Computer-Aided Design of Electrical Energy Systems

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Younghyun Kim[†], Donghwa Shin[‡], Massimo Petricca[‡],
Sangyoung Park[†], Massimo Poncino[‡], and Naehyuck Chang[†]
[†]Seoul National University, Korea, {yhkim, sypark, naehyuck}@elpl.snu.ac.kr
[‡]Politecnico di Torino, Italy, {donghwa.shin, massimo.petricca, massimo.poncino}@polito.it

***Abstract*—Electrical energy systems (EESs) include energy generation, distribution, storage, and consumption, and involve many diverse components and sub-systems to implement these tasks. This paper represents a first step towards the computer-aided design for EESs, encompassing modeling, simulation, design and optimization of these systems. CAD for EESs is a challenging task that mandates a multidisciplinary and heterogeneous approach. We identify similarities and differences between electrical energy systems and electronics systems in order to inherit as much as possible the profound legacy resources of electronic design automation (EDA). We introduce fundamental concepts, from the general problem formulation to the development and deployment of efficient, scalable, and versatile CAD and EDA methods and framework for the optimal or near-optimal EESs.**

I. Introduction

Even in 2009 when the global financial crisis hit and worldwide electrical energy consumption slightly decreased, electrical energy consumption in China and India continued to rise in order to meet their high economic growth. Electrical energy consumption is steadily increasing all over the world; although the growth is driven mainly by rapidly growing countries in Asia, the consumption of industrialized countries still grows faster than the global average. This increase is in part sustained by the increasing number of plug-in electric vehicles (PEVs). An analysis reports that, in California, 5,400 MW additional power generation capacity is required to support the worst case charging scenario that a simultaneous and uncontrolled charging rate of 1.8 kW per vehicle, and it indicates that it is hard to be met during peak hours in summer [1]. Another worst case analysis shows that 160 new large power plants would be needed in the US when people charge their PEV at the same time at 5 PM at 6 kW charge rate, assuming a 25% PEV proportion among all vehicles [2]. Although these are the worst case scenarios, it is true that the emergence of PEV is a big challenge for the electrical grid.

On the other hand, electrical energy production becomes more difficult nowadays; traditional fossil-fuel power plants are environmentally undesirable, and nuclear power plants are facing struggles due to safety issues. Alternative energy sources that produce electricity in a more environmentally-friendly way are becoming increasingly popular thanks to active financial aid from governments. Successful examples include solar energy and wind energy. However, distributed power generation from alternative energy sources, such as solar energy, wind energy, fuel cell energy, and so on, poses another challenge. They are all different in cost, dynamics, life-cycle, capacity, and so on, so finding the optimal size of each source is not a trivial problem [3]. Another emerging approach to solve the energy problems is the use of large-scale energy storage systems (ESSs). Such systems reduce the maximum power generation capacity demand by storing energy during non-peak hours and supplying the energy during peak hours. Demand side management (DSM) is a new concept of energy management to smooth mismatches in production and demand. The energy consumers actively increase or reduce power consumption based on energy producers' requirement, and the energy producers offer incentives for modified energy consumption [4], [5], [6]. This is often utilized for peak power demand reduction by moving demand to off-peak hours and reduces the need for investments in power generation and distribution. Both the ESSs and DSM require sophisticated management methods, which are not trivial. In short, recent efforts against the energy crisis, which involve emerging technologies in producing, storing, and consuming the energy, are making the electrical energy systems (EESs) more and more complex than before.

In spite of increasing complexity in designing and operating the EESs, systematic efforts to achieve the global optimality was not the main focus in the past. Currently, a large body of existing optimization strategies for EESs are based on search-based meta-heuristics such as genetic algorithm (GA), particle swarm optimization (PSO), simulated annealing (SA), and so on [7]. However, there is no guarantee that the best solution found by the meta-heuristics will be the optimal solution. In addition, the majority of these methods are based on "flat" simulation of the system, which is not very scalable for complex multi-scale systems. Current EES design methods will therefore face limits as the complexity of EES will increase.

