Renewable and Cooling Aware Geographical Load Balancing*

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ABSTRACT
This paper explores the benefits of geographical load balancing in terms of efficiently using renewable energy. Practical concerns on dynamic cooling efficiency and dynamic electricity price are included in the model. The problem is modeled using a convex optimization based framework parameterized using real workload, temperature, solar and wind traces. The result suggests that after using geographical load balancing, the renewable energy usage increases significantly and grid usage decreases significantly. Such result holds across seasons.

1. INTRODUCTION
Building cost-saving and environmental-friendly data centers has become an unprecedentedly pressing challenge for the ICT industry. Energy consumption marks a major portion of a data center's running cost [1], while the corresponding carbon emission of electricity usage concerns the society. As the needs for data centers grow rapidly, we will create enormous economic benefit for the ICT firms and fulfill our responsibility of protecting the environment if we can significantly reduce the energy consumption.

Using renewable energy at data centers is one viable option. In fact, some data centers are already partly operated on green energy. Previous research suggests that the data center can even operate almost entirely on renewable energy under the geographical load balancing (GLB) model [8]. Such a model routes the requests to where green energy is available and uses the renewables efficiently, thus requires fairly low green energy supply.

However, the previous GLB model only considers the energy cost to process data requests. In reality, a data center spends a considerable amount of energy on cooling [1], especially in summer. The cost of cooling largely depends on the weather at data center locations. Thus we think of exploiting the geographical heterogeneity of the data centers to reduce cooling cost.

This paper illustrates that, a new geographical load balancing model, which considers energy cost in cooling, is able to reduce the total cost significantly compared to previous models. Furthermore, the improvement in green energy usage leads to much lower carbon emission rate.

We set up an experiment to investigate the economic and environmental impact of our new model. We use real traces of data center workload, renewable energy availability and weather to numerically compute the optimal solution. The cost model of the geographical load balancing system is analytically determined.

Our study leads to three major findings.

First, the new GLB model, the Cooling-aware GLB model, reduces the total cost of the system. This is because it is able to distribute the request to locations with not only cheap energy, but also favorable weather for cooling, thus achieves the overall optimal result. More excitingly, the optimal cost does not vary much with seasonality. This can potentially solve the problem of data center cooling in place with extreme weather, for example large day and night temperature difference.

Second, the Cooling-aware GLB model leads to significant carbon emission savings. The carbon emission level can be reduced by as much as more than 50% compared to the old models. The new GLB model makes more informed deci-

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sion than the old GLB model as it includes the energy for cooling. Because GLB models reduces energy cost at the expense of slight increase in network delay cost, the environmental impact is much greater than the cost impact. If the firms are given incentives for cutting carbon emission, the environmental impact can lead to economic success.

Third, the performance of Cooling-aware GLB is better than using energy storage, both in total cost and in carbon emission, when the aggregate renewable supply is enough to power data centers yet not in vast surplus. This result is from a systematic comparison between the Cooling-aware GLB system and the storage system with various storage capacity in reasonable range. The result suggests that Cooling-aware GLB has a clear advantage over the storage model when the renewable energy generation and storage facilities are not widely established. It requires much less investment in infrastructure and hence can be implemented more easily than the storage model.

2. SETUP

We assume that each data center has a cooling system described in [7], and then modify the model in [8] to include energy cost of cooling. The model can be solved using convex optimization technique as proved in [9].

2.1 The workload

Let J be the set of sources of requests. Each continental state in US has a source of request located at its geographical center. We quantify the amount of request by $L_j(t)$, the mean arrival rate from source $j \in J$ at time interval t. $L_j(t)$ is estimated using real-world traces. The base trend of the workload is taken from a trace at Hewlett-Packard Labs, then the workload of each request source is scaled proportionately to the population of the state, following by a shift along the time dimension according to the timezone.

2.2 The availability of renewable energy

We have three major considerations when modeling the availability of renewable energy:

First, the weather at the data centers is crucial as it determines the renewable energy output per plant unit. We use real traces of wind speed and solar irradiance obtained from [6] [3]. The measurements are in 10 minutes interval. The rate of renewable energy generation per plant unit at each data center is then set to be proportional to the weather data respectively.

