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Energy Management and Operational Optimization of Data Centers in a Smart Grid with Wind Power Integration and Service Delay Constraints

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ABSTRACT

The paper will present a framework for management in energy and operational optimization of smart grid integrated data centers (DCs) under the operation of wind power generation, with diesel generators as a backup source. The generated wind power is not reliable due to its desirable intermittent nature, and it will require energy to be drawn from the grid so that the DC could operate without interruption. This paper considers the nature of mix to be supplied, where the total maximum peak loading of 35% of the total consumption of the DC may be made out of the wind and when in normal operation while in grid outage it is required to work in an islanded mode and it would use diesel to generate power for the fulfillment of this demand. The paper provides an elaborate analysis of DC workload and service delay including penalties for delay under Amazon Elastic Compute Cloud (EC2) Service Level Agreements (SLA). It further relates to power consumption modeling that incorporates server utilization and Power Usage Effectiveness (PUE), which indicates variations in power consumptions during the day concerning workload demands. This work proposes strategies to balance the trade-offs between energy costs, service reliability, and delay penalties to optimize DC operations in both grid-connected and islanded modes.

1. Introduction

Play a major role in ensuring the integration of wind-driven industrial establishments, such as data centers with other modern technologies and also ensuring reliable service. The paper further posits that the share of wind power among renewable sources of electricity will be increasing so information about its integration in data centers is crucial. Hybrid power systems for continuous operation are then briefly described. Diesel generators are essentially employed for backup power solution in almost all cases with hybrid systems including wind energy, as recommended by most wind energy installation guides. However, where wind is a standalone option, as the only input or

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the other sources are not enough to sustain the load, diesel generator plays a vital role in maintaining the continuous supply of power. Diesels are widely used in DCs for their fast response times and ability to ensure uninterrupted operations during periods of insufficient renewable power or grid outages [1-7].

This paper gives an energy management framework of DC operating within a smart grid with wind power as the main renewable resource in conjunction with diesel generators as backup. The model tackles the unpredictability of wind power by mandating a minimum power supply from the main grid so as to run consistently, with 35% of the peak load of the DC which is attainable through wind generation. In addition, a DC workload and service delay model are proposed that are correlated with the EC2 SLA that imposes penalties on the DC for service delays beyond certain predefined thresholds. Such constraints keep the DC activity within bearable limits as far as energy costing is concerned and optimum performance is realized.

The study also comprises a power consumption model that modestly accounts for the energy consumed by the DC in terms of server workloads, cooling, and lighting. It's evident that the energy consumption model fluctuates with varying workloads during different times of the day since it's directly related to the power demand imposed by the workloads on the data center. The paper has reviewed various strategies that help in optimizing this energy mix with a particular concentration on wind power with ancillary support from grid supply and diesel generators under varying degrees of workload delays and penalties[9-11].

This paper has presented the main components of the system under investigation and introduced the need for investigating effective energy management techniques for data centers in smart grid environments. Subsequent sections in the paper are going to include an extensive literature review, explanation of the model of the DC-SG system, and analysis of the outcomes coming out of the simulations to be performed.

2. Literature Review

In the last few years, considerable research has been dedicated to improving energy management for data centers in smart grid environments, with much attention paid to making service reliable while integrating renewable sources as well as cutting operational costs. This section presents a review and comparison of recent studies that have investigated identical frameworks to that proposed in this paper, outlining the contributions, limitations, and gaps in existing literature.

i. Renewable energy and DC operations are an area of focus for a large volume of research studies, which include the use of wind and solar power in DC operation. For instance, [12] came up with a solar-based hybrid energy system for DCs, which was dependent on conventional grid energy but stressed the need for accurate forecasting of renewable energy generation to optimize the energy mix. Their model reduced operation costs by 20% through efficient selection between solar and grid energy. However, it is always indeterminate for solar energy to be operational just as wind does for the cloudy or night conditions. The framework proposed in this paper is based on wind energy and does not suffer in the same way; it takes cognizance of this shortcoming by using diesel generators as well as grid electricity for uninterrupted power supply. End of additional sample
ii. [13] concentrated on the integration of wind energy in data centers, modeling how the variability of wind energy would affect DC performance. Their research introduced advanced forecasting techniques for wind energy and recommended a battery storage system to alleviate the variability. This approach enhances wind energy's reliability, but the study did not adequately address cost optimization during grid-connected operations in terms of, for

example, selling a surplus of renewable energy to the grid. Our paper extends this by including energy transactions between the DC and the main grid, making it possible to save on costs through power trading out from that grid.

