factor. ¹⁹

²⁰ Analyzing the relationship between input and output variables is also useful to find an²⁰
²¹appropriate method. If the relationship between the two is continuous and linear, simple²¹
²²linear models could be effective. ²²

²³ The size of the dataset also plays a role. For some complex models, computation time ²³
²⁴can increase exponentially. Hence, for big data analysis, clustering, classification algo- ²⁴
²⁵rithms, frequent pattern mining are some techniques to divide the dataset into smaller sets ²⁵
²⁶and make it feasible for data analysis [196]. Moreover, big data require traditional ma- ²⁶
²⁷chine learning algorithms to be modified so they can work in parallel computing environ- ²⁷
²⁸ments. Machine learning algorithms generally used for big data analysis are evolutionary ²⁸
²⁹algorithms, regression trees, and neural networks. Among these, evolutionary algorithms ²⁹
³⁰like genetic algorithm, swarm intelligence, and ant clustering are considered more robust ³⁰
³¹as their sub-populations can run on parallel computing resources. Hence, these modeling ³¹
³²methods reduce computation time when run on a GPU, instead of a CPU, on a parallel ³²
³³computing platform. ³³

¹ The ratio of size of the dataset and number of input features is also important to assess¹
²before moving forward. Studies suggested that a single increment in the number of input²
³features might lead to an exponential growth in the dataset [197, 198]. With multiple in-³
⁴put features, the dataset must be big enough to avoid the drawback of a form of 'curse of⁴
⁵dimensionality' that may occur in ML, where increasing dimensions of the feature space⁵
⁶increase the processing power for data analysis, along with the amount of training data to⁶
⁷reach a given model accuracy. Other options could be to reduce the number of features⁷
⁸based on statistical information such as Principal Component Analysis (PCA), probabil-⁸
⁹ity value (p-value), correlation, stepwise regression, and vector quantization and mixture⁹
¹⁰models [198–200]. 10

¹¹ When the relationship among input and output variables is far more complex to identify¹¹
¹²using collected data points, non-parametric methods could be useful. Instead of learning¹²
¹³patterns of given data points, these models generate different distributions to extract more¹³
¹⁴useful information. An example of one such method is Gaussian Process Regression, that¹⁴
¹⁵creates the Gaussian distribution for the set of selected data points. 15

¹⁶ We thus observed that no one method is perfect for modeling in all cases. Model accuracy¹⁶
¹⁷depends on the right choice of modeling method, via thorough assessment of raw data and¹⁷
¹⁸post processing methods available. 18

¹⁹ 19

²⁰Abbreviations 20

²¹		21
²²	ACPI	Advanced Configuration and Power Interface 22
²³	AF_XDP	Address Family eXpress Data Path 23
²⁴	AI	Artificial Intelligence 24
²⁵	AlaaS	AI-as-a-Service 25
²⁶	AR	Adaptive Rate 26
²⁷	BMAP	Batch Markov Arrival Process 27
²⁸	BSS	Business Support System 28
²⁹	CAGR	Compound Annual Growth Rate 29
³⁰	CNF	Containerized Network Function 30
³¹	CO	Central Office 31
³²	COTS	Commodity-Off-The-Shelf 32
³³	CPU	Central Processing Unit 33
	CRAN	Centralized/Cloud Radio Access Network 33
	CRM	Customer Relationship Management 33
	DAG	Directed Acyclic Graph 33
	DDIO	Data Direct Input/Output 33
	DPDK	Data Plane Development Kit 33
	DSA	Domain-Specific Architecture 33
	EPC	Evolved Packet Core 33