Second, the size of the renewable energy plant matters. We scale the renewable generation capacity such that the total renewable energy is c times as much as the total energy demand to process all requests. In our experiment, c varies in [0.5, 4] with step length of 0.5.

Third, we need to find the optimal ratio of solar and wind energy to power the data centers. Previous research [8] suggests that 80% of wind and 20% of solar fits the data center energy consumption characteristics nicely. We adopt this ratio in our experiment throughout.

2.3 The internet-scale system

The internet-scale system consists of a set N of 10 data centers at the Google data center locations in the following states: California, Washington, Oregon, Illinois, Georgia, Virginia, Texas, Florida, North Carolina and South Carolina. The number of servers X_i at data center i is set to be twice as much as the peak load at i if all requests are routed to the nearest data centers.

The system will decide 1) the routing plan $\lambda_{ij}(t)$ and 2) the number of active servers $x_i(t)$ so as to minimize the total cost. The total cost is the sum of delay cost, energy cost and switching cost.

2.3.1 Delay cost

The delay cost represents the lost of revenue incurred due to the delay in processing requests. It comprises the propagation delay d_{ij} from source j to date center i and the queuing delay at i. The propagation delay d_{ij} is calculated to be the time needed to travel between i and j at transmission speed of 200km/ms plus a constant term 5ms. The queuing delay is calculated from the parallel M/G/1/Processor Sharing queue model in which the total load $\lambda_i(t) = \sum_j \lambda_{ij}(t)$ is distributed evenly across $x_i(t)$ homogeneous servers of service rate $\mu_i = 0.1(ms)^{-1}$.

2.3.2 Cooling optimization

The cooling optimization model finds the minimum energy consumption required to maintain the data center at constant temperature $T = 25°C$. A typical data center uses both air cooling and chilled water cooling. Let $x = x_a + x_c$ be the total number of active servers, x_a be the number of those cooled by air cooling and x_c cooled by chilled water. This model finds the best division between x_a and x_c.

Quantitatively, the energy consumption of air cooling is given by

$$c_a(x) = kx^3, 0 \leq x \leq \bar{x}, k > 0 \tag{1}$$

The parameter k is proportional to the temperature gradient between the inside and outside air. The $\bar{x}$ corresponds to the maximum number of the servers that can be cooled by air cooling alone. The cap $\bar{x}$ is proportional to both the temperature gradient and the maximum air flow rate. In our experiment, the air flow rate is set such that when the outside temperature is $20°C$ lower than T, the data center can rely on air cooling entirely at full workload.

The energy consumption of chilled water cooling, on the other hand, is almost linear to the IT demand empirically, i.e.

$$c_c(x) = \gamma x \tag{2}$$

The optimal cooling portfolio can be written as follows:

$$c(x) = \min_{x_c \in [0,x]} \gamma(x - x_c)^+ + kx_2^3 \tag{3}$$

which yields

$$c(x) = \begin{cases} kx^3 & \text{if } x \geq x_s \\ kx_s^3 + \gamma(x - x_s) & \text{otherwise} \end{cases}$$

where $x_s = \min\left\{\sqrt{\gamma/3k}, \bar{x}\right\}$ is the threshold when chiller cooling is necessary.

To explore the impact of seasonality on the performance of the cooling model, we use two sets of temperature data. One is taken from the first week of Jan, 2012 from [5]; the other is take from the first week of July, 2012. The measurements are taken hourly.

2.3.3 Energy cost

The energy cost is the cost of both running active servers and keeping them at constant working temperature. The data centers pay no cost for renewable energy assuming that each data center has its own renewable energy generation facilities and pay no maintenance cost. Thus the energy cost is for using energy from the grid and can be represented as

$$p_i(l(x_i(t)) + c(x_i(t)) - r_i(t))^+ \quad (4)$$

where p_i is the price of electricity, $x_i(t)$ is the number of active servers at that time interval t, $l(x_i(t))$ is energy consumption of active servers in the time interval, or the IT demand, $c(x_i(t))$ is the energy usage for cooling and $r_i(t)$ is the renewable energy availability. In our model, p_i is set to be constant according to the real statistics of each state; l is a linear function of $x(t)$.

