Coupling Models for Cloud Datacenters and Power Grids

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ABSTRACT

We study the impact of rise of renewable growth and cloud computing power consumption, and in particular how the load of cloud computing can be coupled to the grid for the benefit of both. We consider three models: static cloud loads, selfish local-optimization by each datacenter (DC) to minimize power cost (DP-ONL), and load orchestrated by the grid using economic dispatch (GC).

Our results show that dynamic coupling can give large improvements to grid dispatch cost (2.69%), wind absorption (3.97%), and datacenter power prices. However, depending on coupling, both datacenters and non-datacenter customers can suffer from dynamic changes, so both effective and equitable coupling methods require further study.

KEYWORDS

Power grid, Renewable energy, Carbon emissions, Data centers

ACM Reference Format:

1 INTRODUCTION

Recent years have seen the rapid growth of power consumption by hyperscale cloud providers (e.g. Amazon, Microsoft, Google, Alibaba, Baidu) and also large-scale computing companies (e.g. Facebook, Apple, Tencent). While obscured by their rapid cannibalization of enterprise datacenters in recent reports [22], a close look at the data documents their sustained growth at 31% annually through 2018. Recent accelerants such as machine learning [13, 32], and Covid-19 driven digitalization [25, 31] may have increased this rate. With datacenters accounting for more than 5% of power consumption in the Northern Virginia power grid and 2% nationally today, these power loads are already significant. Extrapolated to 2025, the power consumption of these hyperscale providers alone are projected to exceed 5% of US power consumption by 2025.

Concurrently, driven by falling generation costs and growing climate concerns, renewable generation is increasing rapidly around the world. The past decade (2010-2020) has seen the rapid growth of wind and solar renewable power generation, quadrupling in the United States, to reach 11% nationwide, and higher fractions in leading areas such as California (33%) and Texas (21.5%), and across Europe. And more ambitious renewable-portfolio standard (RPS) goals have been set for many of these regions for the coming decades – including California (60%), New York (70%), Europe (33%) all in 2030. This transformation of the power grid has created significant integration challenges, including both decreasing renewable capacity credit and rapid fluctuation in generation mix (wind, solar, fossil-fuel), driven by ever larger fluctuations in renewable generation as their fraction in the power grid increases [33].

Recently researchers [3, 34, 35], startups [1, 30] and cloud computing companies [7, 29] have proposed shifting computing load (power consumption) to save money [14, 28] and also to reduce the carbon emissions of datacenters [5, 8, 18]. However, none of these studies considered dynamic interaction with the power grid, viewing computing as too small a load to change grid dynamics. Perhaps more interesting, are radical approaches to use the dynamic shifting of load to help the power grid improve stability and to absorb more renewable generation (carbon-free power) [12, 16, 36, 37]. All of these studies consider simple model power grids (topology, load), and show that co-optimization can give theoretical benefits. One notable exception studies a single configuration of datacenters as dispatchable loads, highlighting the opportunity for potential synergy [12]. In this study, we explore that opportunity more broadly.

In particular, we consider a wide range of hyperscale cloud configurations, ranging from 3.5% to 14%, reflecting estimates for 2022 and 2027 nationally, but corresponding to 2018 and 2022 in cloud-heavy power grids [2, 4]. We also consider a wide range of renewable penetration (wind), scaling from 15% to 60%, reflecting 2015 and aspirational 2050 in a DOE National Renewable Energy Laboratory Wind Vision Report [26]. Within that space, we consider a spectrum of coupling, ranging from a baseline where hyperscale datacenters act as a constant load, act selfishly to optimize their power cost, and delegate their flexibility to the power grid, allowing it to optimize social welfare for all. Across that space, we examine grid dispatch cost, renewable absorption, as well as impacts on both cloud datacenter and non-datacenter power prices.

Specific contributions of the paper include:

- While increasing datacenter load benefits renewable absorption, dynamic coupling of datacenters can provide further benefits, reducing dispatch cost and increasing renewable fraction by as much as 2.69% and 1.39% respectively.
- The datacenters collectively can exercise market power, both reducing datacenter power prices不同地损害非-DC客户。这是一个需要进一步研究的挑战。
- Selfish datacenter optimization captures less grid benefit than delegation of load flexibility to the grid, but that delegation may be problematic for datacenter efficiency.
which paraphrased tersely says "efficiency increases and price reductions from hardware improvement and some believe it is already faster due to the rise of machine learning (cloud) power consumption in the past decade and extrapolation to 2030 [22]. Even the nominal projection is 31% compound annual growth rate based on data from 2014-2018, with high and low scenarios at 10% CAGR differences. Its widely acknowledged that these projections may be conservative due to the rise of machine learning, and COVID-driven digitalisation.

In today’s cloud computing companies, to meet demand and increase cost-efficiency, sites have grown dramatically, and continue to do so. Today (2020), there are large numbers of 200 MW sites, and large sites today exceed 1 gigawatt [2, 6, 23]. We are interested in modulating these large loads by 20, 40, even 60% under intelligent dynamic control. Our objective is both to increase the efficiency of the power grid in absorbing renewable generation, but also to enable the datacenters (and other customers) to achieve lower prices.

2  BACKGROUND

2.1  Datacenters and Growing Power Use

The history of cloud computing efforts in sustainability is laudable, including significant increases in the efficiency of our digital infrastructure (driving PUE from over 2 to as low as 1.1 for hyperscale cloud datacenters), and increasing the scale and availability of renewable energy in power grids (by enabling financing of new renewable generation through long-term power purchase agreements). However, despite these efforts, the power consumption of the largest cloud operators has continued to grow rapidly. For example, the long-term trend for hyperscale cloud providers in North America is growing annually at 31% per year, and in 2020 surpassing the 2018 total for all datacenters. If growth continues at this rate, and some believe it is already faster due to the rise of machine learning, the power consumption of these hyperscale providers alone will exceed 10% of the world’s total power consumption [11, 22].

Despite extraordinary advances in power management and computing hardware efficiency, both power consumption and associated carbon emissions of the cloud continue to increase. The primary answer for this can be found in Jevon’s paradox, published in 1865 which paraphrased tersely says "efficiency increases and price reductions only increase use, perhaps even faster" [10]. So the continued efficiency and price reductions from hardware improvement and the invention of new uses of computing have driven the growth of computing use. Further, the cloud’s success in increased ease of software development, deployment and scaling, as well as its improved energy efficiency and cost, collectively accelerate the use of computing for all sorts of existing and new applications from internet search to social networking to video streaming to intelligent monitoring to free worldwide videoconferencing.

