Future Generation Computer Systems 136 (2022) 326–341

Contents lists available at ScienceDirect

Future Generation Computer Systems

journal homepage: www.elsevier.com/locate/fgcs

Versatility or validity: A comprehensive review on simulation of Datacenters powered by Renewable Energy mix

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ARTICLE INFO

Article history:
Received 26 March 2022
Received in revised form 17 May 2022
Accepted 9 June 2022
Available online 16 June 2022

Keywords:
Datacenters
Renewable energy
Simulation
Energy saving
Green computing
Benchmarking

ABSTRACT

Nowadays, DataCenters powered by Renewable Energy mix (DCRE) appear worldwide. It brings a hot topic on studying how to fully utilize renewable energy and save brown energy. However, for the vast and complex infrastructure, researchers would perform their studies on a DCRE simulator rather than a real-world DCRE. It brings a question: do these simulators have the same functions and result for the same optimization approach? This paper focuses on the question and proposes the versatility and validity models and relationships for these simulators. We use the term "simulators" broadly, encompassing any general-purpose simulation tools, experiment-purpose simulation approaches, and other simulation works on DCREs. We have reviewed the simulation works for DCRE in the last ten years. After that, we rebut the widespread practice that a simulator has functions for the particular study with an assumed validity. Furthermore, we claim that uniform metrics for both versatility and validity lead to a better simulator. Finally, we back up this claim with comprehensive benchmarking. The experimental results show that the more versatile a simulator is, the better its validity.

1. Introduction

With the age of big data and global informatization, datacenters have become the indispensable infrastructure for modern society [1]. For example, cloud computing is a mature business model in which IT infrastructure and applications are provided as "services" to end users globally. Geographically distributed cloud datacenters are the infrastructure to support these cloud computing services [2]. According to relevant surveys, the energy consumption of datacenters has accounted for 1% of the total global electricity consumption so far, and its growth trend has clear implications for global energy demand and must be analyzed rigorously [3]. Datacenters grow continually, and tremendous energy consumption becomes increasingly severe [4]. Due to its high-energy consumption, the large-scale adoption of fossil energy for electric power has led to the gradual reduction and exhaustion trends of non-renewable energy stored for hundreds of millions of years. It also brought severe pressure to the climate. Fortunately, more experts pay attention to renewable energy because it is inexhaustible and environment-friendly. Now, DataCenters powered by Renewable Energy mix (hereinafter DCRE) appear worldwide. It brings a hot topic on studying the energy efficiency of DCREs, that is, how to fully utilize renewable energy and save the brown energy.

To study the energy efficiency of DCREs, researchers perform experiments on DCREs to prove their optimization approaches. Such experiments hardly run on real-world DCREs because establishing hardware, software, and energy supply are trivial, complicated, and costly. To this end, most researchers prefer simulated DCREs to real-world DCREs. This paper uses the term "simulators" broadly, encompassing any general-purpose simulation tools, experiment-purpose simulation approaches, and other simulation works on DCREs. Fig. 1 shows that about 75% of related works [5–107] adopted simulators in their experiments in the recent ten years. For example, researchers perform an energy-aware task scheduling algorithm on a DCRE simulator to see the optimization effects. Different studies employ different simulations. These simulations look similar but vary in detail. For example, some simulators support solar energy simulation only, and some simulators do not support workload scheduling across datacenters. We conclude two general metrics of simulators: versatility and validity. The versatility is that simulators could provide rich functions for various and complex experimental contexts. The validity is that simulators could correctly show the optimization effects of DCRE in these contexts.

After investigating these simulators, we raise a question: Since their function and implementation details vary, do they maintain the same validity? In other words, are they show the same result for the same optimization approach? The existing works build

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https://doi.org/10.1016/j.future.2022.06.008
0167-739X/

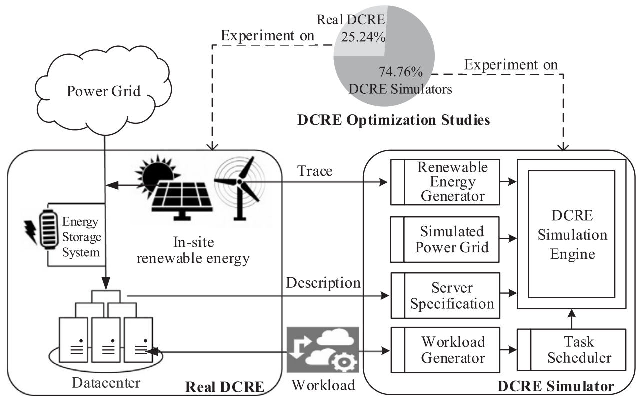

Fig. 1. Experimental approaches of recent studies on DCRE.

versatile simulators to evaluate the effectiveness of their optimization approach, but the validity of these simulators remains unproven. On the one hand, we expect that a scheduler on different simulators under the same context shows the same effects. Otherwise, some simulators are not validated. On the other hand, we are interested to know whether the versatility and validity are trade-offs or win-wins.

After we comprehensively investigated the state-of-the-art simulators, we argue that some have poor validity because the same optimization has different effects on different simulators. We rebut the widespread practice that a simulator with proper functions for a particular study is assumed to be validated by default. We claim that uniform metrics for versatility and validity lead to a better simulator, and the better versatility a simulator is, the better its validity. Such discoveries are backed up with benchmarked experiments. The key contributions of our study are as follows:

(1) Our analysis of state-of-the-art simulators brings a comprehensive view of the research topic. Researchers who study power and renewable energy efficiency could quickly understand state-of-the-art experimental environments and approaches through our work.
(2) The proposed versatility and validity metrics for evaluating the simulators, especially the win-win relationships between two metrics, brings new reference criterion to the design and application of DCRE simulators.
(3) Our summarization on DCRE simulators from many aspects, such as workload, renewable energy, datacenter, battery, and optimization approaches, as well as our benchmarking methods, brings new experiences to the DCRE study.

The remainder of the paper is organized as follows: Sections 2 and 3 analyze the versatilities and the validities of state-of-the-art DCRE simulators, respectively. Section 4 describes our metrics on versatility and validity. Section 5 gives a benchmarking case for the typical simulators. After that, Section 6 analyzes their benchmarking results and discusses the relationship between the two metrics. Section 7 describes the related work. The last section discusses the conclusions and future works.

2. Versatility

By enumerating the search results of the DBLP database, we have collected the papers relevant to "renewable" and "datacenter" in the recent decade. We selected 103 papers [5–107] as related works which contain interesting experimental studies on DCREs. These works addressed the versatile functions of DCRE simulation. After a careful study, we conclude six groups of functions and list the supporting papers in Table 1. The right part of Fig. 1 shows the connections between these functions.

2.1. Workload

The existing works mainly generated the workload by two approaches. On one hand, about half of them generated workloads according to certain rules, such as a Uniform Distribution [29,42,51,77], Poisson Distribution [40,73], Exponential Distinction [13], Zipf Distribution [8], interactive model [14,22,48], data access model [45], and other predictable models [38,41,57] as well as applications models [57,61]. On the other hand, about half of workloads are generated according to the workload traces, among which the most popular ones are Google traces in [11,25,26,46,60,62,63,70,78,84–86,96,97] and Wiki traces in [6,18,35,59,65,71,90]; others are RUBiS traces in [13,16,35,55,59], Internet Traffic Archive in [5,43,52,53,93], World Cup traces in [6,21,46,67,89,99], HP traces in [15,56], NASA traces in [31,43,53], Hotmail traces in [10,49], PlanetLab traces in [72,92], Real Parallel Workloads in [32,68], FaceBook trace in [17,88], Nectar in [90], and other none-publicly-available trace in [23,69,80]. Besides, authors in [66] adopt six real-world workload traces in representative HPC datacenters. Many research works update some features of the traces according to the individual requirements. For example, authors in [53] scaled the frequency and amount of the workload to meet the datacenter performance.

As analyzing the state-of-the-art simulators, the workload or requests generator is essential for the DCRE simulator. The rule-based generator is more regular and good for showing the advantage of the design purpose. However, it may not accord with the practical. The trace-based generator is practical but not flexible enough. Sometimes the expected features may not be highlighted with the trace. Simulators are encouraged to have functions such as scaling and refining trace-based workload generation with customized configurations. Simulators may provide the interface for refining, and users define the refining rules through these interfaces. For example, users prefer to double the workload every night as defined in traces. They put the preference in a configuration. The simulator would generate workload according to both the traces and the configuration. In conclusion, a versatile simulator should support the functions mentioned above.