2.3.4 Switching cost

The switching cost models the delay and wear-and-tear cost when switching on/off servers. In our model, the workload at each data center is updated every 10 minutes. To avoid too frequent switching of server status, we define the switching cost to be

$$\beta(x_i(t+1) - x_i(t))^+$$

where β tells the weight of switching cost. In our experiment, $\beta = 6$.

2.3.5 Storage

Apart from the renewable energy generation facility, the data centers may also install storage capacity. The renewable energy availability displays significant temporal variation; introducing storage aims to obtain soother renewable supply curve.

Quantitatively, we model the amount of electricity storage at time t to be $0 \le es_i(t) \le ES_i$, where ES_i is the maximum storage capacity. Let the amount of change of storage be

$$e_i(t) = \rho(es_i(t) - es_i(t+1))$$

Positive $e_i(t)$ means discharging while negative value means charging. The parameter ρ represents the charging and discharging efficiency. In our experiment we assume perfect charging and discharging, i.e. $\rho = 1$.

In the presence of storage capacity, the energy cost should be written as

$$p_i(l(x_i(t)) + c(x_i(t)) - r_i(t) - e_i(t))^+ \quad (5)$$

2.3.6 Total cost

Now we can formally write our optimization problem as:

$$\begin{aligned}\min_{\mathbf{x(t)},\lambda(\mathbf{t})} & \sum_{i\in\mathcal{N}} p_i(l(x_i(t)) + c(x_i(t)) - r_i(t) - e_i(t))^+ \\ & + \sum_{j\in\mathcal{J}}\sum_{i\in\mathcal{N}} \lambda_{ij}(t)\left(\frac{1}{\mu_i - \lambda_i(t)/x_i(t)} + d_{ij}\right) \\ & + \beta(x_i(t+1) - x_i(t))^+\end{aligned}$$

subject to

$$\begin{aligned} &\sum_{i\in\mathcal{N}} \lambda_{ij}(t) = L_j(t), && \forall j \in J \\ &\lambda_{ij} \ge 0, && \forall i \in N, j \in J \\ &0 \le x_i(t) \le X_i, && \forall i \in N \\ &\lambda_i(t) \le x_i(t)\mu_i && \forall i \in N \\ &0 \le es_i(t) \le ES_i && \forall i \in N \\ &e_i(t) = es_i(t) - es_i(t+1) && \forall i \in N \end{aligned}$$

The boundary conditions essentially model the following real world constraints:

1. The requests from a population center all have to be processed by the geographical load balancing system. Each data center should receive a non-negative amount of work.

2. Each data center has only limited number of servers; it cannot process requests more than its computation capacity at any time.

3. Each data center also has limited energy storage capacity; it cannot store any amount of energy more than that cap.

2.3.7 CO2 emission

Though the optimization is completely based on firm's interest of cost saving, we still want to monitor the amount of CO_2 emission as a worth-noting side-effect. The CO_2 emission arises from the grid electricity usage. The CO_2 emission rate per kW/h varies across different states as each state has different energy source composition. An estimation of the rate can be found at [2].

Let η_i be the rate of carbon emission per kW/h at data center i, the total CO_2 emission is then

$$\sum_{i\in\mathcal{N}} \eta_i(x_i(t) + c(x_i(t)) - r_i(t) - e_i(t))^+$$

2.3.8 Benchmarks for comparison

Our model is the first to integrate practical cooling concerns into geographical load balancing. To show the impact of such consideration, we will compare the result of our model (Cooling-aware GLB) to the old GLB model which doesn't take cooling in the optimization (Cooling-Oblivious GLB) and the model which simply routes all requests to the nearest data centers (LOCAL). For the two benchmark models, the cooling optimization is done after the routing scheme is determined.