Figure 1 shows the recent trajectory of hyperscale datacenter (cloud) power consumption in the past decade and extrapolation to 2030 [22]. Even the nominal projection is 31% compound annual growth rate based on data from 2014-2018, with high and low scenarios at 10% CAGR differences. Its widely acknowledged that these projections may be conservative due to the rise of machine learning, and COVID-driven digitalisation.

In today’s cloud computing companies, to meet demand and increase cost-efficiency, sites have grown dramatically, and continue to do so. Today (2020), there are large numbers of 200 MW sites, and large sites today exceed 1 gigawatt [2, 6, 23]. We are interested in modulating these large loads by 20, 40, even 60% under intelligent dynamic control. Our objective is both to increase the efficiency of the power grid in absorbing renewable generation, but also to enable the datacenters (and other customers) to achieve lower prices.

2.2  Economic Dispatch and Fluctuating Power Generation

The past decade (2010-2020) has seen the rapid growth of wind and solar renewable power generation, quadrupling in the United States, to reach 11% nationwide, and higher fractions in leading areas such as California (33%) and Texas (21.5%), and across Europe. And more ambitious renewable-portfolio standard (RPS) goals have been set for many of these regions for the coming decades – including California (60%), New York (70%), Europe (33%) all in 2030. This transformation of the power grid has produced rapid fluctuation in generation mix (wind, solar, fossil-fuel), driven by ever larger fluctuations in renewable generation as their fraction in the power grid increases.

Modern power grids use economic dispatch (lowest bid cost power first) to select which generators should be used, subject
to transmission capacity and the load profile. Because solar and wind generation has no fuel cost, it is typically bid at $0/MWh, so when available it displaces fossil fuel generation. RPS is an average measure, so the peak renewable generation is much higher, but swings up and down with the availability wind or sun. For example, California’s power grid, CAISO, is reached an annual RPS of 30% in 2019, but on dozens of winter days, reached at over 90% renewable generation for most daylight hours. These swings cause the carbon content of power in the grid to swing by 4x and more. For example, consider a 1-day generation profile for CAISO (see Figure 2) that illustrates how renewable and conventional generation varies across the day. In this example, solar accounts for more than 50% of power midday, but natural gas for 46% at 8pm. Similar phenomena occur in wind-heavy power grids (e.g. ERCOT, Germany), but with different duration and periodicity.

3 PROBLEM AND APPROACH

Power markets and grids have complex dynamics, driven by the myriad transmission, generation, pricing, and dynamic change constraints. Small changes can cause large effects (e.g. a small changes in the real-time market can cause $1000/MWh price changes), or an underestimate of load can produce a sharp rise in prices. We are interested in dynamic load management – such as is possible with a network of datacenters under intelligent control. To explore these impacts, there are no good analytical models, so we resort to simulation, real load and generation profiles, and a realistic power grid. Our objective is the Understand the impact of growth of datacenters and renewable generation in the future power grid, and the potential of dynamic datacenter load control to improve both overall grid and datacenter experience.

To explore the impact of large-scale increases in wind generation and datacenter power consumption in future power grids, we start from a real-grid model, and in a series of power grid simulations successively add these increases to the grid. Using optimal power flow to simulate grid dispatch for a real CAISO/WECC system [? ? ], we explore the expected range of increase for each:

- Wind Penetration: from 15% to 60% of total grid power consumption
- Datacenters: from 2-8 gigawatts spread over 10-40 sites (3.5 to 14%)

The range of wind penetration spans the 2015 level, growing the aspired 2050 goal in NREL’s [? ]. The datacenters span the 2020 level hyperscale cloud level, growing to the projected level in 5-10 years [22]. For all of these scenarios, we explore the effect on dispatch cost, renewable absorption (and carbon emissions), and power prices. Because datacenters are the fastest growing power consumers in the developed world, We focus particularly on the impact of their growth on other consumers, and also on power generators.

At that scale, datacenters will be a critical component of grid power load, and as such, many questions arise about how to couple datacenters and grid for separate or mutual benefit. For example, there a long history of research on datacenter price-optimization or time-shifting load to reduce power prices or carbon emissions [? ]. More generally, we explore dynamic techniques to manage datacenter load – under datacenter or grid control – comparing their effectiveness and impact from several different perspectives.

In particular, we consider three models:

- Uncoupled: datacenters are a constant power load
- Datacenter local control of dynamic load (selfish datacenter cost optimization)
- Grid-wide dispatch cost optimization of dynamic load

Uncoupled reflects the current situation. Data center local control uses the ability to flex workload in time (shifting) within each datacenter to optimize local power cost. Grid-wide optimization gives the flexibility (time shifting) of all of the datacenters to the power grid, allowing it to optimize globally. These studies examine impact on grid dispatch cost, renewable absorption (and carbon emissions), and power prices. However, because the datacenters are such a large fraction of load (dynamic change as much as 10%), it is worthwhile to look at the market power they represent, and therefore their impact on non-datacenter customers power, and in the case of grid-wide optimization, their impact on datacenters.

The resulting insights provide a perspective from which to understand the relationships to design how to best couple datacenters and power grids for both stability and mutual benefit.

4 METHODS

We assess the impact of growing cloud load and renewable generation based on the economic dispatch (ED) model. We use several algorithms to dynamically couple datacenter load to the power grid.

4.1 Notation

To begin with, the model notations are listed in the following table, which are similar as those in [12]. The units for power/load, energy, and phase angle are megawatts, megawatt-hours, and degrees respectively.