2.2. Renewable energy

In their experimental studies, almost all the works employ at least one renewable energy: solar or wind power, except for several exceptions that mention none of the renewable energy at all [24,75,81,83,87]. Besides, tidal power is studied only in [63]. These works generate renewable energy, namely solar or wind energy, through three approaches.

Firstly, quite a few works adopt the real-world photovoltaic power station or wind farms [8,14,42,46,54,56,64,69]. It is costly for the larger equipment investment, so researchers who do not own a power station prefer the next two approaches.

Secondly, most works adopt the publicly available traces. The traces could be either the weather data or power data. Weather traces are raw data, and the simulator calculates electricity according to the generation equation. More than half of works with weather traces adopts the famous MIDC (Measurement and Instrumentation Data Center) of NREL (National Renewable Energy Laboratory) [5,6,12,13,16–18,25,27,31,34–36,43,46,52,54,55,58,59,61–63,65,66,70,89,95]. Moreover, the alternations are the traces from lists in Table 2.

Power traces, such as grid data of Elia Group in [51,73,76] and some non-publicly power traces in [7,22,79], are collected

Table 1
Experiments setup for 103 related works about renewable datacenters,sorted by publish year from 2011 to 2022.

Functions	Items Ref and proportion	
Simulation tools	**1.1 Hardware: the testbed is a real-world datacenter.** Ref: 8,14,17–19,22,28,35,41,42,44–46,49,50,54,56,57,59,61,63,71,93,99,101,103	Proportion: 25.24%
	1.2 Self-made simulator: authors developed a simulator for their research. Ref: 5–7,9–13,15,16,20,21,23–27,29–34,36,37,39,40,43,47,48,51–53,55,58,60,62,64–69,72–76,80,82,83,85,89–91,94–98,100,102,104,105,107	Proportion: 63.11%
	1.3 Third-part simulator: authors adopted the public simulator for their research. Ref: 38,70,77–79,84,86–88,92,106	Proportion: 10.68%
Workload	**2.1 Traces-based: generating workload according to some publicly available traces.** Ref: 5,6,10–13,15–18,20,21,25–27,31,32,34–36,43,46,49,52,53,55,56,59,60,62–72,78,80,84–86,88–90,92–105,107	Proportion: 61.17%
	2.2 Rule-based: generating workload according to some rules or data distributions. Ref: 7–9,14,19,22–24,28–30,33,37–42,44,45,47,48,50,51,54,57,58,61,73–77,79,81–83,87,91,106	Proportion: 38.83%
Renewable energy	**3.1 Solar and wind: authors adopt solar and wind energy.** Ref: 5–23,25–80,82,84–86,88–91,93–107	Proportion: 95.15%
	3.2 Weather traces: authors adopt weather traces to calculate power. Ref: 11,39,44,53,60,68,71,77,82,84,86,88,90,99,103,105	Proportion: 15.53%
	3.3 Power traces: authors adopt power traces directly. Ref: 22,23,29,32,37,40,41,51,57,73,76,79,80,83,107	Proportion: 14.56%
	3.4 Power stations: authors adopt power stations to generate power. Ref: 8,14,42,46,49,50,54,56,64,69,102	Proportion: 10.68%
	3.5 Mathematical simulation: authors adopt mathematical methods to calculate power. Ref: 9,10,15,19,20,21,24,26,28,30,33,38,45,47,48,67,72,74,78,81,85,87,91,92,98,100,101,102,105,106	Proportion: 29.13%
	3.6 Static price: the energy price is constant. Ref: 19,26,37,42,49,50,52,63–65,69,70,71,78,80,95	Proportion: 15.53%
	3.7 Dynamic price: the price model change with time or conditions. Ref: 6,10,15,17,18,20–22,24,27–29,31,34,40,43,45,46,48,54,55,57,58,61,62,65,67,68,72,73,75,76,77,81–83,91,93,96,98,102,105–107	Proportion: 42.72%
	3.8 Carbon emissions: the carbon emissions are estimated. Ref: 15,17,20,22–24,38,39,40,46,52,62,65,66,70,74,80,88,93,97,98,102,105,107	Proportion: 23.30%
Datacenter	**4.1 Server attributes: datacenter specification includes many attributes of servers.** Ref: 5,6,8,10,12–17,19,22,23,25,28,32,35,37,40,42,45,46,49,50,53–57,59,61,63,64,66,69,70–72,76–78,80–82,84–86,91–95,98–101,103,105,107	Proportion: 57.28%
	4.2 Server capacities: datacenter specification is the capacities of servers. Ref: 6,13,31,36,37,60,86,102,106	Proportion: 8.74%
	4.3 Power values: the power model is an enumeration of powers. Ref: 5,6,8,10,12,15,16,25,28,31,32,40,42,45,49,50,53,54,55,61–64,66–68,70,72,76,78,82,84,85,88,91,98,99,106	Proportion: 36.89%
	4.4 Power functions: the power model is a function of powers and continuous working status. Ref: 17,21,22,57,59,60,77,86,90,93,96,97,100,101,103,105,107	Proportion: 16.50%
	4.5 Virtual machine: authors defined VM specification. Ref: 9,22,23,30,33,35,37,38,44,50,52,54,55,59,60,69,70,77,80,84,85,88,92,96,98,100,102,106	Proportion: 27.18%
	4.6 Location: authors mentioned the datacenters' locations. Ref: 6,7,9,10,15,16,20,21,23,31,34,35,55,58,60,65,67,70,71,76,80,82,85,88,97–99,106	Proportion: 27.18%
	4.7 Bandwidth: authors mentioned the bandwidth of servers. Ref: 7–9,16,19,20,23,28,32,35,53–55,59,60,63,85,88	Proportion: 17.48%
Battery	**5.1 Battery energy: authors treated the battery as energy.** Ref: 8,11,12,17,18,23,25,27,28,31,32,39,45,48,50,54,58,61–66,69,74,80,82–87,89–91,94,95,98–101,103,105,107	Proportion: 42.72%
	5.2 Battery optimization: authors proposed an optimization approach for batteries. Ref: 25,31,32,48,61,63,64,69,74,80,82,83,87,99,100,105	Proportion: 15.53%
	5.3 Battery cost: authors consider the cost of batteries. Ref: 11,27,28,31,32,48,54,58,62–64,83,105	Proportion: 12.62%
Optimization approaches	**6.1 Capacity planning: planning how much power is dispatched to which datacenter.** Ref: 11,17,22,26,28,32,42,50,64,74,75,86,89,99,101	Proportion: 14.56%
	6.2 Power control: adjusting the power of servers to meet the requirements. Ref: 5,8,12,18,22,27,29,30,32,34,39,41,43,44,47,48,49,50,52,53,57,58,60–62,66,73,82,83,87,90,95,98,103,105	Proportion: 33.98%
	6.3 VM migration in a datacenter: temporal load balancing in resource layer. Ref: 22,30,33,37,38,44,50,52,54,69,84,92,100	Proportion: 12.62%
	6.4 VM migration among datacenters: spatial load balancing in resource layer. Ref: 9,23,55,60,70,80,85,107	Proportion: 7.77%
	6.5 Task scheduling: temporal load balancing in computation layer. Ref: 12–14,18,19,25,28,34,36,40,42,45,46,48,51,54,56,59,63,68,78,79,80,81,90,91,96,97,102,104,106	Proportion: 30.10%
	6.6 Request dispatch: spatial load balancing in service layer. Ref: 6,7,10,15,16,20,21,31,34,35,58,65,67,71,76,82,88,94	Proportion: 17.48%

from solar and wind power stations and directly applied to the simulators.

The third approach is also a minority. It simulates the power data via mathematical methods. For example, some works simulated wind power through mathematical models [9,21,47]; and wind speeds approximately follow the Weibull distribution [26]. Some works calculated solar radiations of a specified location and time if cloudy effects are ignorable [10,33,38,74,78]; and solar energy follows other similar models [45,85]. Also, some works represented renewable energy through the price model [15,24, 48], carbon emissions [20], or as simple as a total amount of energy over time [30,72]. Some research works predict renewable energy from the previous epoch [19,28] or the HOMER system provided by National Renewable Energy Laboratory [32].

Energy prices and carbon emissions are two additional issues about renewable energy. The price model is associated with renewable energy, grid power and battery. 58.25% of works mentioned price models in their experiments. A few of them adopt static price of the energy, such as the constant, on-peak/off-peak prices in [21,51,58,64,74,82,90], and average price model in [26,37,50,52,69,70,80]. However, the dynamic price model, i.e., the price is shifted with time, is more acceptable than the static one. The dynamic prices are set according to the public traces, such as traces from U.S. Energy Information Administration (EIA) [10,20,24,28,34,46,55,62,72], NYISO [6,27,43,58,65,73,76], FERC [22,34,77], Google IDC [31], IPath [15], as well as the energy prices of Australia [40], Finland [77], New England [45,48], California [17,18], New York [48] and Synergy [91]. Some works also defined [17,18] or leverage [21,29,61,67,75] the sophisticated mathematical mode for energy prices.