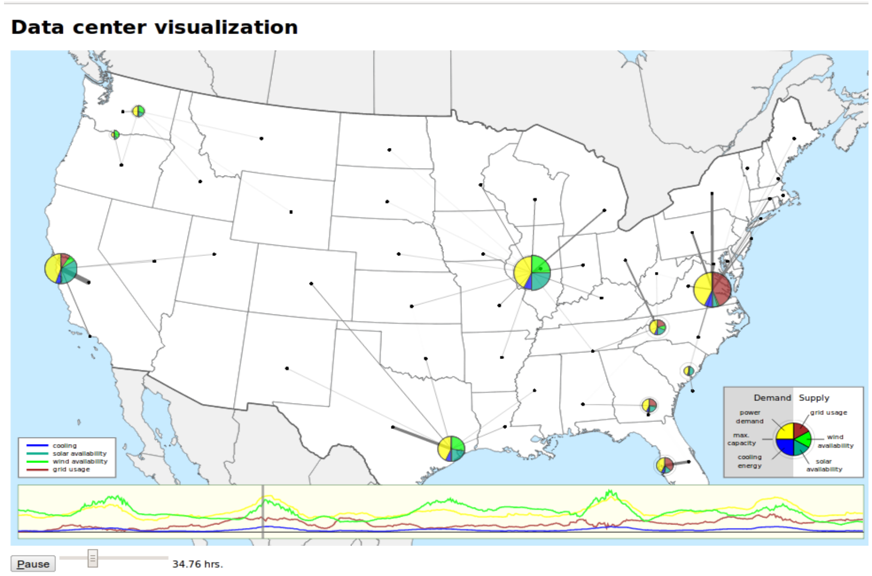

Figure 1: A frame shot of the visualization page.

Meanwhile, we want to compare the performance of our model to one of its alternative, the storage model. The storage capacity is quantified in terms of the time period that the data center can operate entirely on storage at maximum load (excluding cooling requirement). We assume that the storage incurs no running cost. We choose the data center systems with 3-hour-storage and 6-hour-storage respectively as the benchmark.

We will evaluate the results based on 1) the total cost; 2) the grid (brown) energy usage; 3) the CO_2 emission.

3. VISUALIZATION

Our numerical experiment often yields large size of time series data that describes routing plans and data center running status. These data are hard to interpret when in matrix form. Therefore we developed an visualization tool to illustrate these data. Such data visualization allows us to recognize the key characteristics of the optimal solution quickly. It also works as a simple check for the correctness of the solution; we can spot some obviously abnormal behaviors of the solution if they exist.

3.1 Development environment

We want our visualization to satisfy the following requirement. First, it can animate a time series of data fluently. Second, it can easily and efficiently convert the raw input, usually the experiment result in .csv or .netCDF format, to the desired format recognized by the script. Third, it can be integrated into web page or other form of presentation easily.

The final visualization is in Scalable Vector Graphics (SVG) form, a high quality graphics format supporting various animations and flexible edition. The back-end processing, which involves converting input file format and generating the SVG script, is done in Scala. This animation can be embedded into HTML web page. The user can control the animation using the interface on the web page.

3.2 Graphical representation details

The visualization page consists of three components: an animation showing the dynamic status of the geographical load balancing system, a line plot showing the aggregate statistics of energy supply and demand, and a progress bar allowing progress scroll and control.

The animation displays a total of 10 data centers on a U.S. base map. Each data center's status is represented by a sector diagram. The left half of the circle represents the energy demand of the data center: the yellow sector is the energy demand for processing the request, the blue one is the energy demand for cooling. The right half of the circle represents the energy supply: the light green sector represents available wind energy, the dark green one represents available solar energy and the brown one represents the energy usage from the grid. The area of the sector is proportional to the amount of energy. In addition, each sector diagram is surrounded by a dotted circle, which represents the maximum energy usage when the data center operates at full load.

The requests traffic $\lambda_{ij}(t)$ is represented by lines connecting the source j and the destination data center i. The width of the line is linearly proportional to $L_j(t)$, the total size of request from j. The transparency of the line is linearly proportional to $\frac{\lambda_{ij}(t)}{L_j(t)}$, the percentage of the traffic from the source j. A solid black line means all the requests from j are sent to i, while a totally transparent line means no traffic exists between i and j.

The line plot represents four aggregate statistics of interest over time: the yellow line shows the aggregate IT power, the blue one shows the aggregate energy usage on cooling, the light green one shows the aggregate wind energy available, the dark green one shows the aggregate solar energy available. The vertical line represents the progress of the