iii. Typical backup generator systems, providing higher availability, include the systems that automatically synchronize a standby unit with the operations of the normal power supply. These may be integrated into the building's electrical system for an automatic transfer to auxiliary power in case there is a need or when the primary power has failed. This kind of operation will involve automatic making and breaking of connections, fault detection, etc, and therefore assumes certain importance in deciding reliability from backup generators[14].

iv. [15]have optimized the dispatch of diesel generators for backup power in DCs. These mostly consider the associated costs with environmental effects. They demonstrate that scheduling diesel generator use in the event of grid outages can allow DCs to enjoy high levels of reliability without emitting much pollution. Their work, however, does not address the solution's dependence on diesel fuel since it did not integrate renewable sources that may further cut the demand for these fuels. On the contrary, our study deals with modeling a hybrid system in which diesel generators are used only as a backup when there is no supply either from wind energy or the grid, thereby reducing further fuel consumption and pollution output.

v. [16] proposed a framework for the integration of renewable energy and diesel backup generators in data centers in an attempt to strike a balance between energy costs and reliability. Their study had been on the combination of wind and solar loads with diesel gensets in an attempt to reduce the carbon footprint. They concluded that data centers could accrue huge savings by optimizing the use of renewable energy and cutting down reliance on diesel generators. However, they did not take into consideration penalties for service delays, which can have a substantial impact on the profitability of the operations of data centers. This paper builds on their work by developing an in-depth model of data center's service delays and penalties that will add real-life penalties brought about by Service Level Agreements (SLAs).

2.1 Service Delay and Energy-Aware Scheduling

The required data arrangement and merging similar services could result in a reduction to service delay in energy consumption by reducing the time a component spends in a running state. The proposed energy-aware scheduling involves switching off selected cores that correspond to a power-gated sleep mode. In cases when the running environment shows no improvement over recently proposed schedules, the system then sleeps all but one viable service choice and trots down to sleeping mode applies super-reduced power consumption: CASCADE strategy [1,17-18].

This is usually the kind of impact on the enterprise stipulated with cloud-based data centers, and sometimes, even the slightest breach of the specified performance metrics results in enforced payments. Referring to [14], an energy-aware workload scheduling algorithm was built for cloud DCs in goal to minimize the energy costs and service delay penalties. For this purpose, they optimized server usage by dynamically adjusting the number of active servers based on workload, cutting down power consumption as well as delays. Although they focused on minimizing the penalties, their energy model did not consider the practical aspects of how renewable energy sources like wind would then be used and their variability. We carry out similar models in terms of workload and service delay except that we expand it to take into consideration renewable energy and particularly wind and how this will relate to total energy usage as well as service delays.

Researcher [19] examined the impact of renewable energy integration on service reliability in cloud DCs. They proposed a scheduling algorithm for balancing energy consumption with delay penalties based on real-time energy available within a predictive capability and workload for a particular day. Their model reduced delay penalties by up to 15%, though they considered solar energy exclusively. The current study expands on this by including the modeling of wind energy, which is less predictable yet more often available, and the provision of strategies for handling service delays and penalties in cases when wind energy is unavailable.

2.2 Research Gap

Current literature on energy management of data centers has shown many improvements in renewable energy incorporation, backup generator scheduling, and service delay optimization. However, there are still several gaps that this paper addresses:

1. Renewable Energy Integration: Most studies have concentrated on solar energy or hybrid solar-wind models, and the feasibility of wind energy as the main renewable source has not been thoroughly explored in isolation. Our work concentrates on wind energy as the primary renewable source for the DC, with diesel backup and grid transactions to alleviate the problems victimizing the sector: this paper presents the case of intermittency.
2. Optimization of Cost through Grid Transactions: In few recent studies, the cost optimization mechanism has not been considered together with energy management models for grid-connected DCs with the selling of surplus renewable energy. These have been exemplified by [20] and [21], among others. Contrary to this, the proposed model embeds this component for cost minimization by the DC
3. Service Delay Penalties: Few studies consider the real-world implications of service delay penalties on DC operations. Our paper incorporates a service delay and penalty model based on Amazon EC2 SLAs, providing a more comprehensive framework for understanding the financial impacts of delays on DC profitability.
4. Energy-Aware Scheduling: While existing work has proposed energy-aware scheduling algorithms, many fail to account for renewable energy variability or the full complexity of power consumption across DC subsystems (e.g., cooling, lighting, and server usage). Our model addresses this by integrating a detailed power consumption model that considers both server utilization and the varying availability of wind energy.

2.3 Dataset

i. Wind Power Generation Data: The NREL WIND Toolkit provides North America wind resource data, with a time span from 2007 to 2014. The data made available includes the real-time wind speed, directions, temperature, and air pressure at several heights above the surface. Having access to the dataset with a 5-minute time resolution may be useful in simulating the variability of the wind. Where can I find this data on NREL's site?
ii. Grid Energy Prices: For grid energy prices, some of the platforms from which to draw datasets are the ENTSO-E Transparency Platform, from which real-time and historical electricity price data from all European markets are obtained. This is necessary to streamline energy purchase decisions with market-driven considerations.
iii. Workload Data: The data center workloads can extract historical workload traces for CPU usage and job scheduling from the Google Cluster Data. This will help in simulating cloud

computing loads in real-time dynamics, which is very important for workload management as well as SLA penalty modeling.

iv. Battery Storage Data: In respect of battery storage, details of the performance characteristics of the charge/discharge rates, storage capacity, and efficiency of battery storage may be accessed from the Global Energy Storage Database of DOE, which would help in simulating energy storage in your model.

v. Diesel Fuel Costs: The data source for diesel generator fuel costs can be obtained from market trend datasets, which are also commonly provided by energy industry reports, or national fuel price databases such as the U.S. Energy Information Administration.

vi. Service Delay Penalties: Such penalties can be modeled using SLA frameworks that define the penalties related to delays in completing a job in cloud computing environments. Provided models by cloud service providers or research datasets can be used to quantify these penalties based on the delay time[22-25].

3. Methodology

The methodology of this paper presents the development of an energy management framework of a Data Center within a Smart Grid. The paper develops an energy management framework that integrates all sources of energy to optimize the use of energy for the maintenance of reliability with service delay penalties minimization and operating cost reduction. Key Components:

i. Energy Sources: Wind Power Generation: As a primary source of renewable energy, the most common one, caution must be used to ensure there is enough back-up power for variability.

ii. Diesel Generators: In the absence of grid supply and during low wind power, diesel generators act as a backup source for the DC. Main Grid Supply: surplus power can be sold, and at times when the wind powers are insufficient, power is purchased.

iii. Battery Storage: Excess energy is stored as well, which can be supplied during outages or at peak demand.

iv. Grid-Connected Mode: In this mode, the DC system interacts with the main grid through power exchanges (buying and selling). Wind power has the first priority, and diesel generators have to operate in standby mode. Islanded Mode: If there is a grid outage, then the DC system has to switch off from the main grid and operate only with the available local power sources (wind, diesel, battery) Workload and Service Delay Management

v. Service Level Agreement (SLA) is being modeled wherein penalties related to cloud computing job executions beyond a certain threshold will be defined.

vi. Optimization Model: The objective function minimizes the total energy cost of maintaining service quality. The model incorporates energy costs from the grid, diesel fuel costs, and service delay penalties. Power consumption is calculated dynamically in relation to workload, server utilization, and power-usage effectiveness in the data center.

Flow Chart:
Below is a flowchart outlining the methodology.