Electronic design automation (EDA) originated as an outgrowth of an effort against the exploding complexity in electronic systems. Integrating billions of transistors on a chip is made possible by sophisticated design methods that allow designers to model, simulate, synthesize, and verify systems at various levels of abstraction. Scalable algorithms and tools have enabled the generation of complex integrated circuits and electronic systems from high-level, abstract specifications. Interestingly, since algorithms and flow in electronic CAD rely on abstract models, they can easily be adapted to solve similar problems in other domains. Modeling and design automation of biological circuits and systems is one example of such cross-fertilization [8].

In this paper, we discuss fundamental concepts toward application of EDA design methodologies for electronics systems design for the design of EESs. We first introduce in Section II various scales of EESs, and identify multiple abstraction levels.

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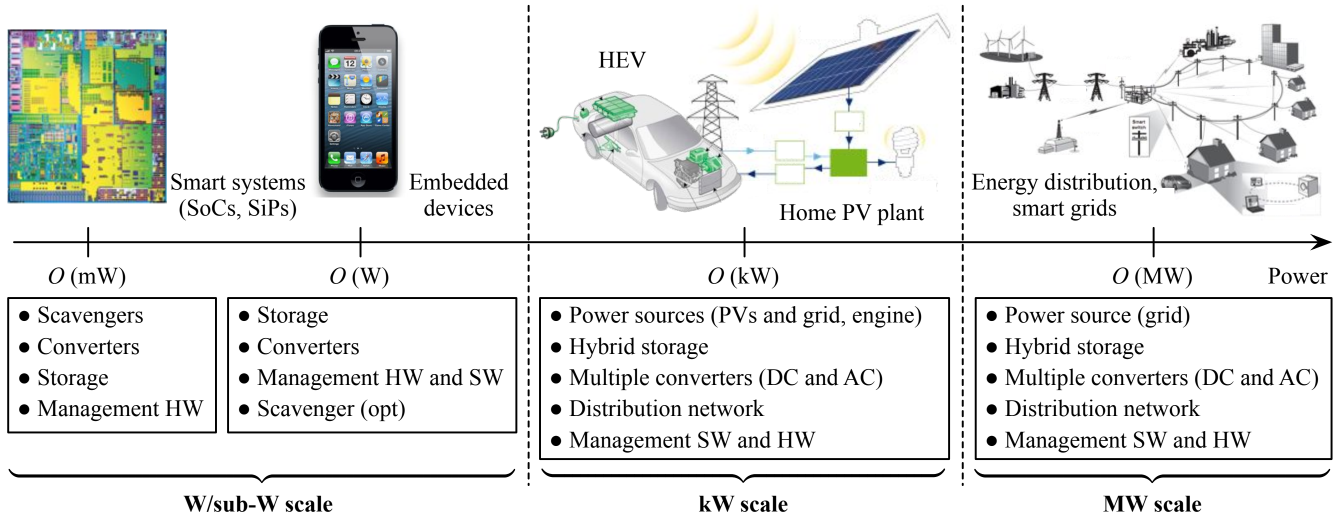

Fig. 1. Various scales of EESs.

Next in Section III we introduce modeling and simulation methods in multi-level and multi-scale, followed in Section IV by EES optimization problems. Our view on the future research is proposed in Section V.

II. Electrical Energy Systems

An EES can be defined as *a system in which electrical energy is generated, stored, consumed, distributed or recycled*. Interestingly, the definition is quite generic and does not limit in any way the application context of such systems; we can in fact think of EESs with quite different scales, both in terms of physical size and magnitude of the involved quantities.

Figure 1 identifies three macro-scales of EESs having similar issues and for which the ideas developed in this paper apply with negligible differences. The figure shows the various scales on a power axis. We envision three macro-scales. The *Watt/sub-Watt scale* comprises electronic devices with quite diverse power levels. On one extreme we have micro-scale systems, which typically host scavengers functioning as power sources, energy storage devices such as thin-film battery or integrated supercapacitors, and the conversion circuitry. On the high-end side of this scale, we have various portable, battery-powered devices such as smartphones, with power consumption levels in up to hundreds of Watts, hosting energy storage devices (mostly batteries) and various conversion devices to generate the many different voltage levels required by different domains (digital, RF, I/O, etc.)