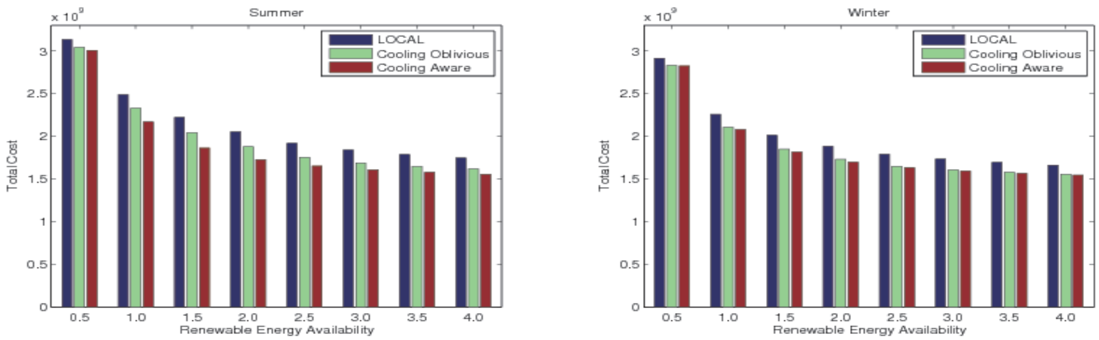

Figure 2: Comparison of optimal costs of Cooling-aware GLB, Cooling-oblivious GLB and LOCAL, with varying renewable energy availability.

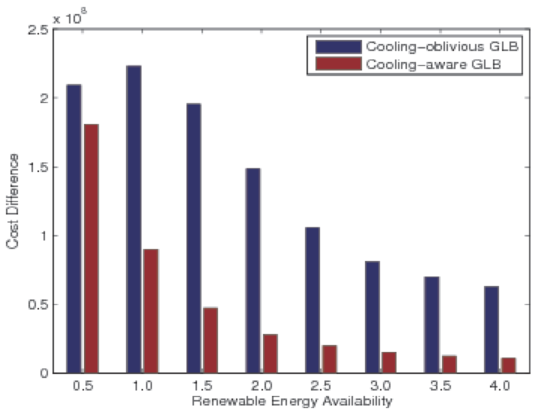

Figure 3: The difference between optimal costs in summer/winter for both Cooling-aware and Cooling-oblivious GLB

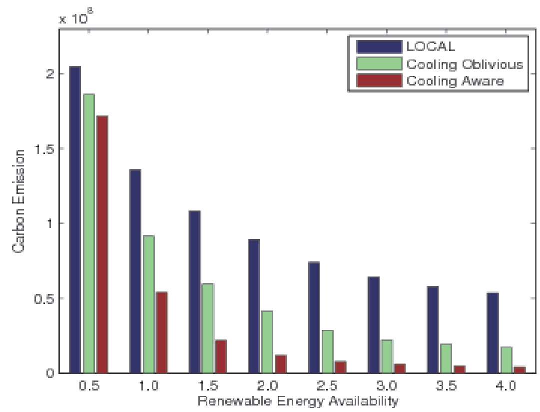

Figure 4: Comparison of carbon emission of Cooling-aware CLB, Cooling-oblivious GLB and LOCAL.

animation.

The progress bar at the bottom indicates the time elapsed of the animation. The user can pause/resume the animation and scroll the animation to desired time interval.

4. RESULTS

4.1 Cost-saving impact of Cooling-aware GLB

The cooling-aware geographical load balancing model reduces firm's energy cost by routing the requests to locations where energy is cheap and cooling is easy. Such savings overweighs the increase in delay cost due to routing. Hence our model matches a profit-maximizing firm's primary interest.

Our first experiment explores the cost savings aspect of the this model. Figure 2 illustrates the extent of total cost savings of our model. We choose the total cost under Cooling-oblivious GLB and LOCAL as the benchmark. The Cooling-aware model has the better cost-saving performance against the benchmarks. This edge is rather clear under two situations. First, in summer when cooling is hard, the Cooling-aware model shows significant improvement even compared to the Cooling-oblivious model; it considers the energy demand for cooling when making routing decisions thus is able to use renewable energy optimally. Second, when the aggregate renewable energy is more than the aggregate demand yet not as much as twice the demand is, some but not all data center locations have surplus in renewables. The Cooling-aware GLB exploits this surplus better than the benchmarks.

We are interested in whether the Cooling-aware GLB model works under all weathers, i.e. how much different the result is when the weather changes. Figure 3 shows the difference between the optimal costs in summer and in winter using each model. The previous Cooling-oblivious model's performance varies significantly with seasonality, whereas our Cooling-aware GLB model's performance is more robust. The result suggests that our Cooling-aware model exploits the heterogeneity in weather to alleviate the energy demand for cooling.