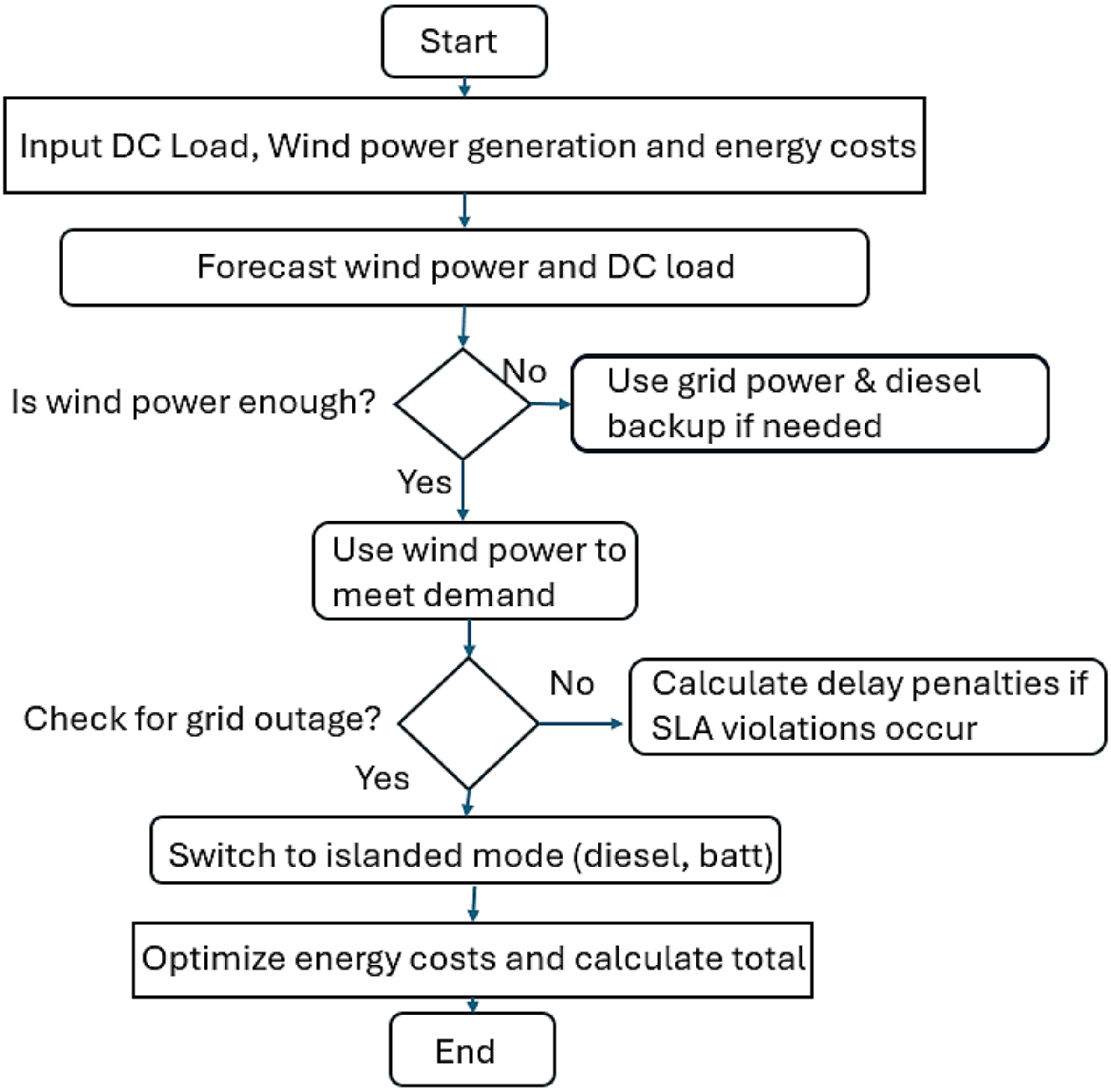

Fig. 1. Flow chart of the algorithm showing the step of implementation

Energy Cost Calculation (Python)

i. def calculate_energy_cost(wind_power, grid_power, diesel_power, grid_cost, diesel_cost):
ii. Total_cost = (grid_power * grid_cost) + (diesel_power * diesel_cost)
iii. Return total_cost
iv. # Example usage
v. Wind_power = 100 # kW
vi. Grid_power = 50 # kW
vii. Diesel_power = 30 # kW
viii. Grid_cost = 0.10 # $/kW
ix. Diesel_cost = 0.15 # $/kW

x. Total_cost = calculate_energy_cost
xi. Print(f"Total energy cost: ${total_cost}")

