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Develop the hybrid DR with HES approach to predict the price and reduce congestion during Load Variation

M. Kamalakkannun[#1], Dr. N. D. Sridhar[*2]

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Abstract: An energy shift was supported by the creation of a digital distributed less CO2 power system, the major components of which are renewable-based producing plants. In 2022, 15 Photovoltaic Power Plants (PVPs) with a total installed capacity of 364 MW are commissioned in India, accounting for 21.08% of the country's total installed PVP capacity. With global carbon emissions gaining significance, reducing carbon emissions in power systems is a critical problem. Carbon expense was first added to an optimization model's goal variables or restrictions in early research. The carbon cost, on the other hand, is unable to reflect the time-varying CO2 emissions brought on by load energy usage. To solve the issue; this study presents a Demand Response (DR) approach that uses Locational Marginal Prices (L MP) on electrical power and carbon emissions to restructure the load demand framework, guiding the demand of an electricity and a carbon perspective. An approach could decrease power system carbon emissions while taking into account the financing of energy purchasing and the conventional DR to Peak Load Shifting (PLS). In the meantime, to account for Monte Carlo sampling, scenario reduction wind power uncertainty, and historical information fitting, approaches are applied. The Hydrogen Energy Storage (HES) system is created to benefit of the CO2 markets and energy at the same time using proper charging methods. The simulation findings utilizing the PJM 5-bus network demonstrate that the proposed Locational Marginal Electricity (LME)-CO2 cost could reduce the power system's carbon emissions while assuring economic performance. The load demand reflects the pattern of changing CO2 emission levels and the variation in power cost when the CO2 emission component is included in pricing.

Keywords: Demand response; Off-Grid Operation; Locational Marginal Price; Full-Scale Tests; Wind Power Uncertainty; GPFC; Hydrogen Energy Storage; Emergency Active Power Shortage

1. Introduction

Reducing carbon emissions is becomes a significant global priority due to the growing significance of the Fossil Energy (FE) issue and global warming. [1]. nearly 40% of global CO2 emissions, in particular, are attributed to China's coal-fired power sector [2]. As a result, reducing carbon emissions in the electricity factory is an important priority to meet carbon neutrality goals and the carbon peaking [3-5]. Most price-based DR research is currently focused on the generation-side approach, in which low-CO2 variables were included as objective variables or limitations associated with CO2 emission prices [7-9]. Studied the ecological advantages of customer engagement to CO2 trading markets and energy via active demand-side management could efficiently decrease CO2 emissions and provide consumers with additional ecological advantages [8-10]. Explored an electrical system design challenges for combined renewable energy distributed production and disaster recovery while accounting for CO2 emissions.

It is unable to control customers' CO2 reduction behavior due to the changing structure of carbon emissions caused by loads at various times [12]. A growing number of researchers from many different sectors conclude that "consumers" rather than "producers" should be held accountable for CO2 emissions from production procedures [13]. Demand for fossil fuel burning in the power system was created by electricity customers, resulting in large carbon emissions [14]. The CO2 emission flow method was used to determine the locational marginal CO2 price, which moves accountability for carbon emissions from the producer to the customer sector. In this study, researchers suggest using an LME-CO2 pricing DR approach based on the unpredictability of wind output and an HES system to increase demand from a "carbon perspective" or "electricity perspective". This method could lower power system carbon emissions while taking into account the finances of power purchasing and the conventional DR to PLS. To the aforementioned discoveries, this research provides a DR method depending on the innovative idea of, taking WPU, LME-CO2 price, and the HES system into account. This work has three key advantages.

- The DR system was LME-CO2 price efficiently reduces electricity system CO2 emissions by lowering the price of energy purchase and the CO2 tax for customers. Furthermore, the LME-CO2 price was used to compute the discharging state and HES charging, allowing the HES system to arbitrage the carbon markets

[#1]Research Scholar, Department of Electrical Engineering, Annamalai University, Annamalai nagar. kamalmanirathnem@gmail.com
*[*2]Associate professor, Department of Electrical Engineering, Annamalai University, Annamalai nagar. sridarnd1@gmail.com*

and electricity at different times.