Sets:
- \( D_n \) Demand loads; demand loads at bus \( n \)
- \( G_n \) Generators; generators at bus \( n \)
- \( I_n \) Import points; import points at bus \( n \)
- \( L \) Transmission lines
- \( L_n^i \); \( L_n^r \) Transmission lines to bus \( n \); lines from bus \( n \)
- \( N \) Buses
- \( R_n \) Renewable generators; Renewable generators at bus \( n \)
- \( T \) Time periods
- \( W \) Wind-farm locations
- \( \Omega \) Scenarios

Parameters:
- \( B_i \) Suscetptance of transmission line \( i \)
- \( C_i \) Generation cost of generator \( i \)
- \( C^{SL}_j \) Load-shedding penalty at load \( j \)
- \( C^{CE}_j \) Curtailment penalty at load \( j \)
- \( C^{CM}_i \) Curtailment penalty at import point \( i \)
- \( C^{CR}_i \) Curtailment penalty at renewable \( i \)
- \( D_{ijt} \) Demand load of consumer \( j \) at time \( t \)
- \( F^{max}_l \) Maximum power flow of transmission line \( l \)
- \( M_{ijt} \) Power production of import \( i \) at time \( t \)
- \( P^{max}_i \) Maximum power output of generator \( i \)
- \( R_{ij} \) Power production of renewable \( i \) at time \( t \)
- \( RU_i \) Ramp-up limit of generator \( i \)
The economic dispatch model solved by the grid is as follows:

\[
\begin{align*}
\text{min} & \quad \sum_{i \in T} \left( \sum_{j \in G} C_i p_{ij} + \sum_{j \in G} \sum_{t \in T} C^d_{ij} d_{jt} + \sum_{t \in T} C^m_{it} m_{it} \right) \\
& \quad + \sum_{i \in W} C^w_{it} w_{it} + \sum_{i \in I} C^C_{it} r_{it} \quad \text{(1a)} \\
\text{s.t.} & \quad \sum_{i \in L_n} f_{lt} - \sum_{i \in L_n} f_{lt} + \sum_{i \in G_n} p_{it} + \sum_{i \in I_n} (M_{it} - m_{it}) \\
& \quad + \sum_{i \in W_n} (W_{it} - w_{it}) + \sum_{i \in I_n} (R_{it} - r_{it}) \\
& \quad = \sum_{j \in D_n} (D_{jt} - d_{jt}), \quad \forall n \in N, t \in T, \quad \text{(1b)} \\
& \quad f_{lt} = B_l(\theta_{lt} - \theta_{mt}), \quad \forall l = (m, n) \in L, t \in T, \quad \text{(1c)} \\
& \quad - R_{D_l} \leq p_{lt} - p_{lt-1} \leq R_{U_l}, \quad \forall i \in G, t \in T, \quad \text{(1d)} \\
& \quad - F_{l}^\max \leq f_{lt} \leq F_{l}^\max, \quad \forall l \in L, t \in T, \quad \text{(1e)} \\
& \quad \Omega_{n}^\max \leq \theta_{lt} \leq \Omega_{n}^\min, \quad \forall n \in N, t \in T, \quad \text{(1f)} \\
& \quad 0 \leq p_{it} \leq p_{it}^\max, \quad \forall i \in G, t \in T, \quad \text{(1g)} \\
& \quad 0 \leq d_{jt} \leq D_{jt}, \quad \forall j \in D, t \in T, \quad \text{(1h)} \\
& \quad 0 \leq m_{it} \leq M_{it}, \quad \forall i \in I, t \in T, \quad \text{(1i)} \\
& \quad 0 \leq w_{it} \leq W_{it}, \quad \forall i \in W, t \in T, \quad \text{(1j)} \\
& \quad 0 \leq r_{it} \leq R_{jt}, \quad \forall i \in R, t \in T. \quad \text{(1k)}
\end{align*}
\]

In this model, power is supplied from conventional thermal power plants (e.g. gas, nuclear, coal), non-wind renewables (e.g. hydro), imports, and wind power plants. We assume that imports, renewable power plants are not competitive agents in the market and have high priority. To reduce the curtailment of these resources, penalty terms \(C^m_{it}, C^w_{it}\), and \(C^C_{it}\) are included. In addition, as sometimes load shedding may happen due to grid capacity or ramp constraints, which we want to avoid, each unit of load shedding is at the cost of value of lost load (VOLL) \(C^{f}_{ij}\).

Given the assumptions, the objective (1a) is to minimize the total dispatch cost, including the generation cost of conventional thermal power plants, penalties of wind/import/non-wind renewable curtailment and load shedding. Note that if we regard the renewable generation in this model as forecasted values, this model is close to the day-ahead economic dispatch.

### 4.2 Economic Dispatch Model

The economic dispatch model solved by the grid is as follows:

\[
\begin{align*}
\text{min} & \quad \sum_{i \in T} \left( \sum_{j \in G} C_i p_{ij} + \sum_{j \in G} \sum_{t \in T} C^d_{ij} d_{jt} + \sum_{t \in T} C^m_{it} m_{it} \right) \\
& \quad + \sum_{i \in W} C^w_{it} w_{it} + \sum_{i \in I} C^C_{it} r_{it} \quad \text{(1a)} \\
\text{s.t.} & \quad \sum_{i \in L_n} f_{lt} - \sum_{i \in L_n} f_{lt} + \sum_{i \in G_n} p_{it} + \sum_{i \in I_n} (M_{it} - m_{it}) \\
& \quad + \sum_{i \in W_n} (W_{it} - w_{it}) + \sum_{i \in I_n} (R_{it} - r_{it}) \\
& \quad = \sum_{j \in D_n} (D_{jt} - d_{jt}), \quad \forall n \in N, t \in T, \quad \text{(1b)} \\
& \quad f_{lt} = B_l(\theta_{lt} - \theta_{mt}), \quad \forall l = (m, n) \in L, t \in T, \quad \text{(1c)} \\
& \quad - R_{D_l} \leq p_{lt} - p_{lt-1} \leq R_{U_l}, \quad \forall i \in G, t \in T, \quad \text{(1d)} \\
& \quad - F_{l}^\max \leq f_{lt} \leq F_{l}^\max, \quad \forall l \in L, t \in T, \quad \text{(1e)} \\
& \quad \Omega_{n}^\max \leq \theta_{lt} \leq \Omega_{n}^\min, \quad \forall n \in N, t \in T, \quad \text{(1f)} \\
& \quad 0 \leq p_{it} \leq p_{it}^\max, \quad \forall i \in G, t \in T, \quad \text{(1g)} \\
& \quad 0 \leq d_{jt} \leq D_{jt}, \quad \forall j \in D, t \in T, \quad \text{(1h)} \\
& \quad 0 \leq m_{it} \leq M_{it}, \quad \forall i \in I, t \in T, \quad \text{(1i)} \\
& \quad 0 \leq w_{it} \leq W_{it}, \quad \forall i \in W, t \in T, \quad \text{(1j)} \\
& \quad 0 \leq r_{it} \leq R_{jt}, \quad \forall i \in R, t \in T. \quad \text{(1k)}
\end{align*}
\]

For each day type, there are 1,000 wind power production scenarios from [127], the average of which is about 15% of load (15% penetration) in Summer, corresponding to the current wind penetration level. The wind scenarios for WDs and WEs in the same season are the same. For higher wind penetration, the production levels are scaled up equally. This reflects the assumption that existing wind locations reflect attractive choices, and can be scaled via larger turbines or local site expansion [27].