Although more than 85% of works have mentioned the carbon emission and carbon tax in the introduction, related works, and conclusions sections, some calculate their optimization effect in terms of carbon reduction, but the detailed studies are still minor. 23.3% of works built models for carbon emission and wholly integrated it into the proposition and experiments. Carbon optimization is by default due to carbon emissions decreasing with renewable energy usage; meanwhile, carbon tax also falls.

By analyzing the state-of-the-art simulators, the approach of directly using power traces or calculating weather traces is mostly for solar and wind energy, representing the primary tendency with moderate fluctuation. However, the public power traces are rare. Simulating by mathematical methods is simple and enough to show the primary tendency. For the long-term scheduling and simulation, the moderate fluctuations have fewer effects on the results, so the mathematical simulation is a good solution, and vice versa. In conclusion, a versatile simulator should support the approaches mentioned above.

2.3. Datacenters

The specifications of DCREs are discussed in four aspects: the server specification, the virtual machine specification, the location, and the bandwidth.

First, very few literature defined the bandwidth unless the cost of the transferring is considered, even so, the bandwidth are mostly set to be 10 Gbps/1 GBps [16,20,23,55,60,63,80,85,88]. We found two exceptions. One considered the bandwidth variations between users and datacenters [34], and the other considered the bandwidth impact on job migration [35]. The above discussion shows that a DCRE simulator abbreviates the sophisticated network model and only sets bandwidth constant.

Second, 25.24% of works applied geographically distributed DCREs in their experimental setup. Among them, the locations of datacenters are either defined according to the location of the energy profiles [7,9,15,16,20,21,23,31,34,35,55,58,60,65,67,80,85,88,97,99], or directly given according to some practical cases [6,10,70,71,76,82,98]. Many DCRE attributes, such as solar energy, time zone, and distances to POIs (Point of Interest), are related to the location. The above discussion shows that a versatile simulator would provide customized location information and attributes.

Third, Virtual Machine (VM) specification is also an option for existing research. By default, a VM layer is not mandatory for DCREs studies; however, 27.18% of works on VM management have provided the VM specification excepting two cases. One exception discussed the VM migration without VM specification because it aimed to propose a general testbed [23]; The other exception gave the VM specification without any discussion on VM management because it treated VMs as a configuration for datacenters and the context for the studies [59,77,88]. The above discussion shows that a versatile simulator should conditionally support VM management, but such support is not intensive.

Table 2
Available weather traces excepting MIDC and NREL.

Ref.	Name	Abbr.
[68]	German Weather Service	DWD
[68]	European Weather Consult	EWC
[11]	Annual US Wind Power Installation	
[90]	Australian Bureau of Meteorology	ABM
[44]	HP solar lab	
[77]	Finland Weather Station	FWS
[77]	Texas Weather Instruments	TWI
[60]	Met Office Integrated Data Archive System: Land and Marine Surface Stations	MIDAS
[71]	Weather Underground	
[82]	Windinder	
[86]	National Solar Radiation Database	NSRDB
[88]	Photovoltaic geographical information system	
[39,84]	Others	

Fourth, the server specification is mandatory. The specification has two folds: one is performance relevant, and the other one is power relevant. The performance-relevant specification includes scale, cores, memory, and storage. Most of the works in item 4.1 of Table 1 directly defined the specification without any reference. A few works defined the specification in terms of known cases, such as the publicly available technical report [6], datacenter infrastructure of IBM and HP [66,70], Eco4Cloud [80], PlanetLab traces, and PUE value [64]. Besides, some works also defined the performance specification by servers' capacities, namely, how fast the servers handled workloads. For example, servers' capacities were 300, 500, 675 and 725 requests per second [6]; servers dealt with up to 2000 requests per second [31]; servers followed the specified workload curve [36] and application profiles [86]; servers processed each task in 10 min on average [13]; servers hosted up to four tasks concurrently [60].

The other is the power. No research simply treat the power as a constant. The simplest and frequently-used power definition is the peak value and idle value [5,8,10,15,16,25,28,31,32,40,42,43,54,55,61–64,67,68,76,78,82,84,85,91], while another optional definition is enumerated power for different working state of servers [6,45,49,50,53,70,88]. To the contrary, the sophisticated method is modeling as the function of a continuous variable, such as the CPU utilization [22,57,59,77] and the workload being processing [17,21,60,86,90]. Additionally, SPEC power data is a common trace being followed by many works [12,32,36,37,61,66,72].

By analyzing the state-of-the-art simulators, they mainly provide sophisticated server specifications. However, a few provide virtual machine configuration and locations, and quite a few provide the bandwidth specification. A flexible server specification, including the max–min, enumeration, and functional power models, is essential because we can only adjust the server specification but not the renewable energy. The location of the datacenter is also attractive. It should be paid more attention to because the different locations bring the various renewable energy features and workload along time. In conclusion, a versatile simulator should support a highly customizable server modeling and provide a flexible specification of a datacenter based on the above description. Significantly, the servers' power modeling should be elaborately supported.

2.4. Battery

Energy Storage System (ESS), as batteries in DCREs, take important roles in a datacenter environment. As shown in Table 1, 42.72% of works treat battery as a special energy, and among them the battery specification are quantitatively defined in [11,23,25,27,28,31,32,45,54,62,63,66,69,74,80,82,83] . First of all, the 13/44 works leveraged battery management to optimize energy utilization, such as configurable capacities and charge/discharge strategies. Second, the 12/44 works treated the battery cost, such as battery life and charging costs, as one optimization goal. Third, the rest only use the battery as a short-time energy buffer and no detail about the battery configuration.

The batteries' specification includes their capacity, charge /discharge power and time, Depth of Discharge (DoD), and lifecycle. First, capacity is generally a constant; however, some battery optimization studies leveraged a dynamic capacity model that changed with the energy usage [74,83]. Second, charge and discharge powers are also constants, except authors in [11,25] modeled them as time-related curves. Third, charge and discharge opportunities are acknowledged. DCREs charge batteries when renewable energy is excessive or otherwise discharged. Exceptionally, authors in [62] charged batteries when the electricity price was low or otherwise discharged. Fourth, most works set a limitation of DoD as a constant [27,32,54,62,63,66,69]. DoD and the battery life are negatively correlated, and a few works treated them as optimization goals [27]. Fifth, battery lifecycle negatively correlated to the charging/discharging frequency. Most works set the maximum charging/discharging frequency as a constant. Alternatively, the Ah-Throughput model of batteries represented the fixed amount of charging times before the batteries are replaced [32,66]. In addition to the above five factors, some works also considered others. For example, self-discharging was a function of time [69]; energy loss from a single charge was a constant [25,28,65,82].

By analyzing the state-of-the-art simulators, battery support is a key function but is ignored by most simulators. Batteries could work automatically, and the triggers of charging and discharging are extendable for the more sophisticated algorithm. In the scenario of with and without batteries, the schedulers are different. Therefore, during the simulation, the status of batteries, such as charging and discharging, lifecycle, and cost, should be well logged. In conclusion, a versatile simulator should support battery simulation and provide a comprehensive battery configuration.

2.5. Algorithms

In the existing research, the energy consumption optimization goals of DCRE are maximizing renewable energy utilization, minimizing energy costs, and minimizing carbon emissions. The three goals overlap more or less. For example, the energy cost is cut down if DCRE fully utilizes renewable energy and minimizes brown energy, the same as the carbon emissions. However, in some cases, the three goals have trade-offs. For example, when a datacenter consumes a larger proportion of energy from public grid power at a lower price, the energy cost decreases, but the carbon emissions increases because the grid is powered by brown energy.

All the works in Table 1 show that matching energy generation and energy consumption are their generalized goals. Many proposed approaches in different system layers accomplished such a goal. As shown in Fig. 2, the electric layer has capacity planning, which is not studied in the IT area. The resources layer has power management, including power provisioning for servers, cooling, and renewable energy supplement. For adjusting the energy consumption of DCREs, the well-known VM migration in this layer is applied to both temporal load balancing and spatial load balancing. However, the cross-region VM migration is exceptionally costly for network traffic; even the VM migration within a datacenter also consumes extra energy. The alternative approaches are "the computing layer task scheduling for temporal load balancing" and "the services layer request dispatching for spatial load balancing".