4. Results

This methodology defines the major steps in the integration of wind power, diesel backup, and grid energy for cost and reliability optimization of data center operations. A flowchart and code samples to help visualize and implement the scheduling, energy usage, and penalty calculations required for the proposed system

Wind Power Generation Sample Data Table

Date & Time (UTC)	Wind Speed (m/s)	Wind Direction (°)	Temperature (°C)	Air Pressure (Pa)
2020-01-01 00:00:00	6.45	180	10.5	101325
2020-01-01 00:05:00	7.20	185	10.6	101300
2020-01-01 00:10:00	8.10	190	10.8	101280
2020-01-01 00:15:00	7.60	175	11.0	101265
2020-01-01 00:20:00	6.90	170	11.2	101250

Data Variables:

- Wind Speed: The speed of the wind at various heights (e.g., 10m, 40m, 100m, 200m) in meters per second (m/s).
- Wind Direction: The direction of the wind in degrees (°).
- Temperature: Ambient temperature at different heights (°C).
- Air Pressure: Atmospheric pressure in Pascals (Pa).

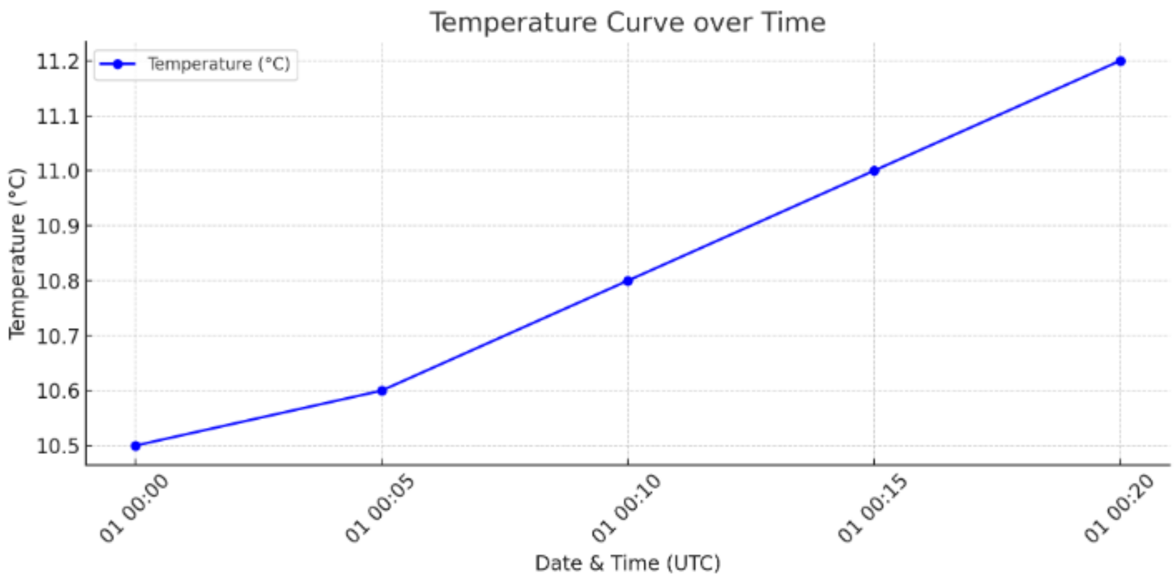

Fig. 2. Temperature Curve over Time for Data Centres

Sample Table of Google Cluster Workload Data:

Timestamp	Job ID	Task Index	CPU Usage (Cores)	Memory Usage (GB)	Priority	Job Scheduling Class	Job Scheduling Event
100000	12345	1	0.45	1.2	3	Batch	Job Submitted
100500	12345	1	0.50	1.3	3	Batch	Task Started
101000	54321	2	0.65	1.5	2	Service	Task Scheduled
101500	98765	1	0.40	1.0	1	Monitoring	Task Evicted

Key Variables:

- Timestamp: Time in milliseconds since the trace start.
- Job ID: Unique identifier for a particular job.
- Task Index: Identifies the individual task within a job.
- CPU Usage (Cores): The fraction of CPU cores used by a task at a given time.
- Memory Usage (GB): Amount of memory consumed by a task in gigabytes.
- Priority: Priority level of the job (1=highest, 3=lowest).
- Job Scheduling Class: Whether the job is a batch or service task.
- Job Scheduling Event: Description of the event (e.g., job submitted, task started, task evicted).