1	ETSI	European Telecommunications Standards Institute	1
2	FLPA	Functional-Level Power Analysis	2
	GAM	Generalized Additive Model	
3	GBP	Greedy Bin Packing	3
4	GPU	Graphics Processing Unit	4
	HEVC	High Efficiency Video Coding	
5	ICT	Information and Communication Technology	5
	IDS	Intrusion Detection System	
6	IN	Intermediate Node	6
7	IPr	Infrastructure Provider	7
	ISP	Internet Service Provider	
8	KVM	Kernel Virtual Machine	8
9	L2	Layer 2 (or Level 2)	9
	L3	Level 3	
10	LLC	Last Level Cache	10
	LPI	Low Power Idle	
11	LXC	Linux Containers	11
12	MANO	Management and Orchestration	12
	MCF	Multi-Commodity Flow	
13	MEC	Multi-access edge computing	13
14	MIPS	Millions of instructions per second	14
	ML	Machine Learning	
15	MOPTS	Million operations per time slot	15
	MOS	Metal-Oxide-Semiconductor	
16	NANOG	North American Network Operators' Group	16
17	NFV	Network Function Virtualization	17
	NIC	Network Interface Card	
18	NUMA	Non-Uniform Memory Architecture	18
19	O&M	Operation, administration, maintenance and management	19
	OPEX	Operational Expenditure	
20	OS	Operating System	20
21	OSS	Operational Support System	21
	OvS	Open Virtual Switch	
22	PAD	Problem-Approach-Development	22
	PDU	Power Distribution Unit	
23	PMC	Performance Monitoring Counter	23
24	PNF	Physical Network Function	24
	PoP	Point of Presence	
25	PTN	Public Telecommunications Network	25
26	PTNO	Public Telecommunications Network Operator	26
	QAT	Quick Assist Technology	
27	RAPL	Running Average Power Limit	27
28	RES	Renewable Energy Sources	28
	RRH	Remote Radio Head	
29	SBA	Service-Based Architecture	29
	SDN	Software-Defined Networking	
30	SGW	Serving Gateway	30
31	SLA	Service-Level Agreement	31
	SMT	Symmetrical Multithreading	
32	SoC	System-on-Chip	32
33	SPEC	Standard Performance Evaluation Corporation	33

1	SPOF	Single Point of Failure	1
2	SRIA	Strategic Research and Innovation Agenda	2
	SR-IOV	Single-Root Input/Output Virtualization	
3	SVM	Support Vector Machine	3
4	TCO	Total Cost of Ownership	4
	TCP	Transmission Control Protocol	
5	TOE	TCP Offload Engine	5
	vBBU	Virtual Baseband Unit	
6	vCPU	Virtual Central Processing Unit	6
7	VDU	Virtual Deployment Unit	7
	VE	Virtual Entity	
8	VM	Virtual Machine	8
9	VNF	Virtual Network Function	9
	VNFD	Virtual Network Function Descriptor	
10	VNI	Virtual networking index	10
11	WSC	Warehouse Scale Computing	11
12			12
13			13
	Availability of data and materials		
14	The dataset supporting the conclusions of this article is available in the PowerMeasurementAndModelingRawData		14
15	repository, where we present all triads (Triads.xlsx) mined from the corpus. This is the data which was digested to produce		15
16	the statistics shown in section 3. The repository also carries a second file (NodeAttributes.xlsx), which tabulates the		16
17	number and label attributes of the nodes.		17
	Competing interests		
18	The authors declare that they have no competing interests.		18
	Authors' contributions		
19	Etienne-Victor Depasquale contributed to the conceptualization of this paper, the methodology, formal analysis,		19
20	investigation, resources, writing of the original draft, data curation and visualization.		20
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23 Figures

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Figure 2: A taxonomy of detected approaches, coherent with the scientific method

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Figure 3: A top-level division of the developments, with frequency of occurrence shown as percentage

Figure 4: A taxonomy of power models, with frequency of occurrence shown in line thickness and as percentage

Figure 6: Approaches to solving challenges in category P1; utility metric U_{A_k} shown in line thickness and as percentage

Figure 7: A directed acyclic graph showing the distribution of research into power measurement & power consumption models in virtualized networking and computing environments

Figure 11: Approaches to solving challenges in category P2; utility metric U_{A_k} shown in line thickness and as percentage

Figure 12: Approaches to solving challenges in category P3; U_{A_k} shown in line thickness and as percentage

Figure 13: Approaches to solving challenges in category P4; utility metric U_{A_k} shown in line thickness and as percentage

Figure 14: Approaches to solving challenges in category P5; utility metric U_{A_k} shown in line thickness and as percentage

Figure 15: Approaches to solving challenges in category P6; utility metric U_{A_k} shown in line thickness and as percentage

Figure 16: Approaches to solving challenges in category P7; utility metric U_{A_k} shown in line thickness and as percentage

Figure 17: Approaches to solving challenges in category P8; utility metric U_{A_k} shown in line thickness and as percentage

Figure 20: Approaches to solving challenges in category P11; utility metric U_{A_k} shown in line thickness and as percentage

Figure 21: Approaches to solving challenges in category P12; utility metric U_{A_k} shown in line thickness and as percentage

Figure 22: Approaches to solving challenges in category P13; utility metric U_{A_k} shown in line thickness and as percentage

Figure 23: An overview of the thematic analysis of the research space

Figure 26: Frequency of modeling methods used in research studies included in this survey

Figure 27: Frequency of monitoring tools used in research studies included in this survey