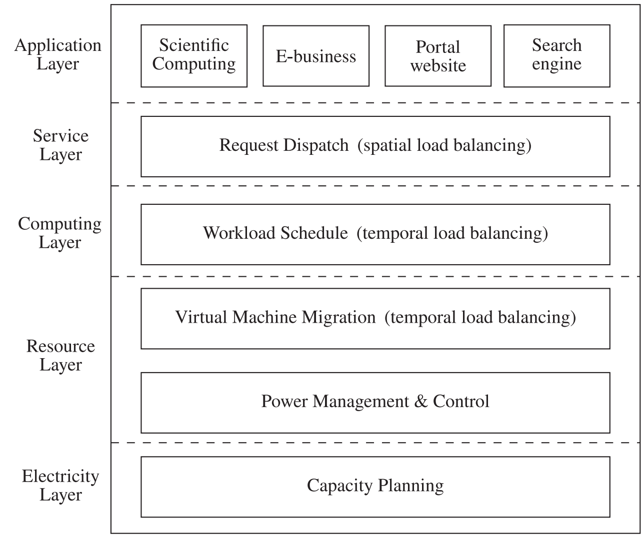

Fig. 2. Optimization approaches and their layers.

Some works are beyond these basic approaches: the VM based elastic resource allocations to workloads [58], the Green SLA for DCREs [72], the optimized impact of battery size on the green coverage percentage [74], the bargaining solution to power markets [75], the study on the feasibility of the "Minimum Percentage Supply" for DCRE on 60 degrees north latitude [77], the container-based task scheduling among DCREs [85], the accurate electrical and IT models and negotiation loop process [86], the adaptive performance and energy-aware scheme for Fog-IoT [87], and the proactive content caching at the network level [91].

By analyzing the state-of-the-art simulators, all levels of DCRE, such as resource, computing, and service layer, contain the distributed algorithms. In other words, all these layers have the space to optimize. Therefore, a general-purpose simulator should support a pluggable and customizable interface for the optimization algorithm in these layers. For example, the temporal and spatial load balancing, VM management, and task scheduling support the former, while the request dispatch supports the latter. In conclusion, a versatile simulator should support the interfaces of all levels mentioned above.

3. Validity

As a simulator, accuracy, which shows whether the simulated results follow the actual results, is a commonsensible measurement for validity. Nevertheless, this section redefines effectiveness as the measurement for validity instead of accuracy. According to the experimental studies of 103 related works in Table 1, the simulators in [7,9,14,30,33,38,39,41,89,94] whose accuracy and effectiveness are assumed to be good (no evaluation at all), and then half of the rest employ two ways to prove their accuracy, while half of the rest prove their effectiveness.

First, some works explain or qualitatively analyze the accuracy of their simulators, such as comparing the simulated results with the numerical calculation [18,29,48,93,97], discussing the implementation details of the simulator's key components [20,35, 69,76,77,81,84,87], emphasizing that the experiments covers all aspects [23,40,60,71,82,88,95], and showing that the experimental results follows acknowledged rules [8,31,37,44,47,54,73,74,79,90,96]. Such qualitatively analysis are specific to their scenarios, respectively and compared with proven rules in this field to verify the accuracy of the results. For example, the author compares the proposed dynamic Geographical Load Balancing and energy buffering management scheme (GLB) with the conventional performance oriented load balancing scheme(PLB) to verify whether the proposed scheme follows the rules of the traditional scheme [31]. We could not abstract the general rules from them.

Second, very few works compare the simulated results with real-world results to see whether they are consistent. It is the most reliable evaluation. However, it is tough to compare the simulated and the real-world energy utilization of datacenters, which have identical specifications of servers, energies, and workloads. Only five simulators [13,26,27,46,72] find real-world energy utilization traces associated with the corresponding servers, energies, and workloads. Unfortunately, their experimental datasets are not publicly available.

The first evaluation lacks conviction and generality. The second one is convincing, but it needs universal, multifarious, realistic, and flexible trace data. Such trace is difficult to obtain. Defining the validity of simulators as accuracy is straightforward, but the evaluation is hard to reach. It is also difficult to develop a DCRE simulator whose results are exactly the same as the real-world DCRE. Moreover, accuracy is a sufficient condition of validity. DCRE simulators are for examining the optimization effect of algorithms. Therefore, they are valid if they are fair for these algorithms. Half of works use the third evaluation approach which compares proposed algorithms with baselines on their simulator, and prove their algorithms have better renewable energy utilization and less brown energy consumption than baselines, respectively [5,6,10–12,15–17,19,21,22,24,25,28,32,34,36,42,43,45,49–53,55–59,61–68,70,75,78,80,83,85,86,91,92]. With this evidence, they implicitly believe their simulators are effectiveness, in other words, these works prefer effectiveness to accuracy. However, does the same optimization on different simulators show the same effects under the same context? These works with the third evaluation only compare different algorithms on the same simulator, but not the same algorithm on the different simulators.

To this end, the validity of the simulator defines the effectiveness that measures the optimization effect of the same algorithm on different simulators, rather than the accuracy in measuring the simulation results. This opinion is not supported by state-of-the-art research so far and is the motivation of our research.

4. Metrics

According to the summarization on existing DCRE simulators in terms of versatility and validity in the previous two sections, this section proposes metrics of versatility and validity. The former discusses the simulators with distinguishing functions selected from the state-of-the-art research; The latter concerns the effectiveness, namely the optimization effect of the same algorithm on simulators. In other words, the most effective simulator has the best validity. The following section will explore the relationship between versatility and validity by benchmarking.

4.1. Typical simulators

Table 3 gives the various functions supported by existing simulators. These functions are represented as item numbers from Table 1. They belong to four groups: workload (item 2.x), renewable energy (item 3.x), datacenter (item 4.x), and battery (item 5.x). The functions in a group may be exclusive or compatible. For example, a simulator can generate wind and solar energy through weather traces (item 3.1) and power traces (item 3.2). However, it cannot simulate the datacenter with static power (item 4.3) and dynamic power (item 4.4) together. We plan to cluster the existing simulators into typical ones because the combinations of these functions in four groups are diversiform. For example, its workload and the generation mode of renewable energy are either trace-based or rule-based; The power consumption model of the datacenter is either discrete or mathematically simulated.

Then Table 3 shows the typical simulators, their given names, and their function. The functions supported by these simulators cover all the state-of-the-art research. None-typical functions such as energy price, carbon emissions, bandwidth, and optimization approaches barely affect the simulator's validity, so they are not listed in Table 3.

- **Trace:** the *trace-simulator* adopts the traces-based generators for workload, renewable energy, and datacenter, as well as supporting the sophisticated power functions, VM, and battery.
- **Value:** the *value-simulator* is the same as the *trace-simulator*, except it adopts enumerable values as powers and does not support VM and battery.
- **Rule:** the *rule-simulator* adopts the rule-based generators for workload, renewable energy, and datacenter, as well as supporting the power functions, but not VM and battery.
- **Base:** the *base-simulator* contains the minimal functions for DCRE simulation, namely the rule-based generators for workload, renewable energy, and datacenter.

4.2. Measurements

For the DCRE simulators, the most important simulation results are two folds: the DCRE's energy consumption and renewable energy generation, represented as two curves along the simulation time. This paper names them c-curve and g-curve, respectively.

Definition 1 (*Generation Curve and Consumption Curve (g-curve and c-curve)*)**.** The generation curve, short for g-curve, refers to the curve whose x-axis is simulation time and y-axis is the amount of generated renewable energy at the time. While the consumption curve, short for c-curve, refers to the curve whose x-axis is simulation time and y-axis is the amount of consumed energy, including renewable energy and brown energy, at the time. Both the g-curve and c-curve show the time-series simulation results, and the "producer–consumer relationship" changed over time. Such changes represent whether the c-curve, which is adjustable through the algorithms, follows the g-curve, which is natural and unadjustable in the runtime environment.

Fig. 3 shows examples of g-curve and c-curve where (1)(2)(3) represents stable phase, no wind phase and fluctuant phase, respectively. The data was from a datacenter with onsite wind power in Inner Mongolia, China. The green line is a c-curve, and the red line is a g-curve. They are almost matching in the stable period (wind) due to the capacity design of the datacenter. Nevertheless, their gap is also evident in the fluctuated or deficient period (wind). However, for this example, the datacenter does not run any green-aware scheduler so that the c-curve is stable and does not follow the g-curve.

Fig. 3 does not employs the batteries, so the g-curve and c-curve do not contain the batteries discharging and charging, respectively. According to the discussion in Section 4.2, batteries are a renewable energy consumer as they are charged and are a renewable energy generator as they are discharged. They improve renewable utilization.

Table 3
Typical simulators, their given names and functions.