There are three levels of generation cost for conventional generation: 1 $/MWh (nuclear), 2 $/MWh (coal), and 4 $/MWh (gas), corresponding to the fuel price. Following [12], the imports and renewables are assumed to be non-dispatchable due to long-term commitments and goal of reducing carbon emissions, but they can be curtailed at a cost of 500 and 1000 $/MWh (100 $/MWh for wind) respectively. The value of lost load (VOLL) is set as 1000 $/MWh for load shedding. As LMP at a bus represents the marginal dispatch cost of adding 1MW load, we expect that the LMP may go negative when some type of curtailment arises. On the contrary, it can go very high when load shedding happens.

Datacenters are 200 MW at each site, and presumed to operate at 70% utilization [2, 6, 23], but well below the largest sites that already exceed 1.5 gigawatts [2]. In discussions with infrastructure developers at all of the leading hyperscale cloud companies, their primary design targets all exceed 1 GW per site. In our simulations, the
200 MW datacenter are added to random buses of the test system, ensuring that the associated bus has the capacity to support a 200 MW datacenter; this reflect cloud companies doing site selection often driven by business considerations external to the power grid (e.g. tax breaks, jobs, internet hookups, etc.).

4.4 Metrics
We use the following metrics.

- **Grid Dispatch Cost** – the objective function for economic dispatch in power grid simulations. Also called social welfare in electricity market clearing models[12].
- **Renewable Fraction** is the fraction of power each type of generation, including conventional power plants, non-wind renewables, imports, and wind in our model.
- **RPS** aka renewable portfolio standard, defined as the ratio of absorbed renewable generation to the total power consumed (load).
- **Carbon Emission Rate (CER)** reflects the average emissions per unit power at a particular time in year, calculated by summing the emissions from the total active generation into the grid divided by the power consumed.
- **Price** is the average locational marginal price (LMP) across the grid and intervals, weighted by power demand. This is closely related to the prices that customers (both datacenters and non-datacenters) pay for electric power.
- **Capacity Variation**. The average change in power level at a datacenter site between adjacent one-hour periods. We use the mean absolute difference to measure capacity variation, defined as:

\[
\frac{1}{23} \sum_{t=2}^{24} |l_t - l_{t-1}|
\]

Unless otherwise specified, the results reported are the average of the eight day types (see Table 1, weighted appropriately for the number of weekdays and weekend days).

4.5 Implementation
The economic dispatch model and the load control schemes in Section 6 are implemented in Julia 1.3.1 and solved with Gurobi Optimizer 8.1.1[9]. To accelerate the simulations with different parameter combinations, we parallelize the simulation instances with the multiprocessing package in Python.

For the base case, we ran the simulation over 100 scenarios and present the average results in Section 5. Because the simulation for some coupling models can be computationally expensive, results in Section 6 are only based on one wind scenario (details in Appendix A). We expect to evaluate the coupling models on more wind scenarios soon.

4.6 Datacenter-Power Grid Coupling Models
We consider a scenario where datacenters have some load flexibility, but must catch up within a 24-hour day. Thus, key parameters are:

- **Dynamic Range**. The magnitude of the interval over which datacenter load can be adjusted. The larger dynamic range, the greater the load flexibility.
- **Backlog**. The quantity of work by which the datacenter lags average progress (constant load). Backlog is always positive, reflecting the fact that work can only be deferred as in [29].

Thus the formal flexibility constraints are:

\[
\text{load}_{\min} \leq l_{it} \leq \text{load}_{\max}, \forall i, t
\]

That is, all datacenter loads are always within the dynamic range. Let \( \text{avgLoad} \) denote the average load requirement, then datacenter \( i \)'s backlog update can be written as:

\[
\text{backlog}_{it} = \text{backlog}_{i,t-1} + (\text{avgLoad} - l_{it})
\]

The backlog is always non-negative and must be zero at the end of the day to satisfy the average load constraint:

\[
\text{backlog}_{i,24} = 0, \forall i
\]

4.6.1 Datacenter-controlled Local Optimization.

**Online Dynamic Programming (DP-ONL)**. In reality, datacenters don’t have the full knowledge of future prices, so in each interval they schedule the load levels according to some type of price prediction and load constraints instead. Therefore, we propose the following online algorithm, in which the expected cost for the future intervals is estimated with the future hour’s day-ahead LMP and average LMP at the datacenter location, reflecting a type of price prediction with limited information.

**Algorithm 1 Online Dynamic Programming (DP-ONL)**

<table>
<thead>
<tr>
<th>Input:</th>
<th>day-ahead price ( p(t) ), local average price ( \bar{p} ), accumulated backlog ( \text{accuBacklog} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Output:</td>
<td>load level ( l(t) ), updated backlog ( \text{newBacklog} )</td>
</tr>
<tr>
<td>1.</td>
<td>Get the set of feasible load levels ( L_f ) that satisfy the load constraints.</td>
</tr>
<tr>
<td>2.</td>
<td>( l(t) = \text{argmin}_{l \in L_f} l \cdot p(t) + (\text{accuBacklog} + \text{avgLoad} - l) \cdot \bar{p} )</td>
</tr>
<tr>
<td>3.</td>
<td>( \text{newBacklog} = \text{accuBacklog} + \text{avgLoad} - l(t) )</td>
</tr>
<tr>
<td>4.</td>
<td>return ( l(t), \text{newBacklog} )</td>
</tr>
</tbody>
</table>

We expect that this algorithm is mainly driven by the relation between current hour’s day-ahead price and local average price: under the load constraints(4)(5), when \( p(t) > \bar{p} \), the datacenter will choose the lowest feasible load level, and vice versa.