The *kW scale* not only includes systems like home energy generation systems (e.g., based on photovoltaic (PV) panels), but also systems such as hybrid electric vehicles (HEVs). The most evident difference here with respect to the W/sub-W scale is the explicit presence in some form of AC voltage/currents (in particular load), which requires specific conversion step usually not employed in the smaller scale (except in the case of AC power sources such as piezoelectric scavengers). Finally, the largest scale is the *MW scale*, which generically encompasses all large-scale energy distribution systems, in which devices involved in the energy distribution (i.e., wires and cables) take a much more relevant role than in the previous scales because the spatial scale is large in these systems.

Similarly to an electronic system, also EESs can be represented at different abstraction levels; obviously, the functionality and the semantics of each level is different in the two classes of systems. While in electronic systems the levels are typically device/transistor, gate, register transfer level (RTL), and system level, in EES we envision the following terminology. An *element* is the atomic unit of the hierarchy and represents objects such as a battery cell, a PV cell, a power device, and so on. Various elements can be combined to make up a *sub-system*, which performs a specific function (possibly including non-electronic operations) such as refrigeration, heating, moving, and so on.

There may be an optional *module* level between the element level and sub-system level; this level may represent a simple aggregation of “elements” (e.g., assembling multiple battery *cells* to get a battery *pack* or multiple PV cells to get a PV panel), or an electrical device such as a power electronic circuit and an electromechanical transducer. Finally, “sub-systems” are integrated into an *energy system*, representing the highest possible abstraction level. In spite of the difference in names and representation, we can notice a good degree of similarity between abstraction layers in EESs and electronic systems.

An example of a home EES is shown in Fig. 2. This EES is composed of several sub-systems: a PV generator, various home appliances, and a PEV. The PV generator and the home appliances are a power generator sub-system and power consumer sub-systems, respectively. Since the PEV contains energy storage devices, the PEV operates as an energy storage sub-system when parked and connected to the home EES. The PEV energy storage sub-system is composed of power converter modules and energy storage elements/modules. The Li-ion battery module is composed of multiple Li-ion battery elements, a cooling module, peripheral circuits for monitoring and protection, and so on. Detailed implementation at lower level is abstracted and hidden at each level. For example, sub-system-level modeling of the home EES does not consider how the Li-ion battery cells are connected inside the PEV.

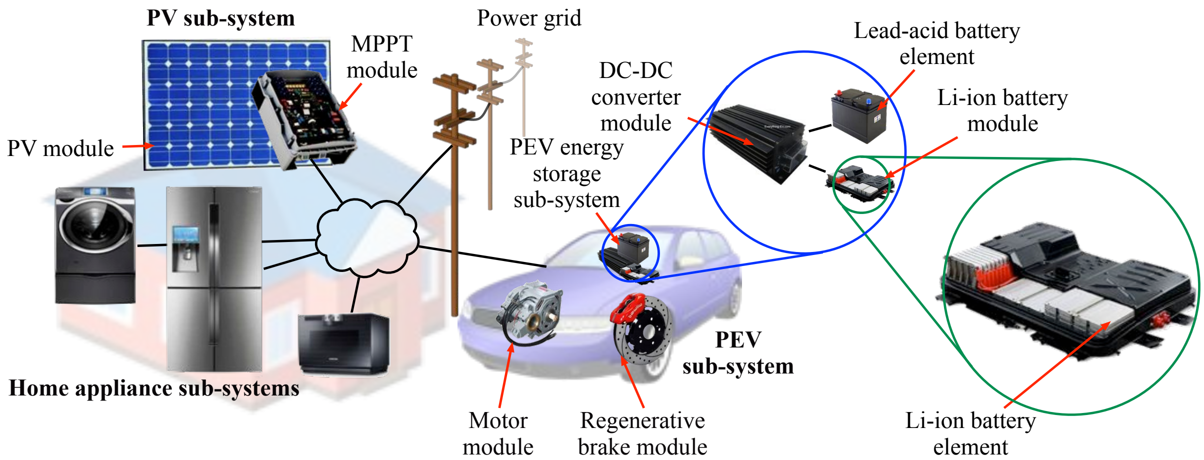

Fig. 2. Home EES composition in different levels of abstraction.

III. Modeling and Simulation

A. Abstraction and Modeling

The system components and their inter-behavior should be abstracted and modeled to be integrated into a design framework. We need an appropriate method of description for them in the design framework, which can be manipulated and transformed as we want. As we have experienced in the field of EDA, a design methodology or an automation flow only can be developed based on the sound and complete basis of the modeling and abstraction.