Functions	2.1	2.2	3.1	3.2	3.3	3.4	3.5	4.1	4.2	4.3	4.4	4.5	4.6	5.1	5.2
Trace	✓	×	✓	×	✓	×	×	✓	×	×	✓	✓	✓	✓	×
	[8,11,12,17,18,23,25,27,28,31,32,35,39,45,48,50,54,55,58,59,61–66,69,70,74,80,82–87,89–95,98–101,103]														
Value	✓	×	✓	×	✓	×	×	✓	×	✓	×	×	✓	×	×
	[5,6,10,13,15,16,20,21,26,34,36,43,46,49,52,53,56,60,67,68,71,72,78,88,96,97,102,104]														
Rule	×	✓	✓	×	×	×	✓	×	✓	×	✓	×	✓	×	×
	[7,9,14,19,22,30,33,37,38,40,42,44,57,76,77,81]														
Base	×	✓	✓	×	×	×	✓	×	✓	×	×	×	✓	×	×
	[24,29,41,47,51,73,75,79]														

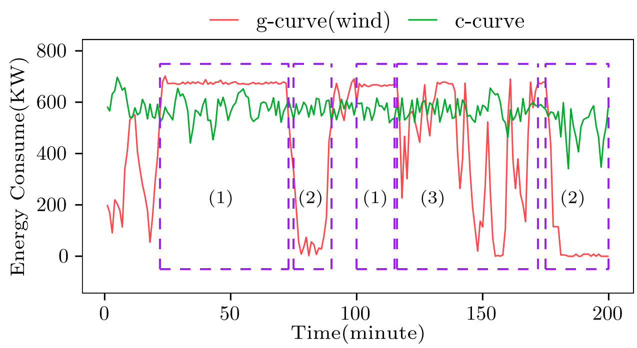

Fig. 3. Examples of g-curve and c-curve.

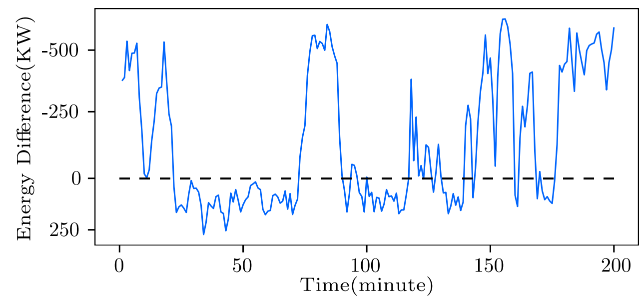

Fig. 4. Examples of d-curve.

Given a benchmark case designed in Section 5, the constraints of c- and g-curves are simulators, datacenters, and optimization algorithms. Comparing the two curves obtains the metrics of versatility and validity for simulators. This paper proposes two types of metrics: curve metrics, such as curve gap, and curve deviation, are calculated by the curves data subtraction; renewable metrics, such as renewable utilization and renewable proportion, are calculated by curves data aggregation.

(1) Curve metrics

Definition 2 (*Difference Curve (d-curve)*)**.** The difference curve refers to the difference between c-curve and g-curve of a datacenter. The x-axis is simulation time, and the y-axis is a gap, which is the amount of consumed renewable energy minus the amount of generated energy at the time. A positive gap means the renewable energy is deficient, while a negative gap means it is sufficient at that time.

Metric d-curve: the versatility and validity of a simulator. Firstly, supposing the simulator has functional drawbacks or a carelessly designed simulation case, the datacenter may significantly suffice/lack renewable energy if the d-curve is remarkably higher/lower than the x-axis. Secondly, supposing the simulator has a fine-tuned scheduler, the datacenter may primarily consume renewable energy rather than brown energy if the d-curve is stabilized and closed to the x-axis. Fig. 4 shows the d-curve of the traces in Fig. 3, an un-optimized case.

Definition 3 (*Curve Gap*)**.** The curve gap is the extent to which the c-curve is separate from the g-curve. Mathematically, absolute error is the difference between measured or inferred and actual values. Let $g(t)$ be a g-curve, $c(t)$ be a c-curve, and the curve distance a time t be the absolute error $|c(t) - g(t)|$. Then a curve gap, denoted as κ, is the accumulative value of curve distances in duration T. κ equals the area between two curves.

$$\kappa = \int_0^T |c(t) - g(t)| \mathrm{d}t = \sum_{t=1}^{T} |c(t) - g(t)|$$

Metric κ: the validity of a simulator. The curve gap κ measures the validity of the simulator when the d-curve is proper. The larger κ indicates poor validity for the defective mechanisms such as time synchronization, insufficient resources containers, and stable resources distribution, while the smaller κ indicates the opposite.

Definition 4 (*Curve Deviation*)**.** Curve deviation is the extent to which the separation between c-curve and g-curve fluctuates. Let D be the curve distance set for every unit of time in duration T. $D = \{\ d_i = |c(i) - g(i)| 1 \le i \le T\ \}$, then the curve deviation δ is the standard deviation of D.

Metric δ: the versatility of a simulator. The energy deviation measures the versatility of the simulator when the d-curve is proper. Usually, δ maintains a small value for both the workload and the renewable energy generation are regular, and so do the optimization effects of schedulers. A large δ indicates that the simulator does not support some functions or fails to meet some situations. For example, a simulator supports power values rather than power functions, which have more flexible and finer-granular power states.

(2) Renewable metrics

Definition 5 (*Renewable Utilization*)**.** Renewable utilization μ is the extent to which renewable energy powers the datacenter. It refers to the proportion of consumed renewable energy in all generated renewable energy.

$$\mu = \frac{renewable\_energy\_consumption}{renewable\_energy\_generation}$$

Definition 6 (*Renewable Proportion*)**.** Renewable proportion ρ is the extent to which renewable energy replaces brown energy to power the datacenter. It refers to the proportion of renewable energy in consumed energy (including brown energy).

$$\rho = \frac{renewable\_energy\_consumption}{energy\_consumption}$$

Table 4
Datacenter specification.

Datacenter	Total MIPS (×1000 W)	Full-load power (×1000 W)	Host	
			Type	Size
DC_A	1504	5600	Powerful Normal	10 20
DC_B	1392	5200	Powerful Normal	15 10
DC_C	1056	5100	Normal Weak	15 15

Table 5
Host specification.

Host type	CPU number	MIPS	Power model	Idel power (watt)	Full-load (watt)
Powerful	8	8000	Linear	1200	2400
Normal	6	7200	Linear	1000	1600
Weak	4	6800	Linear	820	1800

Metrics (μ, ρ): the versatility and validity of a simulator. The utilization and proportion jointly measure both the versatility and validity.

- ($\mu\uparrow$, $\rho\uparrow$): "High Utilization and High Proportion" shows that both versatility and validity are good. Firstly, renewable energy generation is less than the energy consumption of full-loaded power but close to the actual energy consumption as much as possible. Secondly, the scheduler is also effective.
- ($\mu\uparrow$, $\rho\downarrow$): "High Utilization and Low Proportion" shows poor versatility. The datacenter consumes most renewable energy but still demands additional brown energy, for inadequate renewable energy caused by functional drawbacks, such as defective test cases and inaccurate energy models.
- ($\mu\downarrow$, $\rho\uparrow$): "Low Utilization and High Proportion" shows poor versatility. The datacenter consumes a few proportions of renewable energy while discarding the rest, for the excessive renewable energy caused by functional drawbacks, such as defective test cases and inaccurate energy models.
- ($\mu\downarrow$, $\rho\downarrow$): "Low Utilization and Low Proportion" shows poor validity, while whether the versatility is good or not is unknown.

5. Benchmark case

This section gives a simulation case as a benchmark. The case configuration conforms to the real-world situation of the datacenters. It defines the detailed configuration of the datacenters, the specification of the renewable energy associated with the datacenters, the workload specification, and the scheduling algorithms. The four typical simulators run the case to see whether the versatility or validity are trade-offs or win-win.

5.1. Datacenter

According to the statement in Section 2, most studies choose three to four geographically distributed datacenters for experiments. Therefore, the case has three geographically distributed datacenters, which contain different numbers and types of hosts and batteries. Tables 4 and 5 show the specification of the datacenter and the host, respectively.

Locations of datacenter DC_A, DC_B, and DC_C conform to the renewable energy traces; that is, they are far from each other enough that their renewable energy generation at any time is different. The precise position is indifferent since the

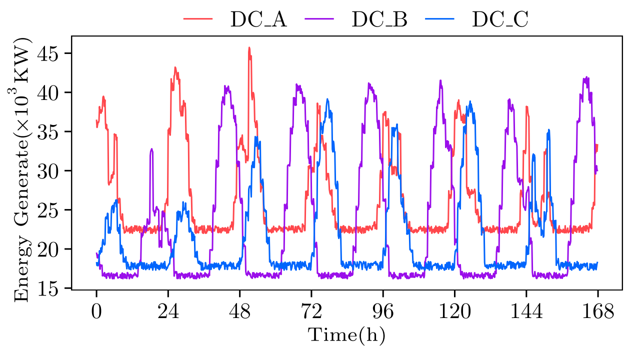

Fig. 5. G-curves of three datacenters over a week.