4.2 Environmental impact - CO2 savings

The geographical load balancing method model benefits from routing requests to where energy price is low. When the data centers have on-site renewable energy plant as in our setting, renewable energy becomes cheap; the model allows optimal usage of these renewables and thus has an desirable side-effect: reducing carbon emission.

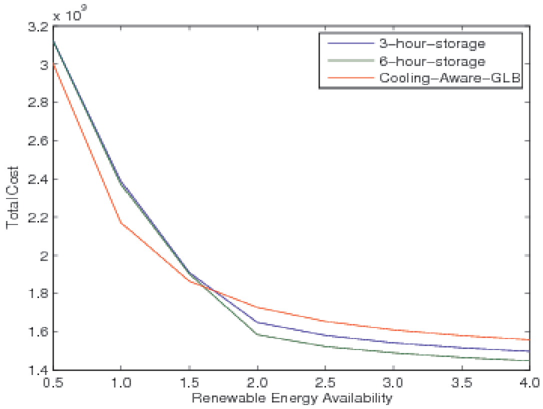

Figure 5: Comparison of optimal costs of the storage model and the Cooling-aware GLB model.

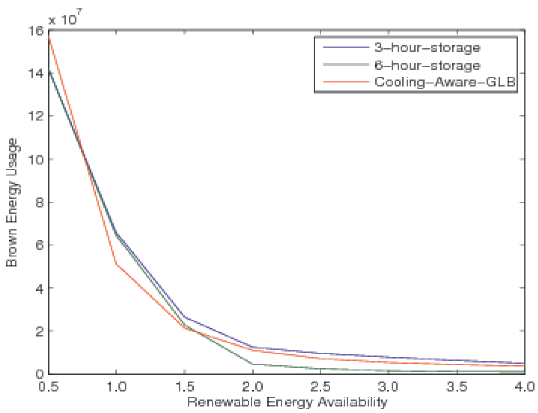

Figure 6: Comparison of brown energy usage of the storage model and the Cooling-aware GLB model.

We can quantify the amount of CO2 emission via multiplying the grid energy usage of each data center location by the CO2 emission per energy unit. Figure 4 shows the CO2 emission comparison of each model in summer. By using the Cooling-aware GLB model, the aggregate carbon emission can be reduced by more than 50% as compared to LOCAL if the total renewable energy supply is equal to the total IT demand. If more renewable energy is available, the carbon emission of Cooling-aware GLB is even less than half of that of Cooling-oblivious GLB.

The environmental impact of our new model is significant. This result is achieved even when we do not include the benefit of reducing carbon emission in the model. If the firm is given incentives for being environmental friendly, we believe the new model will certainly have more advantage in the cost-saving aspect.

4.3 GLB versus Storage

One alternative way of using renewable energy efficiently is to store the extra renewables at some moments for future use. Unlike the geographical load balancing model which changes the energy demand curve in each location to match the supply, using energy storage reshapes the energy supply curve to fit the demand. We are interested in the characteristics of performance of both methods. In this experiment, we compare the cost curve and the brown energy usage curve of using GLB and using storage. Since our experiment starts at midnight, the time when the data centers are likely to have used all of its storage for batch jobs [7], we assume that the storage starts empty.

Figure 5 illustrates the trend of optimal costs of these models with respect to varying renewable availability. We notice that the Cooling-aware GLB has cost advantage when the total renewable energy is less than 1.5 times of the aggregate IT demand. The storage model, on the other hand, has cost advantage when the renewable energy supply is in large surplus.

Figure 6 shows the comparison of brown energy usage of each model. The result suggests that the Cooling-aware GLB model needs less energy from the grid compared to the 6-hour-storage curve when the total renewable supply is less than 1.5 times of the total IT power demand. Moreover, it needs less grid energy than the total renewable energy compared to the 3-hour-storage model in almost the entire renewable availability interval except when the renewable availability coefficient is 0.5. The environmental impact advantage of our new model is even more significant compared to the cost advantage.

We thus can conclude that our model is better than the storage model when the renewable generation facilities are not saturatedly established yet; it requires less prior investment on infrastructures.

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