Assuming datacenters determine power levels with the DP-ONL algorithm, we then embed datacenters’ selfish optimization into the grid’s operation— as datacenters are taking larger and larger fraction of the power consumption, their optimization behaviors may affect grid dynamics. For example, when several selfish datacenters shift load to a low-priced interval together, the price in that interval can go up, which contradicts the assumption of dynamic programming that the prices are given. The simulation mainly consists of hourly running DP-ONL and solving the economic dispatch model, which models the process that load forecast for datacenters in the economic dispatch is closer and closer to their actual behaviors.
Algorithm 2 Grid Simulation with DP-ONL Datacenters
1: Initialize each datacenter’s load level to the average value for all the 24 hours.
2: Solve the economic dispatch model, and record each datacenter’s local average LMP.
3: for each time interval \( t \) do
4: Each datacenter determines \( l(t) \) and updates backlog using DP-ONL.
5: Solve the economic dispatch with updated load levels. (load in \( t + 1, \ldots, 24 \) remains unchanged)
6: end for

Offline Optimized (OFFL). To approximate the best possible selfish-optimization for DCs, we try to use full knowledge of the prices from economic dispatch to design an optimal load schedule with pattern similar to DP-ONL, which only chooses load levels among the minimum, maximum, and the average. Let \(-1, 0, 1, 0 \) denote the three load levels respectively, this task is equivalent to finding a set of sequences with the form of \([-1, 0, 1, 0, \ldots, 0]\) such that the total power cost is minimized. To this end, we design a heuristic search method that iteratively tries to shift load to exploit the price difference in different intervals, and undo the action if datacenters’ total power cost goes up. Although this method doesn’t guarantee that the final result is optimal, it finds better load schedule in terms of power cost than DP-ONL in most of the cases.

Algorithm 3 Offline Optimized Search
Output: Set of load level sequences \( L \).
1: Initialize each datacenter’s load sequence as \([0, \ldots, 0]\) for all the 24 hours.
2: Solve the economic dispatch model.
3: contFlag = true
4: while contFlag do
5: contFlag = false
6: for each datacenter do
7: \( i, j = \text{argmax}_{i, j} p(i) - p(j), \ s.t. \ l(i) \in [0, 1], \ l(j) \in \{-1, 0\}, \ i < j \)
8: Shift load from \( i \) to \( j \), and solve the economic dispatch.
9: if DCs’ total power cost decreases then
10: contFlag=true
11: else
12: Revert the change.
13: end if
14: end for
15: end while

4.6.2 Grid-controlled Optimization (GC) of Datacenter Flexibility
Under this model, the full flexibility of the datacenter load is given to the power grid dispatch as in [7]. That is the grid dispatch can set the datacenter’s load within the dynamic range for each hour, subject to the 24-hour average capacity and backlog constraints, and there is no local control of the power level. As is usual, the grid dispatch algorithm acts to maximize the social welfare measured by dispatch cost.

While we think it’s unlikely that datacenters would relinquish this much control to the power grids, we study this approach to see how more selfish datacenter control techniques compare with it in terms of impact on power grid, datacenters, and other customers.

5 IMPACT OF GROWING DATACENTER LOAD AND RENEWABLE GENERATION
We first consider datacenters as static loads in the base case, which means each datacenter’s load is constant at the average load level (140 MW) across all the intervals (i.e. hours).

5.1 Datacenter Load Growth

We first analyze the impact of adding 10-40 datacenters (3.5-14% of average load) to the base system, under 15% wind penetration. Figure 3 shows how the grid dispatch cost changes as we add datacenters. As the number of datacenters increases, the dispatch cost first decreases as more import and wind generation are consumed. From 10 to 25 datacenters, the dispatch cost decreases by 2.7%, with 30% less wind curtailment and 14.2% less import curtailment. However, at the highest numbers of datacenters, the transmission constraints become critical, and the increased load is serviced increasingly by conventional generation keeps, producing and increasing dispatch cost of 0.9% from 35 to 40 datacenters. In addition, the amounts of renewable and import curtailment reflects that absorption challenge still exists. Also shown in Figure 3, the average price of power increases with the growth of datacenters, rising from ~$28.6/MWh (10 datacenters) to $6.5/MWh (40 datacenters). The total grid revenue increases much faster because the total power consumption increases by 15% from 10 to 40 datacenters.

Figure 3: Dispatch Cost and Average LMP by Number of Datacenters (15% Wind)

![Figure 3: Dispatch Cost and Average LMP by Number of Datacenters (15% Wind)](image)

Figure 4: Average LMP, across datacenters — Spatial variation. (15% Wind)

![Figure 4: Average LMP, across datacenters — Spatial variation. (15% Wind)](image)
Figure 4 captures one day of power cost variation across the different datacenter locations - the spatial variation in LMP. The orange line shows the median power cost, for each of the 24h in the day. For each hour, the box captures the interval between the first and third LMP's quartiles. In Figure 4(a), the 10 datacenter scenario has excess renewables, so as their production increases in the afternoon (coastal wind). This causes power prices decrease in some locations, producing a wider variation in power price amongst the data centers. In Figure 4(b), the greater load associated with the 40 datacenters eliminates the excess, not only eliminating the negative prices, but even slightly increase the highest LMPs. When supply is tight, the pricing variance across datacenters is much smaller.

5.2 Renewable Generation Growth

Next we consider how the growth of renewable generation affects the grid. We first fix the number of datacenters at 20, and scale up actual WECC wind generation from 15% to 60%, corresponding to the Wind Vision goal for 2050 [?]. Then we change the number of datacenters and wind penetration together and get 4 cases: (10, 15%), (20, 30%), (30, 45%), (40, 60%).

5.2.1 Dispatch Cost. Figure 5(a) shows the change of dispatch cost with growing wind penetration. From 15% to 60% penetration, most of the elements of dispatch cost remain constant, with a small decrease in generation cost. Wind curtailment increases sharply due to the grid's inability to absorb the increased wind generation. While the dispatch cost also increases sharply with the combination, added datacenters eliminates 11.2% and 14.3% wind curtailment in (30, 45%) and (40, 60%) cases respectively (Figure 5(b)), which is more evident than the benefits in Figure 3.

5.2.2 Generation Mix. In Figure 6(a), as wind generation increases, it squeezes out the fossil-fuel based generation, ultimately displacing 39.8% of that generation. In addition, it shows the diminishing marginal absorption of wind generation; it grows 4-fold, but quantity absorbed grows only 2.2x. When both datacenters and wind generation are increased (Figure 6(b)), the additional load slightly increases the ratio of wind generation but also slightly increases the fossil-fuel based generation, resulting in a lower RPS.

5.2.3 Price. Next we consider power prices, plotting the average prices in Figure 7 for several different wind penetration levels. The blue marks, correspond to 20 datacenters, show that wind penetration drives prices down. But, because the wind generation fluctuates, the variability (average standard deviation of 24-hour prices) of prices is high. The red marks correspond to a scenario where datacenters are increased along with wind penetration, produces higher average prices, but similar levels of variability.