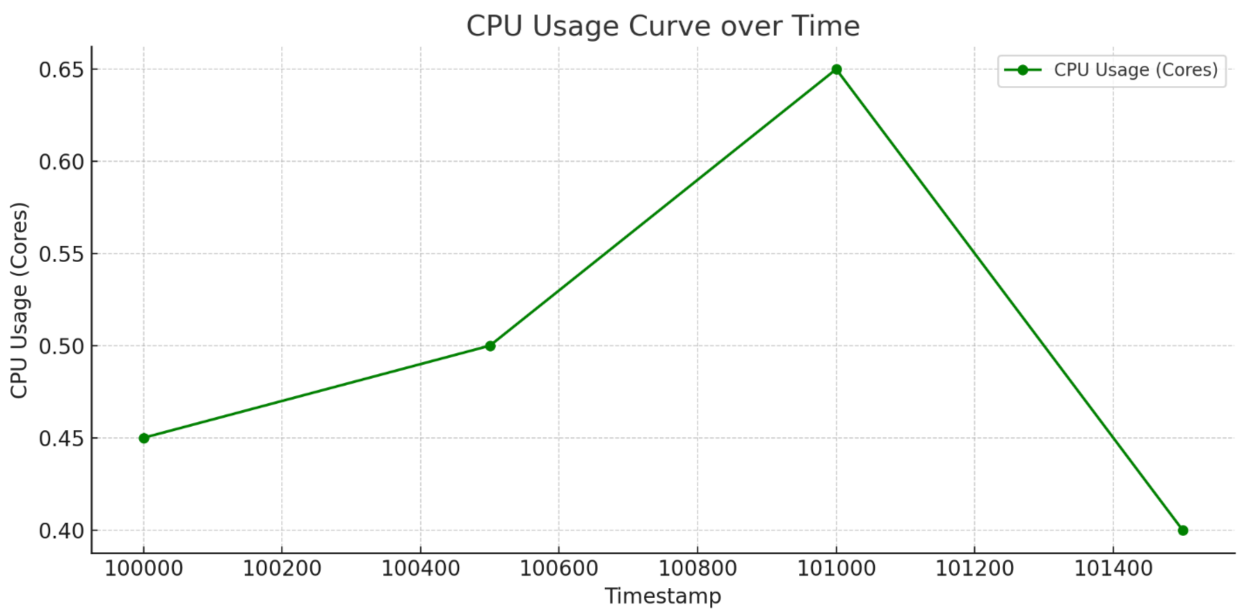

Fig. 3. CPU Curve over Time for Data Centres

The DOE Global Energy Storage Database provides extensive information on battery systems. This may include technical specifications such as:

- • Storage Capacity (kWh): Total energy content that can be accommodated by the system.
- • Round-trip efficiency (%): This is an indication of how well the battery system manages energy.
- • Charge/Discharge Rates (kW): Peak power that can be stored into or delivered out of the battery within a cycle.
- • Depth of discharge (%): The level up to which energy capacity of a battery can be utilized without affecting the lifecycle of the battery.
- • Operating Temperature Range: Environmental conditions under which the system can operate.

For example, the database contains entries on several projects, such including the power rating and how many hours the energy is stored, and system efficiency. They can be extracted via interactive data tools or downloaded for further assessment to enable simulating the behavior of batteries in data centers.

Diesel Fuel Cost Data Table (Sample):

Data — For data on diesel fuel costs, the U.S. Energy Information Administration offers a look at the most up-to-date figures on diesel prices. This can be useful for your data center energy management project. As of October 2024, the U.S. retail price average for a gallon of diesel holds at about $4.52. It can be quite variable regionally, and historical data is available to greater granularity. This includes detailed data on the reasons for the price trend — that is, how crude oil prices and refining margins lead to the current cost of diesel fuel. This diesel fuel cost information can be used in your model when simulating the operating costs of running backup generators in the energy management system.