The EESs are required to be more dynamic and flexible in these days, and a systematic way of design becomes essential to build a reliable and efficient system. EESs have been regarded as a stable system so far. Therefore, the design aims at satisfying the requirement such as capacity and reliability given in a design time. The optimization and validation of the system design have been done in offline manner. However, the shift of the energy sources from fossil fuel and nuclear energy to the renewable energy sources amplifies the instability of the energy supply, and the demand of energy also becomes more dynamic where even a market-based system [9] is getting popular concept in many countries.

We need an appropriate system description method to deal with such a dynamics-induced ambiguous situation in the modern EES. Unfortunately, there have been no serious attempts to provide standardized description and models in spite of many individual efforts on the modeling and optimization of the EES. Unlike the EDA field, the vendors only provide information that they think are important. For instance, even for a battery, which is one of the most fundamental elements, the vendor-provided information varies case by case.

One example is the datasheet of a representative rechargeable Li-ion battery, the US-18650 from Sony; it provides discharging curves at several different constant currents and temperatures as illustrated in Fig. 3 [10]. They also provide charging curve with a standard charging protocol, and change in its characteristics according to the storage condition. This is actually a substantial amount of information. However, it is insufficient to build a model that considers, for instance, transient response characteristics for load demand fluctuation.

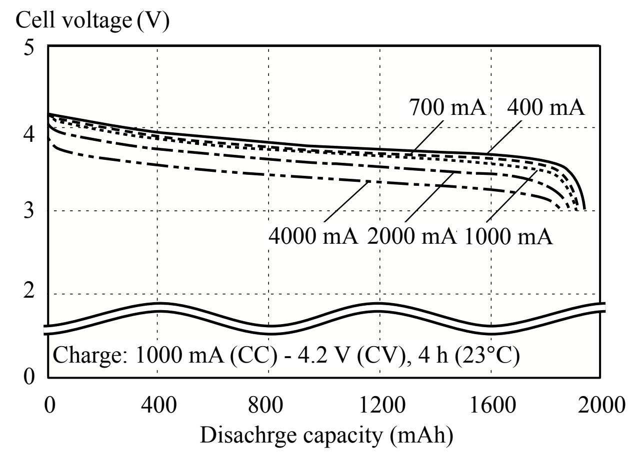

Fig. 3. Discharging curves of Sony US-18650 battery from datasheet [10].

It is reported that the battery lifetime varies by up to 14% with a fluctuated load even though the average load is the same [11]. As a result, we should perform additional experiments to obtain parameters not in the data sheet if we want to develop accurate enough model for this battery.

Another example is the datasheet of the CR3032 from Energizer, a Li coin battery, which provides only one discharging curve with a constant current. However, it provides discharging characteristics for a pulsed current load and change of internal resistance according to the state-of-charge (SOC)[1] as illustrated in Fig. 4 [12]. The information in the datasheet of this battery can be used to build a model that accounts for the transient characteristics of the battery. However, it provides only one battery discharging curve for a constant current load. Therefore, the extraction of internal resistance value as a function of SOC is limited. It also does not provide any information related to the temperature where the temperature difference of the battery seriously affects the capacity fade[2] of the battery over time [13].

A recent study attempts to categorize the information in

[1] A normalized remaining capacity in the battery
[2] Normalized irrecoverable loss of battery capacity over cycling

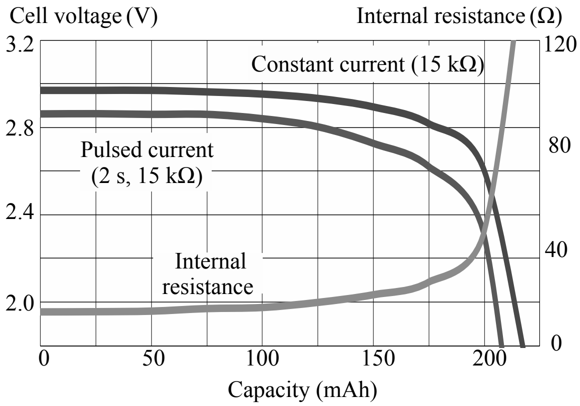

Fig. 4. Discharging curves of Energizer CR3032 from datasheet [12].

the datasheet of the batteries and estimate the available model accuracy from the datasheet information [14]. This study clearly shows that the most of battery datasheets provide only very limited information without any systematic effort. Most studies related to the development of accurate battery models in literature build a model for a specific instance of a battery and are not applicable to a different battery device. The accuracy of the model is significantly improved only with proper set of data as we discuss in the following section. Those who want to develop a systematic way of EES design should define such an *information standard* where such ad-hoc datasheet information discourages the development of complicated EESs.