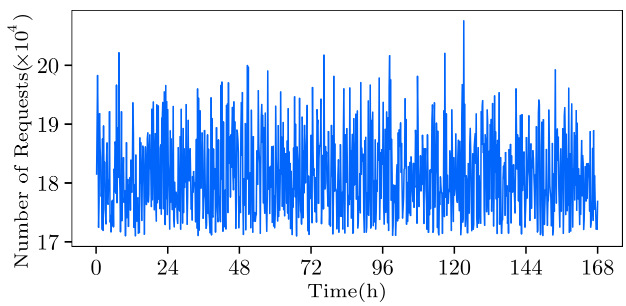

Fig. 6. Timely curve of requests.

optimization algorithms do not select geographical information as the scheduling criteria. Only DC_A has a battery system that maximum supports the full-loaded DC_A running for one hour.

5.2. Renewable energy

In this case, each datacenter is equipped with solar and wind energy. The solar and wind energy curves refer to the energy data of the Measurement and Instrumentation Data Center (MIDC). The traces contain irradiance and wind speed for every minute of the corresponding month in 2011. Fig. 5 shows the g-curves of three datacenters over a week.

In order to obtain the apparent results, the amount of renewable energy should be neither seriously sufficient nor deficient. However, the benchmarking case does not scale the MIDC dataset. Instead, it carefully designs the specification of the datacenters, and makes sure that the available renewable energy of each datacenter at any time is between the total idle power and peak power of the datacenter.

5.3. Workload

The workload is from Google cluster-usage traces in February 2011, which define each request's required CPU, memory, storage, and maximum waiting time. Fig. 6 shows the number of requests generated in a week.

The original Google traces do not adapt to the configured resources of DC_A, _B, and _C in this case. Therefore, we scale the number of generated requests of Google traces so that the datacenter has sufficient resources to perform them. However, we do not change the distribution of the requests of original Google traces. Such distribution conforms to the Poisson distribution, as shown in Fig. 7.

Table 6
Scheduler description.

	Load-balance	Green-awareness
Spatial	The dispatch step considers workload balance among datacenters	The dispatch step considers renewable energy for datacenters
Temporal	The scheduling step considers the available resources of the severs. The allocation step performs workload balance among the servers	The scheduling step considers the available renewable energy of the datacenter. The allocation step performs workload concentration among the servers
Capacity-All: Spatial load-balance temporal load-balance		
Capacity-Green: Spatial load-balance temporal green-awareness		
Green-Capacity: Spatial green-awareness temporal load-balance		
Green-All: Spatial green-awareness temporal green-awareness		

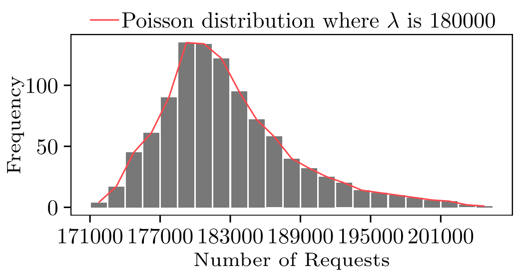

Fig. 7. Request Distribution(Google traces).

5.4. Schedulers

To better evaluate the effectiveness of typical simulators, the case selects four schedulers, which mix the goals of load balance and renewable energy utilization. The workload of a datacenter is tasks generated from requests that have been dispatched to the datacenter. When and where (on which server) these tasks are executed is determined within the datacenter. Therefore, a scheduler contains three steps: the request dispatch among datacenters, the task scheduling within a datacenter, and the task allocation in a datacenter:

- The dispatch step determines which datacenter accepts the request, concerning load balance or available renewable energy of datacenters.
- The scheduling step determines whether a task is executed immediately or not, concerning the available renewable energy of the datacenter.
- The allocation step determines which server a task is allocated to, concerning the load balance among servers in the datacenter.

Four schedulers, namely Capacity-All (CA), Capacity-Green(CG), Green-Capacity(GC), and Green-All (GA), are designed for the combined goals of spatial/temporal load balance and spatial/temporal green-awareness. Table 6 explains these schedulers.

6. Benchmark results

This section benchmarks the typical simulators concluded in Section 4.1 on the test cases mentioned in Section 5. After analyzing the metrics defined in Section 4.2, we claim that the simulator affects the optimization results of the schedulers. For example, the same scheduler leads to different renewable utilization in the different simulators under the same test case. The simulation results show that the more versatile, the more valid a simulator is.

6.1. Purposes

For the same case, schedulers and workload, we perform the benchmark on four typical simulators from different aspects following these Research Questions (RQs):

RQ1: Whether the typical simulators have the same simulated datacenters power?

RQ2: To what extent does the simulated power conform to the available renewable energy?

RQ3: Do the schedulers have the same effectiveness on typical simulators regarding renewable utilization and proportion?

6.2. Implementation details

Repeatedly developing these self-made simulators is costly despite their common grounds. Therefore, several studies that emerged after 2018 employ the third-part tools for their simulation, such as Plug4Green in [34], CloudSim in [66,84,88], Philharmoni in [73], DCWorms in [74] , MATpower in [75], RenewSim in [80], EcoMultiCloud in [81], SimGrid in [82], and iFogSim in [96]. Nevertheless, we do not treat them as the implementation of typical simulators and benchmark them for the following reasons: First, it is unfair to compare them for their implementation techniques vary. For example, they use different programming languages and run on different platforms. Second, none of these tools whose functions match the typical simulators exactly.

CloudSim, including its extensions, is the most popular simulator even though it does not naturally support geographically distributed and renewable energy-powered datacenter simulation. To this end, the four simulators, named Trace, Value, Rule, and Base, are our extensions on CloudSim according to the functions in Table 3. Most important, the Base is the minimal extension on CloudSim. It only contains the necessary functions of the DCRE simulator.

We perform a long-term simulation of the benchmarking case. The simulation time is 30 days but the execution time of the simulator is within five minutes. Among 28 works that employ the MIDC weather traces (see Section 2.2), 24 works mention the simulation time, and 22 of them are no more than a month. For example, one day in [16,17,36,43,59,61], two days in [63], one or two weeks in [25,34,46,52,55,58,65], and one month in [6,12, 18,27,31,62,70,95]. Through analysis, the solar energy has a daily periodicity, and the diversity of wind energy is also demonstrated well in a one-month MIDC traces. For the sake of presentation, we select 24 h of tracking data and hourly display it on g-, c- and d-curves because these curves have daily periodicity, while we monthly aggregate 30-days tracking data to κ, δ, (μ, ρ) and show them on the plots.

6.3. RQ1: C-curves

Taking DC_B as an example, Fig. 8 shows the c-curves of the four simulators under the four schedulers within a day. Fig. 8 marks the observations on these curves, and Table 7 explains the reasons and the rules for these observations.

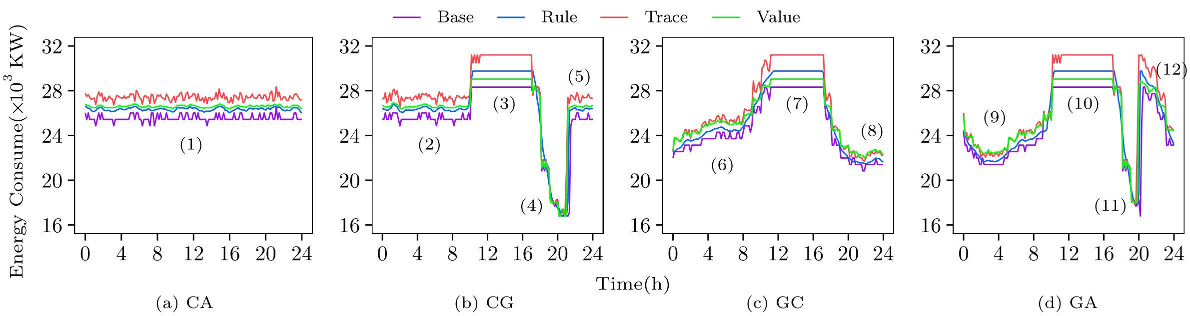

Fig. 8. c-curves of the four simulators under the four schedulers.