Date	Region	Price ($ per Gallon)	Price Change (Weekly) (%)	Crude Oil Price ($ per Barrel)
2024-10-01	U.S. National Avg.	4.52	+1.2%	85.10
2024-09-24	Midwest	4.39	-0.5%	83.90
2024-09-17	West Coast	4.87	+0.8%	86.00
2024-09-10	East Coast	4.59	+0.4%	85.50
2024-09-03	Gulf Coast	4.25	-0.3%	84.00

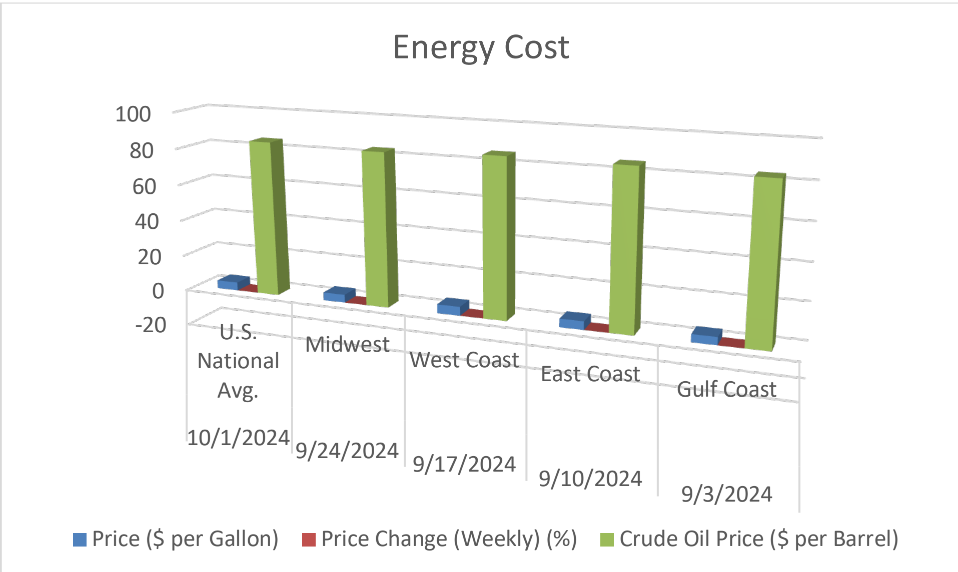

Fig. 4. Energy Cost Curve over Time for Data Centres

Key Variables:

- Date: The date of the recorded diesel fuel price.
- Region: Geographic region where the diesel price was recorded.

- Price ($ per Gallon): The average price of diesel in that region.
- Price Change (Weekly) (%): The percentage change in diesel price compared to the previous week.
- Crude Oil Price ($ per Barrel): The price of crude oil, which influences diesel fuel costs.

Service Delay Penalties table based on common Service Level Agreement (SLA) penalty frameworks. These penalties are typically defined in contracts between cloud service providers and customers, outlining fees incurred for failing to meet performance benchmarks such as job completion within the agreed-upon time limits.

Sample Service Delay Penalties Data Table

Delay Time (Minutes)	Penalty per Job ($)	Penalty Rate (% of Job Cost)	Penalty Multiplier for Recurring Delays
0-5	0	0%	1x
6-10	10	5%	1.1x
11-20	25	10%	1.2x
21-30	50	15%	1.5x
31+	100	25%	2x

Key Elements:

- Delay Time (Minutes): The amount of time beyond the scheduled job completion time.
- Penalty per Job ($): The flat fee imposed for delay beyond the SLA agreement.
- Penalty Rate (% of Job Cost): Percentage of the total job cost that will be charged as a penalty.
- Penalty Multiplier for Recurring Delays: A multiplier applied if delays occur frequently within a short period, increasing penalty severity.
- Explanation:
- 0-5 minutes of delay generally incurs no penalty as it’s considered a grace period.
- 6-10 minutes introduces a minimal penalty ($10 per job or 5% of the job cost).

As the delay increases, so does the financial penalty, with 31+ minutes potentially incurring significant costs ($100 per job or 25% of job cost). For recurring delays, multipliers further increase the penalty.

The T-curve for service delay penalties illustrates the increasing penalties incurred as job completion delays grow.