B. Automated Multi-Level Modeling

A battery is an electrochemical device that involves complicated chemical reactions resulting in many non-idealities of its behavior. The battery performances are deeply characterized by the weight of these non-idealities, so that the battery cannot be simply considered to behave as a trivial ideal voltage source. The non-ideal aspects characterizing the battery performance can be mostly due to the rate-capacity and the recovery effects [15], which are observed in all types of batteries with some variations depending on the chemistry. The effective capacity of a battery is inversely correlated with the magnitude of the discharge current (i.e., rate-capacity effect), while, in the idle period or even for small current loads, the battery can recover a small percentage of capacity loss (i.e., recovery effect).

The battery models belong to three main categories: analytical, electrochemical and electrical circuit-based. In general, analytical and electrochemical approaches are very accurate thanks to the adoption of complex and rigorous mathematical equations. Nevertheless, the practical use of these models is limited from the high computational effort required to determine the numerical solution in each iteration of the simulation. Models based on an electrical circuit equivalent have been recently proposed to overcome such limitations. These models demonstrated to be properly accurate in estimating the battery performance and very easy to be integrated into co-simulation scenarios that make use of standard EDA tools.

Several circuit equivalent models have been proposed in literature. According to the different battery characteristics that are modeled, they can be divided into three categories: Thevenin-based [16], impedance-based [17], and R-C models [18]. Thevenin-based models are capable of predicting the transient response (variable current loads) with a relatively high accuracy, but they are not very accurate in predicting the steady state response (constant current loads). Impedance-based models can only predict the battery performance for some fixed SOC, while, on the contrary, R-C models have been proposed to estimate both steady and transient responses of battery voltage. In order to obtain an effective and accurate battery modeling, the circuital elements appearing in all the electrical models have to be assigned with proper numerical values. In most of the cases, this modeling approach requires costly laboratory infrastructures and time-consuming phases of measurement [19], [20]. Therefore, researchers have started to explore alternative methods to devise parameters for models populating. A rapid and automatic test system for deriving model parameters has been successfully applied to some Li-ion batteries in [21]. Although this approach is less time-consuming than previous methods, complex laboratory equipment is still assumed to be available for the user. Recently, some works have shown the possibility to build efficient battery models solely from the information available in the datasheet of the battery provided by the manufacturer [16], [22], [23].

The datasheet of a battery is a heterogeneous collection of various experimental data summarizing physical, chemical and electrical battery characteristics. As shown in a more recent work [14], datasheets of similar battery families provide, in general, the same sets of data. Common experimental measurements given by the datasheets are: battery lifetime vs. constant discharge currents (used to estimate battery lifetime) and battery voltages vs. SOC for different constant current discharge rates (used to estimate battery voltage response in static workload conditions). Other information essential to model the transient response of the battery voltage (i.e., battery voltage vs. time for pulse discharge currents) is, however, very rare. Moreover, some datasheets provide battery measurements in different operating conditions (i.e., different ambient temperatures) and, less often, the impact of long-term effects on the battery capacity loss (i.e., cycling and storage capacity fading). In [14] authors propose a design paradigm that to take into account the different amount of datasheet information in the generation of a battery model in a systematic methodology. The key-point of the methodology is translating different types of data into electrical circuit models characterized by different accuracy levels. Therefore, more information available implies the possibility to derive more detailed models.