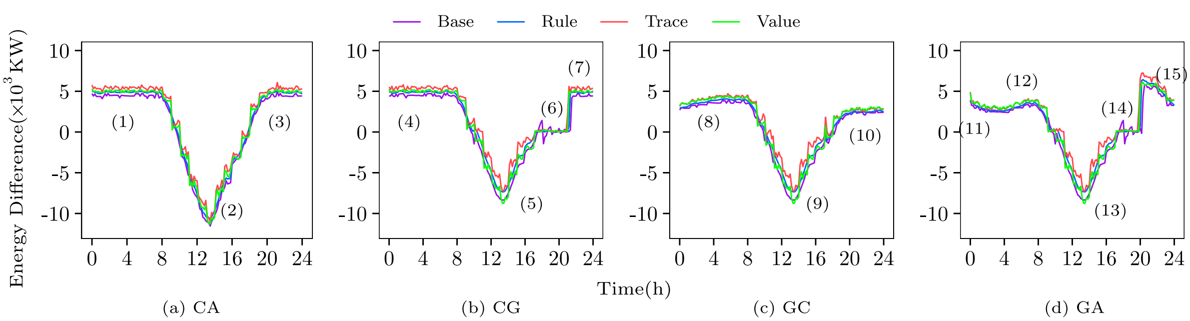

Fig. 9. d-curves of the four simulators under the four schedulers.

Table 7
Observations (Obs.) and their explanations.

Obs.(1)	Flat and none-overlapped curves	Scheduler	CA
Reason	Task generators and power models of four simulators vary. It results in gaps among c-curves. The CA scheduler balances the workload to datacenters and ignores the renewable energy issues. Therefore, c-curves are flat.		
Rule	For a valid simulator, c-curves with a CA scheduler follow the "workload curve."		
Obs.(2)(5)	Flat curves	Scheduler	CG
Reason	The CG scheduler is temporal green-awareness. Solar energy is scarce for a long time at night, so the green scheduler does not actually work. To this end, the datacenter is busy executing the timed-out tasks, and the energy consumption is stable.		
Rule	For a valid simulator, a CG scheduler degrades to a CA scheduler when renewable energy is scarce.		
Obs.(3)(7)(10)	Curves reach the peak and keep for a while	Scheduler	CG, GC, GA
Reason	The peak is the maximum power of the datacenter. For the green-awareness schedulers, the datacenter executes tasks as much as possible when renewable energy is sufficient in daylight.		
Rule	For a valid simulator, c-curves with green-awareness schedulers reach their peaks when renewable energy is sufficient. It indicates that the datacenter is full-loaded.		
Obs.(4)(11)	Curves descend and reach the valley soon	Scheduler	CG, GA
Reason	The valley is the amount of renewable energy. The temporal green-awareness schedulers postpone tasks when renewable energy is getting less at dusk. Therefore, the workload of the datacenter decreases, and so does the energy consumption.		
Rule	For a valid simulator, c-curves with temporal green-awareness schedulers descend and reach the valley when renewable energy changes from sufficient to insufficient.		
Obs.(6)(8)(9)	Curves descend/ascend	Scheduler	GC, GA
Reason	When the datacenter with the spatial green-awareness schedulers is not full-loaded (renewable energy is insufficient), its energy consumption approximately equals its available renewable energy because the amount of allocated workload determines the former and is dominated by the latter.		
Rule	For a valid simulator, c-curves with the spatial green-awareness schedulers partially follow g-curves.		
Obs.(12)	Curves reach the peak, then descend	Scheduler	GA
Reason	Like Obs.(5), the temporal green-awareness part of the GA scheduler makes the datacenter busy executing time-out tasks firstly, so the datacenter is full-loaded. Then spatial green-awareness part of the GA scheduler allocates less workload to the datacenter, so the datacenter is not full-loaded, and its energy consumption decreases.		
Rule	For a valid simulator, c-curves with the GA scheduler reach the peaks and descend soon when renewable energy becomes scarce and remains for a long time.		

6.4. RQ2: D-curves

Taking DC_B as an example, Fig. 9 shows the d-curves of the four simulators under the four schedulers within a day. D-curve is the difference between c-curve and g-curve. Therefore, the closer d-curve is to the x-axis, the more renewable energy is utilized. Fig. 9 marks the observations on these curves, and Table 8 explains the reasons and the rules for these observations.

Many factors influence the curve gap for the four simulators, such as the power model, schedulers, and renewable energy.

Table 8
Observations (Obs.) and their explanations.

Obs.(1)(3)(4)(7)	Curves are flat	Scheduler	CA, CG
Reason	Datacenter with the CA scheduler gets a stable workload, so its energy consumption is stable. At night, renewable energy is stable and scarce; meanwhile, the CG scheduler degrades to the CA scheduler. To this end, d-curves are flat.		
Rule	For a valid simulator, d-curves with the temporal load-balance schedulers are flat when the renewable energy is stable and scarce.		
Obs.(2)(5)(9)(13)	Curves descend to the valley, then ascend	Scheduler	CA, CG, CG, GA
Reason	G-curves increase and decline drastically in daylight. In contrast, c-curves are subject to relatively minor changes under the constraint of idle and peak powers. So d-curves and g-curves show the opposite trends.		
Rule	For a valid simulator, d-curves descend to the valley if g-curves ascend to the peak when renewable energy is sufficient in daylight.		
Obs.(2)(5)(9)(13)	The valley of CA curves ((2)) is lower than others ((5)(9)(13))	Scheduler	CA, CG, CG, GA
Reason	The CA scheduler does not consider the renewable energy features.		
Rule	For a valid simulator, the CA scheduler has the worst optimization effects.		
Obs.(6)(14)	Curves are close to the x-axis	Scheduler	CG, GA
Reason	Renewable energy becomes insufficient at dusk. The temporal green-awareness schedulers postpone incoming tasks to make energy consumption approximately equal to available renewable energy.		
Rule	For a valid simulator, d-curves with temporal green-awareness schedulers are closed to the x-axis when renewable energy changes from sufficient to insufficient.		
Obs.(8)(10)(12)	Curves at (8)(10)(12) are closer to the x-axis than (1)(3)(4)(7)	Scheduler	GC, GA
Reason	Spatial green-awareness schedulers allocate tasks according to the available renewable energy. Their d-curves are closer to the x-axis than those of spatial load-balance schedulers.		
Rule	For a valid simulator, the GC and GA schedulers have better optimization effects than the CA and CG schedulers.		
Obs.(15)(11)	Curves reach the peak, then drop	Scheduler	GA
Reason	The temporal green-awareness part of the GA scheduler does not work when renewable energy is scarce at night. The datacenter is busy executing time-out tasks and becomes full-loaded. D-curves reach their peaks for a while. After that, the spatial green-awareness part of the GA scheduler allocates tasks to other datacenters, the workload decreases, and the datacenter is not full-loaded, so d-curves decrease. The "Obs.(11)" happens periodically.		
Rule	For a valid simulator, the GA scheduler has the best optimization effects.		

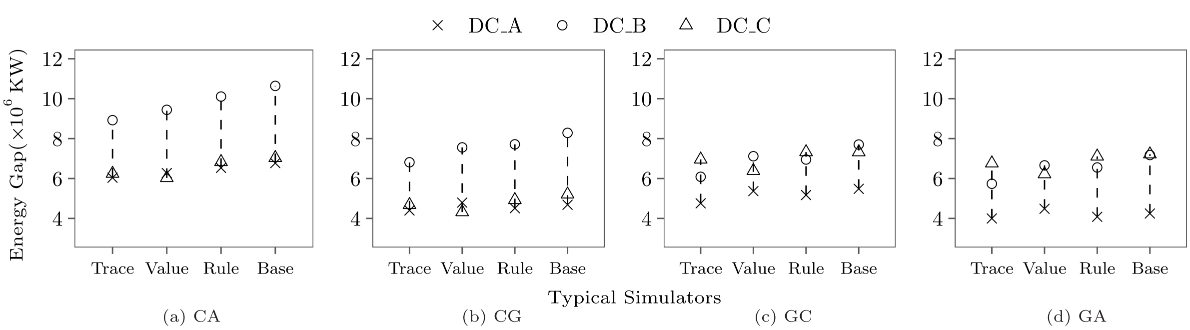

Fig. 10. Curve gap for four simulators with four schedulers.

Among them, the available recommendation energy is the most remarkable one. On the one hand, when renewable energy is insufficient, the d-curves of the four simulators are nearly overlapped, and the values are about 5000 kwatt, shown as the flat parts of all d-curves in Fig. 9. On the other hand, datacenters perform more tasks when renewable energy is sufficient. At this time, the simulator's validity difference starts to be noticed. As shown in the non-flat parts of all curves in Fig. 9, the *base-simulator* (purple curve) is always below the other simulators (other curves); the *trace-simulator* (red curve) is always above; and the rest two simulators in the middle, namely *value-simulator* (green curve) and *rule-simulator* (blue curve), are nearly overlapped.