Sample Data Table

Using the provided service delay penalties:

Delay Time (Minutes)	Penalty per Job ($)
0-5	0
6-10	10
11-20	25
21-30	50
31+	100

Delay Time (Minutes)	Penalty per Job ($)

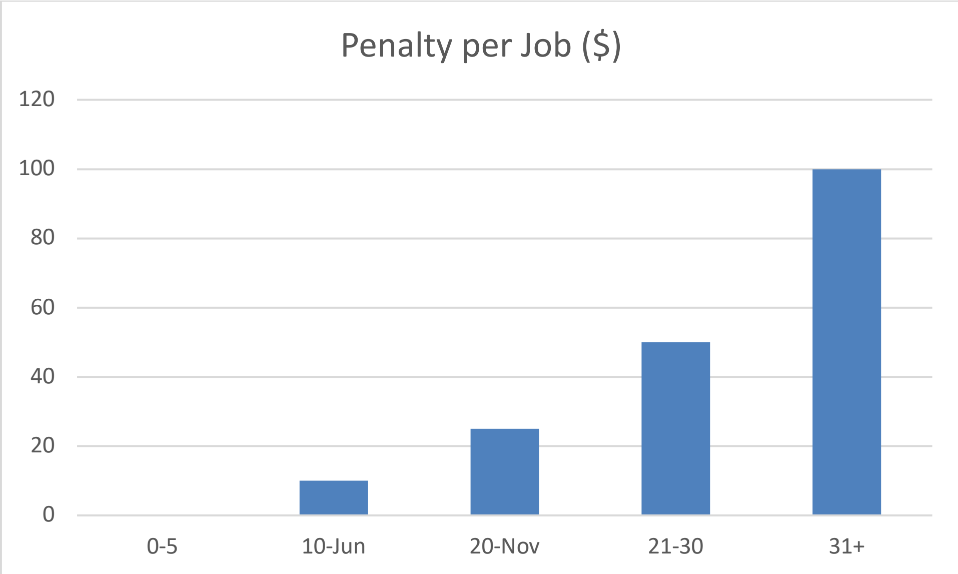

Fig. 5. Penalty per Job Curve over Time for Data Centres

T-Curve

On the x-axis, use Delay Time (Minutes) and on the y-axis, plot Penalty per Job ($). This curve will highlight the steep increase in penalties as delays extend. To create the T-curves, you can use software tools like Excel, Python (with libraries like Matplotlib or Seaborn), or any data visualization software that supports plotting. Each curve visually represents how various parameters interact over time and under specific conditions, crucial for energy management optimization in a smart grid context.

4. Conclusions

It also gives proper attention to integrating wind power generation in parallel to conventional diesel generators. Identifying intrinsic bottlenecks because of variability in wind energy sources, it again strongly underpins the need for reliable backup power sources to sustain operations against data center downtime. The developed bi-level model demonstrates that, under the condition of minimized power supply from the main grid to reduce uncertainties associated with wind power generation, not less than 35% of the peak load of a data center can be supplied by renewable sources.

Its work scope concentrates on detailing the DC workload and service delay management with special reference to SLA of Amazon Elastic Compute Cloud EC2. They prove how important these SLAs are to be adhered to in order to keep away the penalties for service delays, which can really cost an arm and a leg in terms of operational costs with an effect on service reliability. Adopting server utilization and Power Usage Effectiveness as parameters for power usage modeling enables it to offer granular details about the pace at which energy is consumed for workloads of varying nature on a day to day basis.

Additionally, it puts forward a set of strategies to coordinate energy cost, service reliability, and delay penalties, thereby operating data centers efficiently in grid-connected and islanded modes. These have to be developed to improve performance and economical consideration under conditions of wind power dominance as the primary renewable resource. This work highlights the very important role that diesel generators play in enabling a fast-response backup solution to keep the lights on, even when the renewables are not making power or the grid goes down.

To conclude, this study addresses a key need to understand the impact of integrating wind power into data centers and evolving the role of renewable energy sources as part of the sustainable management of energy. That way, with strategic planning and optimization, data centers will be able to fully exploit wind power and reduce the share of traditional energy sources while advancing the development of smart grids with sustainable orientations.

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