Table I formalizes the modeling design space into a coherent multi-level modeling approach. Although characterized by different implementations, all the model levels allow for reproducing a least one effect of the first order (e.g., lifetime, SOC, steady-state response, transient response) with progressively higher accuracy. Moreover, models belonging to a specific accuracy level can be extended to reproduce other battery characteristics by including second order effects such as environmental phenomena (i.e., ambient temperature) and/or irreversible capacity loss (i.e, long time effects as cycling or storage capacity fading). Another contribution of the methodology presented in [14] is that the related framework used to generate variable-accuracy battery models is fully automated and very easy to be integrated in standard EDA tools since models are designed as MATLAB functions to

TABLE I. ACCURACY LEVELS IN THE AUTOMATED MULTI-LEVEL MODELING METHODOLOGY.

	Level-1	Level-2	Level-3
I order effects	✓Lifetime [23] ✓SOC	✓Lifetime [24] ✓SOC ✓Steady-state response	✓Lifetime [18] ✓SOC ✓Steady-state response ✓Transient response
II order effects	Level 1 [25] + Temperature	Level 2 [22] + Temperature	Level 3 [26] + Temperature
II order effects	Level 1 + Capacity fading	Level 2 [27] + Capacity fading	Level 3 [28] + Capacity fading

populate with battery parameters. In this scenario, the designer can easily obtain a fast and low-cost preliminary performance examination of a consistent set of batteries without resorting to any specific knowledge of battery modeling.

However, one problem that arises with this approach is that not all the datasheets provide the required information to populate a specific model. This information is quite rare because manufacturers do not consider to provide experimental measurements for battery characteristics modeling. They somewhat give the only information expected to be of interest for their potential customers. Therefore, the lack of a precise standardization of the information contained in a battery datasheet is an evident limitation. Nevertheless, the work proposed in [14] establishes a clear relation between the information needed to derive a model and the related accuracy level that can be expected. This represents the first step through the establishment of a standardization of requirements necessary to build battery models that manufacturers can adopt in their battery datasheets.

C. System Simulation

The next step of standardized component modeling is simulation of the components and integrated systems. Experimenting with EESs or their components is not only time-consuming and costly, but sometimes even dangerous due to high voltage and high current. This makes the simulation step as essential as it is in the electronic systems design. Simulation of EESs has distinct benefits for fast development and optimization when integrating individual components.

The W/subW scale simulation typically focuses on the transient behavior for a short-time duration. For circuit level simulation, general circuit solvers such as the SPICE and its variations are widely used [29]. MATLAB/Simulink, which is a general equation solver available for multi-scale simulation, can be used for this scale simulation. Some simulators have specific focuses. SIMPLORER simulator is a power electronics specific simulator with electro-thermal modeling [30]. SIMES is designed with an emphasis on heterogeneity of storage elements for hybrid ESSs [31]. The simulation tools have standard circuit component models such as R, L, C, switching devices, and IC, as well as EES component models such as battery [32], [33], solar cells [34], [35].

The kW scale EES simulation is for EVs [36], [37] or individual buildings. Components in EESs of this scale are more heterogeneous than smaller scale EESs. Thermal, mechanical, and chemical behavior become more important as the system includes devices such as motor models [38] and fuel cell models [39], [40]. Additional interactions among system components, e.g., thermal flow, torque transfer, and fuel feed, are modeled in addition to electrical signal and power. MATLAB/Simulink is widely used for simulation of EESs in this scale. EnergyPlus is a widely-used building-level general energy simulator for electric power, airflow, solar thermal, and photovoltaic simulation [41].

Hardware-in-the-loop (HIL) simulation is an intermediate solution between pure software simulation and pure hardware platform [42] applicable for small- and mid-scale EESs. Some components are real hardware, whereas the other components are simulated in a computer, and they interact through sensors and actuators. Using real hardware components increases the accuracy that software models cannot provides [43], [44]. Meanwhile, the software components enable cost-efficient, fast, and safe simulation. It has been widely adopted for engine control units (ECUs) for automotive system development. Recent advances in computing performance made it possible to perform HIL simulation for power electronics design, which has much faster transient than mechanical devices. HIL simulation reduces testing power electronics controllers [44], [45]. A simulated fuel cell model and EV model is integrated real battery to test a fuel cell-battery hybrid EES of an EV in [42].