5.3 Summary

Rapid growth in renewable generation presents absorption challenges for the power grid. Growing demand from datacenters helps, but amounts of renewable curtailment still exists and the RPS can even drop because the mismatch between additional consumption and renewable supply. In the following section we will show whether and how coupling datacenters and grid optimization can further increase the renewable absorption.
6 COUPLING DATACENTER LOADS TO THE POWER GRID

With the rapid growth of datacenter power consumption, the flexibility of computing load provides opportunities for co-optimization with the power grid. So, we consider three alternatives for coupling: no coupling, selfish DC cost-minimization, and global grid optimization by the power grid as defined in Section 4. We examine the impact on the power grid, the datacenters, and the other non-DC grid customers. The trends are summarized here, but detailed are included in Appendix B.

6.1 Impact on Power Grid

6.1.1 Dispatch Cost. To highlight the impact of dynamic coupling, we consider DP-ONL (selfish DC) and GC (grid control) relative to the constant datacenter power case (no coupling). Figure 8 shows the dispatch cost impact of coupling model for several wind and datacenter scenarios.

First, consider a narrow dynamic range for datacenter load flexibility, the solid bars in Figure 8. Across the board, both DP-ONL and GC reduce dispatch cost by 1% (nearly 270–400 thousand dollars/day), but GC does slightly better in most cases. In the situation where generation is tightest (15% wind, 30 DC’s), GC doubles the improvement achieved by DP-ONL.

When the dynamic range increases, the coupling models produce more than 2x larger reductions in all cases, except where generation is tightest. In this case, the DP-ONL (selfish) causes significant harm, increasing dispatch cost by 0.75%. Deeper study shows that this is due to overshifting as datacenters respond to price signals and collectively their dynamic actions cause more conventional generation.

Dispatch reduces cost by reducing renewable curtailment penalties. In Figure 9, in the 15% wind case 78% comes from a mix of wind (red) and other renewable curtailment (green). In the 60% wind case, all of the 92% decrease comes from reducing wind curtailment. We examine these dynamics more closely in following sections.

The scatterplot in Figure 10 illustrates overshifting by DP-ONL, (30 DCs, 15%, [0.4, 1.0], SummerWD). Ideal behavior shown as red line. When DP-ONL increases the datacenter load (to the right on x-axis) it produces corresponding increases in conventional (fossil-fuel) generation; this means the datacenter load increase is not improving renewable absorption. When DP-ONL decreases load (to the left on x-axis), it hopes to reduce conventional generation – by the corresponding amount. As the plot shows, such generation is often reduced, but not by the same amount. Overall, DP-ONL’s dynamic management across the 30 DCs increases conventional generation by 1.518 MWh in one day, incurring higher dispatch cost and lower RPS than fixed power datacenters.

Figure 8: Change in Dispatch Cost by Wind Penetration, Datacenters, and Dynamic Range

Figure 10: Overshifting Example: DP-ONL, 30 DCs, 15%, [0.4, 1.0], SummerWD.

6.1.2 Resource Mix. Let’s consider the generation mix more generally, looking at how grid coupling affects renewable absorption, as captured by the RPS (or renewable fraction). In Figure 11(a), we consider the addition of wind to the power grid increases the RPS; this reflects growth of renewable absorption. As we saw in Section 5, there is significant growth in curtailed wind as well, so the result of a 4-fold increase in wind produces only a 1.54–1.67-fold increase in RPS (for a fixed load). With additional datacenters, load increases, but when they are constant loads, the increased load actually decreases RPS. The mechanics of this are that the overall load increases faster than increased absorption, and the explanation for this is that the additional load has weak correlation with the availability of excess wind power.

Figure 9: Contribution to reduction is dominated by reduced curtailment - GC examples (30 DCs, [0.4, 1.0]).
In Figure 11(b), we examine the effectiveness of adding wind generation, plotting the wind capacity credit, which is defined as the ratio of absorption to the installed capacity during a specific period (i.e. capacity factor). The capacity credit falls quickly with increased wind in all cases, corresponding to findings [33], and we include a historical line for the U.K. from [33] for reference. This also corresponds to the increasing wind curtailment we saw in Section 5, and shows that our simulation configuration behaves in fashion similar to real production grids.

As more datacenters are added, (from 10 to 30 DCs), capacity credit improves significantly, particularly for higher wind penetration (about 2.7%). In addition, active datacenter grid coupling further increases the benefit with GC giving a consistently larger benefit than DP-ONL, and this benefit generally increases with larger dynamic range (Appendix B).

Coupling approaches generally improve RPS, the improvement from coupling approaches gets larger as wind penetration increases (Figure 12). DP-ONL’s overshifting impacts RPS negatively at low wind levels, and particularly with large dynamic range. This damage is mitigated at higher wind penetration. In contrast, GC gives robust improvement, growing with wind penetration and dynamic range. For 60% wind penetration, the RPS improvement with 40 DCs reaches 1.4% RPS.

Let’s focus more narrowly on how coupling affects datacenter carbon emissions (RPS). In Figure 13, the constant datacenter bars (red) show the increase in RPS attributable to increased load. This improvement is significant, but limited because the constant load does not adapt to high RPS times. With dynamic coupling methods, DP-ONL and GC can increase RPS by additional 0.1%–1.7%, with the benefit growing as higher wind penetration creates more high-wind periods. GC significantly outperforms DP-ONL, with a maximum benefit more than doubling the RPS benefit from constant load.

6.1.3 Power Price. To assess the impact on consumers, we consider average power price. We first consider overall power grid prices, and then break this down into DC and non-DC power prices, as is shown in Figure 14. Starting from the left, overall power price shows that increased wind penetration causes decreased power prices, and the increase of datacenter load produces higher prices. At lower load and wind penetration, DP-ONL and GC appear to increase competition for power — working against the dynamics of the grid, producing higher prices. At higher wind fractions, both DP-ONL and GC have more room to work smoothly with the grid, shifting power to mitigate competition, and reducing average price. GC, with its global view does this more effectively.

In the DC and non-DC graphs, we can see that datacenters experience larger decrease in prices as wind penetration increases in the base case, and the ability to dynamically shift the load enables DP-ONL and GC to deliver even larger decreases. The non-DC customers have much higher prices across the board for the 10-DC case, but when load is increased to 30 DCs, the non-DC customers have much lower prices, with the advantage diminishing as the wind penetration grows.