We calculate each datacenter's curve gap (metric κ) for four simulators with four schedulers. Fig. 10 shows the results, where the symbols represent the datacenters.

As discussed in Section 4.2, the smaller κ, the better validity of the simulator is. Fig. 10 shows three observations for all datacenters.

- For four simulators, κ increases with *trace*-, *value*-, *rule*-, and *base-simulator*. The better versatility, the better validity of a simulator is.
- For four schedulers, κ decreases with CA, CG, GC, and GA. The more consideration of renewable energy, the better the optimization effect is.
- For the three datacenters, no evidence shows that κ is related to the DC_A, DC_B, and DC_C, for their capacities and power vary.

We calculate each datacenter's curve deviation (metric δ) for four simulators with four schedulers. Fig. 11 shows the results.

As discussed in Section 4.2, the smaller δ, the better the versatility of the simulator is. In Fig. 11, no matter which schedulers or datacenters, the curve deviation of *trace-simulator* is always the smallest, that of *base-simulator* is the largest, and that of *value-* and *rule-simulator* is similar in the middle. Such observation accords with our design goals in Table 3: *trace-simulator* has the optimal functional configuration, while *base-simulator* only has essential simulation functions.

Combining the above two metrics, the versatility and validity of *trace-simulator* are the best, while those of *base-simulator* are the worst. It initially shows that versatility and validity are win-win. Section 6.5 further studies this issue with renewable metrics (μ, ρ).

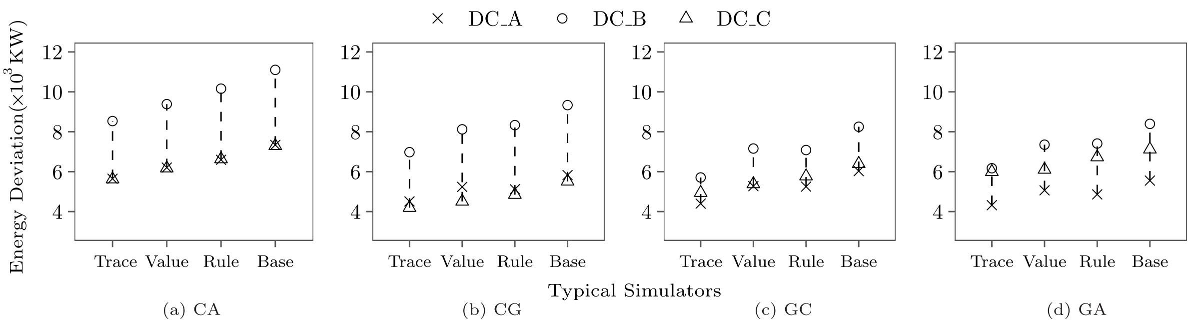

Fig. 11. Curve deviation(metric δ) for four simulators with four schedulers.

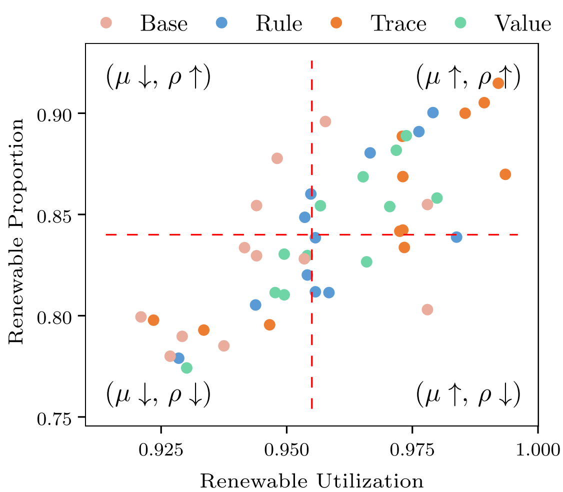

Fig. 12. The 48 groups of metrics (μ, ρ) points for the benchmark case.

6.5. RQ3: Utilization and proportion

The renewable utilization and proportion (μ, ρ) jointly measure both the versatility and validity. We estimate 48 groups of metrics (μ, ρ) to see the relationship between μ and ρ. (4 simulators $\times$ 4 schedulers $\times$ 3 datacenters). We draw them on a scatter plot whose the *x*-axis is μ, and the *x*-axis is ρ, as shown in Fig. 12, in which symbols ↑ and ↓ represent relatively large and small values, respectively. Section 4.2-(2) explains that (μ ↑, ρ ↑) means both versatility and validity are good, (μ ↑, ρ ↓) and (μ ↓, ρ ↑) mean poor versatility, while (μ ↓, ρ ↓) means poor validity and unknown versatility. We expect to see μ increase with ρ because (μ ↑, ρ ↑) is the necessary condition that "validity and versatility are win-win". The observation proves μ and ρ are positively related, confirming our expectations.

Further, (μ ↑, ρ ↑) means both validity and versatility are good. In Fig. 12, the (μ, ρ) pairs of the *trace-simulator* are closer to the top-right corner, while those of the *base-simulator* are closer to the bottom-left corner, compared with other pairs which represent the *value-* and *rule-simulator*. Since simulators are the primary factors that bring different (μ, ρ) pairs, schedulers also have their influence. For example, the *base-simulator* under the GA scheduler has better (μ, ρ) than the *trace-simulator* under the CA scheduler, although the latter is more valid and versatile than the former. The example explains why several points of the *trace-simulator* appear in the bottom-left corner, while several points of the *base-simulator* appear in the top-right corner. Such observations also verify the d-curve analysis in Section 6.4.

7. Related work

As a survey, we study two issues in this paper: the versatility and validity of DCRE simulators, and the survey about renewable energy utilization in datacenters. Sections 2 and 3 discuss the former well. This section introduces the latter.

Wang et al. [108] discussed the research progress of sustainable datacenter in smart grids, reviewed the challenges faced by renewable energy such as solar energy and wind energy, and emphasized the necessity of a hybrid energy power system. Huang et al. [109] comprehensively summarized the datacenter from the perspective of energy producers, and discussed various integration methods and the most advanced control methods, so as to find new methods to improve energy efficiency and reduce carbon emissions. Rostirolla et al. [110] reviewed the efforts of other disciplines in datacenter architecture, infrastructure scale, and renewable energy management to improve the flexibility of datacenters and the efficiency of renewable energy. Nayak et al. [111] reviewed renewable energy-based resource management in cloud computing and discussed the impact of load on renewable energy usage. Katal et al. [112] discussed various mechanisms to reduce the power utilization of the datacenter and put forward the challenges of building a green datacenter.

To the best of our knowledge, quite a few works review energy-saving approaches for datacenters from the aspect of renewable energy, and none of the surveys analyze the versatility and validity of DCRE simulators as we do. We do not limit our research to reviewing work. We also proposed benchmarking cases and experiments for the simulators. Our works demonstrate that a simulator with the best versatility also has the best validity.

8. Conclusion and future work

In this paper, we review the various simulators for DCRE (Datacenters powered by Renewable Energy mix) in the last ten years. We focus on the two questions: Whether these simulators have the same result for the same optimization approach, and how to evaluate the results? Whether the versatility and validity of a simulator are trade-offs or win-win. The main technical challenges are formalizing the typical simulators, versatility and validity, and their metrics, and designing a uniform benchmark case. The analysis and experimental results demonstrate that a simulator with the best versatility also has the best validity. Researchers who study power and renewable energy efficiency could quickly understand state-of-the-art experimental environments and approaches through our work. Moreover, our abstraction, formulation, metrics, and benchmarking cases bring new references and new experiences to the DCRE study. The win-win rule also gives the direction of developing better DCRE simulators.

Based on the above discovery, our work can be extended in multiple directions. To improve versatility, researchers could try to dig out new functions not covered by existing simulators so far.

These new functions could be a cross-regional green-awareness scheduler on geographically distributed DCREs, a sophisticated battery system that improves energy efficiency, and a multifarious energy model that supports more types of renewable energy. We expect a general-purpose simulator with our metrics as a guideline for the studies of the energy-efficient DCRE.

CRediT authorship contribution statement

Jie Song: Conceptualization, Methodology, Software, Validation, Data curation, Writing – original draft, Funding acquisition. **Peimeng Zhu:** Formal analysis, Investigation, Resources, Visualization. **Yanfeng Zhang:** Writing – review & editing. **Ge Yu:** Supervision, Project administration.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This paper is supported by the National Natural Science Foundation of China 62162050, 62072082.

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