Smart grid is a good example of multi-level modeling and simulation of a large-scale EES [46], [47], [48]. System components are modeled in different levels as necessary. When developing high-level management schemes for a smart grid, some system components are simplified for long-term simulation of massive number of components. For example, small load devices are modeled with only a few parameters: active time length and power consumption [46]. On the other hand, some components may be modeled in circuit level to precisely evaluate [47]. In the MW scale system for a city or region, geographical location becomes an important factor due to long distance for energy distribution [49], [50]. The simulators heavily depend on statistical data, such as weather statistics and census data [51].

Each simulation model puts emphasis on different characteristics and phenomena of the components, trading off between accuracy and simulation speed. Components of interests are modeled in low-level for high accuracy, while other components are simplified for high speed. Selecting a proper level of modeling accuracy is thus important to achieve accuracy and speed requirements as we discussed earlier. So far, selection of modeling accuracy for each EES component is done mainly in a manual manner. Automated model refinement, which uses high-level models for fast initial simulation of wide design space and low-level models for accurate simulation for narrowed design space, will be a good strategy to achieve both the goals.

IV. SYSTEM OPTIMIZATION

Optimization of electronic systems performed by EDA tools has various criteria, e.g., critical path latency, peak/average power consumption, silicon area, and so on. The optimization tools find design solutions that maximize or

TABLE II. MAPPING OF EES OPTIMIZATION PROBLEMS TO ELECTRONIC SYSTEM OPTIMIZATION PROBLEMS.

Problems		Electrical energy system	Electronic system
Design-time optimizations	Configuration	System components selection [52]	
	Size	System components sizing [7], [53], [54], [55]	Buffer, memory sizing
	Interconnect architecture	Energy system component interconnect	On-chip interconnect
		(ESS) Charge transfer interconnect [56]	
Runtime optimizations	Dynamic reconfiguration	Energy storage bank reconfiguration [57]	Memory reconfiguration
		PV module reconfiguration [58]	
	Lifetime	SOH management [59]	Non-volatile memory wear-leveling
	Transfer	Energy transfer among system components [60], [61]	Data transfer among memory devices
		Energy transfer scheduling [62]	Task scheduling
	Load management	Demand side management (DSM) [63]	Dynamic power management

minimize some of the criteria given as the objective functions while some other criteria are given as constraints. Some design criteria conflict each other, which require multi-objective optimization methods [64]. Meta-heuristic algorithms are widely studied for such multi-objective optimization problems for VLSI [65], [66].

EES design also involves multi-objective optimizations. Typical optimization criteria are initial (capital) cost, operating cost, maintenance cost, lifetime, weight and volume, pollutant emission, loss of power supply probability, and so forth. EESs put emphasize on different criteria by the scale and application of the system. Small, portable W/sub-W systems typically run on limited energy, e.g., battery or energy harvesting, and so runtime load management to operate the system longer is critical. The EDA field has the best expertise in optimizations of such small EESs. Design-time energy harvesting system optimization is an active research topic in the EDA field as well [53], [54]. Battery-aware [67] and DC–DC converter-aware [68] dynamic voltage and frequency scaling (DVFS) techniques are example of runtime load management. Large (typically grid-connected) MW scale EESs focus more on initial cost, maintenance cost, power generation cost, pollutant emission [69], reliability [70], and so on. They are supposed to be built and operated for multiple years, and thus cost analysis becomes more complex taking account interest rate and inflation rate [7].

Optimization problems for EESs are categorized into design-time optimizations and runtime optimizations. Design-time optimization is finding the best EES configuration and size for given statistics and/or prediction on the power generation and consumption. Runtime optimization is dynamic management of the EES adaptive to actual conditions of power generation/consumption, system aging and faults, and so on. Left side of Table II presents some of design-time and runtime optimization problems of EESs. These problems have been tackled by various optimization methods. Search-based meta-heuristic algorithms are useful also for EES optimization [7]. Other general optimization algorithms are widely utilized. Examples include dynamic programming for managing EV battery system [60], neural network for battery-supercapacitor hybrid storage [61], linear programming solver for EV charging planning [71]. A combined multi-objective optimization and a multi-criterion decision making technique is utilized as well [72]. IBM ILOG optimization tools are representative commercial tools for solving optimization problems in EES such as scheduling power generation, energy price bidding, and so on [73].