6.2 Impact on Datacenters

6.2.1 Power Cost. Figure 14(b) shows the impact of dynamic management on datacenter power prices. For 10 DCs the prices are much lower than the overall grid, and decrease faster than the static model as wind penetration is increased, producing at most 14.5% decrease relative to the base (GC, 60%, [0.4, 1.0]). For 30 DCs,
prices start higher due to supply shortage, but fall below the grid as wind penetration is increased.

To highlight differences we subtract the non-DC customers price change from datacenters price change and get Figure 14(d), which demonstrates the differential impact on different customers. With 30 datacenters and conservative dynamic range ([0.6, 0.8]), both control schemes benefit datacenters more. However, when the datacenters control their load levels with large dynamic range ([0.4, 1.0]), they can cause more harm (up to 6 $/MWh) to themselves, again suggesting the possible harm from overshifting.

To understand if this also produced large variability for individual datacenters, we summed the hourly capacity changes for each datacenter, showing the results in Figure 16 (30 DCs).

Both DP-ONL and GC change datacenter capacity for external purposes. DP-ONL optimizes locally for a single datacenter’s power cost, and GC allows the power market to use datacenter flexibility to optimize dispatch cost. As can be seen in Figure 15(b), this often produces a wide range of power levels, across the 30 datacenters. To understand if this also produced large variability for individual datacenters, we summed the hourly capacity changes for each datacenter, showing the results in Figure 16 (30 DCs).

These results show that DP-ONL creates significant variation in capacity with hourly changes averaging 6-8MW (4-6%) with

Figure 14: Power Price by Wind Penetration, Datacenters, and Dynamic Range. (a,b,c). Relative change in prices (DC - non-DC), 30 DCs. (positive: favors non-DC, negative: favors DC)

Figure 15: Spatial and Temporal Capacity Variation (30 DCs, 60%, [0.4, 1.0] SummerWD). Top to bottom: total curtailment in the grid (base), DC power price (base), DC capacity.

Figure 16: Average Capacity Change (normalized by average capacity) by Wind Penetration and Dynamic Range, 30 Datacenters
small dynamic range and 16-22MW (11-16%) with large dynamic range. Under DP-ONL the capacity variation increases steadily with wind penetration, and has maximum value for 60% wind penetration. These changes are well beyond the zero variation scheduler’s assumption, and present an open challenge to cloud scheduling studies. The situation for GC is much more dramatic. For small dynamic range, GC produces much larger hourly changes of 15 MW (11%), and with large dynamic range 40-42MW (28-30%), but with little relationship to wind penetration. These large changes correspond to random distributions of capacity across the flexibility! This difference is illustrated in Figure 17. The maximum change (e.g. 120 MW for [0.4, 1.0] range) happens more frequently under GC, which causes the difference in average capacity change. Datacenter scheduler simulations show that such large changes can damage the utility of computing resources.

![Figure 17: Capacity of for 30 DCs, 60%, [0.4, 1.0], SummerWD), only 10 DCs shown for readability.](image)

6.3 Impact on Non-Datacenter Customers

As shown in Figure 14(c), non-DC customers show trends similar to the overall grid average – because non-DC is the majority of grid customers. Despite that, the coupling models and dynamic management have a significant impact on non-DC prices. So we drill down into distributions non-DC costs (see Figure 18). We present the cumulative distribution function (CDF) for non-DC customers based on change in cost (ranging from a 60% reduction to a 20% increase). At low datacenter load and wind penetration, for both DP-ONL and GC, nearly 50% of the non-DC customers experience harm, about 10% price increases. DP-ONL limits the harm better (~8% vs. >10%). With 30 DCs and low wind, competition arises, in this case non-DC customers split, with both more experiencing harm and more gaining large benefit. GC outperforms DP-ONL significantly. At higher wind penetration, the situation is much better with only 30% (DP-ONL) and 20% (GC) experiencing harm, and many experience cost reductions of 30-40%. At 60% wind penetration, the effects from DP-ONL and GC look similar, as there is little competition for power. Essentially no customers are harmed, and 40% see slight harm, less than 5%. Many non-DC customers see more than even 60% benefit.

6.4 Summary

Both of the coupling approaches can improve renewable absorption and reduce power cost. However, the impact largely depends on system conditions (wind penetration, total load, dynamic range). In addition, coupling approaches can produce differential impact on power cost of datacenters and the other customers, which may raise concerns about fairness.

Overall, GC gives more stable benefit and avoids the possible harm from local selfish behaviors, but it produces more variation in datacenter capacity, which potentially harms datacenter efficiency.

7 RELATED WORK

We believe that our work represents the first large-scale datacenter dynamic power management coupled with grid studies. We briefly review the most closely related work below.

**Datacenters as Demand-Response.** Several researchers have proposed the use of datacenters for demand response, typically exploring the impact on local computing workloads. For example, several studies explore priority, batch jobs, and time shifting of workload [20]. Another effort designs a market where the economic benefits of demand-response are distributed as incentive to flexible colocation customers. [19]. Demand-response is a rare activity, typically less than 10 periods a year, and these approaches typically target small fractional power reductions (e.g. 10%). In contrast, our study focuses on daily coupling with large dynamic range – up to 60%. Further, we consider multiple datacenters large enough to shift dispatch in the power grid, and the rapid growth of wind penetration.

**Datacenters as Dispatchable Loads.** The closest related work comes from the Zero-carbon cloud project, which proposed power grid dispatch of datacenters – when zero carbon power was available in
excess [3, 34, 35]. Work within Zero-carbon Cloud explored the impact of coupling these datacenters with the grid, showing that under grid control, and dispatched only when excess renewable energy is available, the ZCloud datacenters could increase grid renewable absorption (RPS), reduce dispatch cost, and reduce renewable curtailment. Recent studies have considered more moderate versions of this vision, allowing the grid to control some of the datacenter capacity (rather than all of it), in schemes similar to our grid control (GC). These efforts explore spatial and temporal load shifting, and have demonstrated grid benefits of reduced price variation, improved renewable absorption, and lower dispatch cost [16, 36].

Local Selfish Optimization. Many research efforts have explored intelligent control of a flexible datacenter load to reduce energy costs[15, 20, 21], or utilize either local or grid renewables to reduce carbon emissions[5, 17]. These approaches include dynamic programming, optimal control, prediction, and recently even machine learning. These algorithms can trigger temporal load shifting, utilize local renewable generation, or charge/discharge batteries. However, all of this work assumes that the local datacenter is a small load relative to the grid, and thus dynamic management cannot affect grid prices or dispatch. In contrast, we study large datacenters that definitely can affect power markets, and that coupling is the primary focus of our study.