An interesting approach in EES optimization is developing solution methods inspired by electronic CAD. Table II shows couple of similar problems of electronic system optimization on the right side of the corresponding EES optimization problems. Energy in an EES is mapped to data in an electronic system, and energy producer/consumer/storage is mapped to data producer/consumer/storage. This similarity encourages us to make use of electronics system optimization methods for EES optimization. An example shows that the negotiated congestion routing algorithm, which is introduced for FPGA routing, can be used for routing on an ESS charge transfer interconnect [56]. The key of this approach is transforming criteria of electronic CAD into criteria in EES. While some criteria such as initial or maintenance cost are easily transformed, some others are not. For example, energy efficiency is an important criterion because some energy is lost during conversion and transfer, but data conversion and transfer do not incur loss of data. Note that the correspondence Table II is only an example we suggest; different problem mapping might give a better solution method.

Despite high complexity of the optimization problem, we anticipate to achieve an innovative and globally optimal solution by adoption of EDA design methodology. Fortunately, EDA companies have long experience of combatting with high complexity. IBM, one of the leading EDA companies, is running the "Smarter Planet" project, and building a smarter EES is a part of it [74]. They provide solutions in building, monitoring, management, and optimization of EESs [75].

V. FUTURE PERSPECTIVE OF CAD FOR EES

We have several issues as a future work for the development of the systematic design framework of the EESs. First, we should develop a standardized format of component information. The standard bridges the gap between the datasheet information and expected model accuracy. It should provide category and hierarchy for the behavior of the battery, and requirements for the datasheet information with a theoretical foundation. Next, we should develop a method to describe the behavior of the components. It should be given in a theoretically well-defined format. The design framework that allows us to automate the design flow will be founded on the basis of the standard data format and behavioral description.

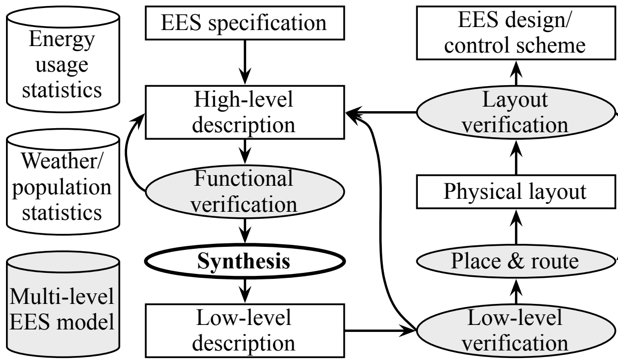

Fig. 5. EES design flow.

Another research direction we propose is transforming more problems in EESs into similar problems in electronic systems to apply rich existing design and optimization methods. We map objectives and constraints of EES to corresponding criteria in the electronic systems design. The standard description we discussed in this paper is necessary for modeling heterogeneous system components.

We further anticipate that the standard modeling the EES components would be the key for high-level synthesis of EESs. Similar to the electronic system synthesis, the EES synthesis automatically generates element-level implementation from a system-level description of an EES as shown in Fig. 5. We discussed single-level simulation and optimization methods in this paper (gray blocks). A standard library of multi-level models would enable the missing synthesis step, where the design is refined, optimized, and verified from the system level down to sub-system, module, and element levels. The input would be the system-level description of EES requirements from based on electrical energy demand, weather, population, and so on. We may need to give an EES design as an input in case of incremental design that we expand or modify the existing EES (e.g., electrical grid). Output would be an EES design which describes the layout and connection of atomic EES elements. Optimal runtime management schemes shall be derived with the optimal design in each level.

VI. Conclusions

Electrical energy systems (EESs) are becoming increasingly complex in terms of size, architecture, and heterogeneity of components; this results in the virtual impossibility of modeling, designing, and optimizing such systems without resorting to a systematic methodology that mimics the approach followed in electronic computer-aided design (CAD).

In this paper, we share great opportunities for the electronic design automation (EDA) society to contribute to the EES design and optimization in a much more efficient way. This work has presented a first attempt in this direction, by (1) outlining similarity and differences among the two worlds of EESs and electronic circuits, (2) defining scales and abstraction levels, and (3) introducing multi-level abstraction component modeling as the first step of this automated design framework. We also studies some of the issues that arise in simulation and optimization of EESs as the next step to be addressed in the future developments of our methodology.

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