8 SUMMARY AND FUTURE WORK

Rapid growth in renewable generation leads to the challenge of renewable absorption, but load flexibility from growing datacenter load can help. We propose three coupling models—static cloud loads, selfish local cost optimization by each datacenter (DP-ONL), and load orchestrated by the power grid using economic dispatch (GC)—and evaluate them with different levels of wind penetration, datacenter load, and load flexibility. Our results show that both dynamic coupling models generally improve grid dispatch cost (as much as 2.69%), wind absorption (as much as 3.97%), and datacenter power prices. However, care should be taken to avoid possible harm to datacenters and the other customers. Comparing the two dynamic coupling models, GC gives more stable benefits than DP-ONL at the cost of about twice average capacity change, which is problematic for datacenter efficiency. That coordination may be necessary to achieve the best results for both datacenters and the power grid.

Although not realizable, results of OFFL indicates room for improvement of DP-ONL, that more power price benefit can be achieved with less capacity variation. It also suggests that in reality it’s possible to enhance datacenter selfish optimization with future information in the grid and coordinated behaviors.

REFERENCES


A DEMAND AND WIND SUPPLY

Figure 19 shows the load profiles of different day types and the wind production scenario (No. 1000) used in coupling approach studies. While the demand usually peaks around noon, wind production peaks in the late night or early morning, which is a mismatch and a reason for the absorption challenge.

![Load Profile and Wind Supply](image)

Figure 19: Load Profile and Wind Supply in Coupling Model Studies. (a) Load (20 Additional DCs included) for Each Day Type. (b) No. 1000 Wind Scenario for Each Season, 15% Level

B DETAILED RESULTS OF COUPLING APPROACHES

The tables in this section correspond to the trends we summarize in Section 6 and contain the detailed numbers if only changes are provided in previous sections. Table 2 shows the dispatch cost in the base case and relative change with DP-ONL and GC, corresponding to Figure 8.

Table 2: Dispatch Cost ($) by Wind Penetration, Number of Datacenters, and Dynamic Range. Relative changes are listed for DP-ONL and GC.

<table>
<thead>
<tr>
<th># of DCs</th>
<th>Wind</th>
<th>Range</th>
<th>Base</th>
<th>DP-ONL</th>
<th>GC</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>15%</td>
<td>[0.6, 0.8]</td>
<td>-0.95%</td>
<td>-1.1%</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>[0.4, 1.0]</td>
<td>-2.23%</td>
<td>-2.73%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>30%</td>
<td>[0.6, 0.8]</td>
<td>-0.32%</td>
<td>-0.57%</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>[0.4, 1.0]</td>
<td>-0.76%</td>
<td>-1.01%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>45%</td>
<td>[0.6, 0.8]</td>
<td>-0.15%</td>
<td>-0.41%</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>[0.4, 1.0]</td>
<td>-0.36%</td>
<td>-0.63%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>60%</td>
<td>[0.6, 0.8]</td>
<td>+0.13%</td>
<td>+0.42%</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>[0.4, 1.0]</td>
<td>+0.38%</td>
<td>+0.8%</td>
<td></td>
</tr>
</tbody>
</table>

Table 3 and Table 4 present the detailed renewable fractions, corresponding to Figure 12 and Figure 11(b) respectively.

Table 3: RPS by Wind Penetration, Number of Datacenters, and Dynamic Range. Absolute changes are listed for DP-ONL and GC.

<table>
<thead>
<tr>
<th># of DCs</th>
<th>Wind</th>
<th>Range</th>
<th>Base</th>
<th>DP-ONL</th>
<th>GC</th>
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<tr>
<td></td>
<td>15%</td>
<td>[0.6, 0.8]</td>
<td>32.09%</td>
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<td></td>
<td></td>
<td>[0.4, 1.0]</td>
<td>40.59%</td>
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<td>30%</td>
<td>[0.6, 0.8]</td>
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<td></td>
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<td></td>
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<td>60%</td>
<td>[0.6, 0.8]</td>
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</table>
Table 4: Wind Absorption by Wind Penetration, Number of Datacenters, and Dynamic Range. Absolute changes are listed for DP-ONL and GC.

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<thead>
<tr>
<th># of DCs</th>
<th>Wind Range</th>
<th>Base Wind Absorption</th>
<th>DP-ONL Wind Absorption</th>
<th>GC Wind Absorption</th>
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<tr>
<td>10</td>
<td>15% [0.6, 0.8]</td>
<td>+0.28% +0.62%</td>
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<tr>
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<td>0.4, 1.0</td>
<td>+1.24% +1.74%</td>
<td>+0.99% +1.29%</td>
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<td>81.72%</td>
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<tr>
<td>30</td>
<td>15% [0.6, 0.8]</td>
<td>+0.44% +0.59%</td>
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<td>+0.35% +0.48%</td>
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<td>0.4, 1.0</td>
<td>+1.24% +1.74%</td>
<td>+0.99% +1.29%</td>
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<td>95.97%</td>
<td>75.17%</td>
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</table>

Table 5 contains the detailed statistics of datacenter capacity, which suggests DP-ONL and GC are comparable in terms of standard deviation but DP-ONL outperforms GC in average capacity difference.

Table 5: Statistics of Capacity Variation by Wind Penetration and Dynamic Range, 30 Datacenters. (Avg Local Stdev.: average standard deviation of 24-hour capacities per site)

<table>
<thead>
<tr>
<th>Wind Range</th>
<th>Coupling Approach</th>
<th>Avg Hourly Difference</th>
<th>Avg Local Stdev.</th>
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<tr>
<td>[0.6, 0.8]</td>
<td>DP-ONL</td>
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<td>GC</td>
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<td>DP-ONL</td>
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<td>DP-ONL</td>
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<td>DP-ONL</td>
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<td>GC</td>
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<td>50.91</td>
</tr>
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<td>DP-ONL</td>
<td>8.36</td>
<td>17.30</td>
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<td></td>
<td>GC</td>
<td>15.59</td>
<td>17.31</td>
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<td>[0.4, 1.0]</td>
<td>DP-ONL</td>
<td>21.42</td>
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<td>GC</td>
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<td>17.75</td>
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<td>GC</td>
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