- The CO2 emission component in the pricing, the load required to reflect changes in the price of power, but also reflects shifts in carbon emission rates. The aim for reducing CO2 emissions will be reached since the load need will change from periods of high to low CO2 emissions.
- The ideal location for HES system installation is determined by researchers installing HES systems on different buses.

2. The definition and calculation of the LME-carbon price

2.1 LME price

The LME price was established by the nodal power inflow or outflow [15]. Once linked to a different place (i.e., a different vehicle), every participant, whether providers or customers, will have the same clearing price [16]. The LME pricing method is an optimal power flow issue with constraints.

2.2 LMP

An LME CO2 price, which serves as the clearing price for the CO2 market, serves as the basis for calculating the LM price. The CO2 emission flow approach was used in this study to compute the locational marginal CO2 price. The CO2 emission flow rate, denoted by the abbreviation R(tCO2 /h), was defined as the number of CO2 emissions Fb or Fi that pass through a branch or bus in a certain amount of time, as illustrated following.

$$R = \frac{dF}{dt}$$

$$X_b = \frac{R_b}{P_b} \quad (2)$$

$$X_x = \frac{\sum_{g \in G_x} + P_g X_g + \sum_{b \in B_x} + P_b X_b}{\sum_{b \in B_x} + P_b} = \frac{\sum_{g \in G_x} + P_g X_g + \sum_{b \in B_x} + R_b}{\sum_{b \in B_x} + P_b}$$

(3)

The subscripts b and i in the above formulae signify branches and buses, correspondingly.

The CO2 Emission Flow Rate (EFR) of branch b is denoted by R_b. Active Power Flowing (APF) as P_g; I_g indicates the generator's Carbon Emission Intensity (CEI); G_i^+ as instill power into bus i; Pb as APF of node b; B_i^+ as collection of all nodes that flow into bus i.

An increase in CEI inside a bus as the unit power consumption was raised was characterized as the LME-CEI, abbreviated as η^I(tCO2 /kWh).

$$\eta_x^X = \frac{X_x^{\Delta P_x} \cdot \sum_{b \in B_x} + P_b^{\Delta P_x} - X_x \cdot \sum_{b \in B_x} + P_b}{\Delta P_x} \quad (4)$$

where ΔP_x signifies the growing unit power consumption of bus i; $P_b^{\Delta P_x}$ as bus i to the increase of power load and $P^{\Delta Pi}$ as APF of node b to the increase of unit electricity load. The LMCO2 price π^C could be calculated by multiplying the locational marginal CEI by the CO2 TPU of CO2 emission, as shown follows.

$$\pi_x^C = \eta_x^X \times c \quad (5)$$

Where c - price of the volume of user-generated CO2 emissions per unit. The LMCO2 price and the LMEP are combined to form π_x^E.

π_x^C to determine the LMECO2 price π_x as follow,

$$\pi_x = \pi_x^C + \pi_x^E \quad (6)$$

3. Demand Response and Energy Storage system model

3.1 Demand Response model

Power customers to the planned DR method would make an attempt to reduce their costs, particularly power and CO2 TCs, by altering their power usage behavior. This approach takes into account a price to DR in which participating customers move load out on Peak Price Periods (PPP) and in during Low Price Periods (LPP).

3.1.1 Objective function

The LME-CO2 price DR method's goal function is to reduce overall usage cost C_B^{USE}. It is equivalent to maximizing expense reduction by shifting burden C^{USE}, more information is provided below.

$$minC^{USE} = C_0^{USE} - C_B^{USE} \quad (7)$$

$$C_0^{USE} = \sum_{t=1}^{T} \pi_t^x \cdot P_t^{load} \quad (8) \qquad (1)$$

$$C_B^{USE} = \sum_{t=1}^{T} \pi_t^x \cdot \left(P_t^{out} - P_t^{in}\right) \quad (9)$$

3.1.2 DR Constraints

The load DR algorithm's restrictions include the following: branch power flow limitations, security, load transfer and load balance constraints.

(i) Branch Power flow constraints

$$\begin{cases} P_t^x = U_t^x . \sum_{y \in x} U_t^y . \left(G_{xy} . \cos\theta_{xy} + B_{xy} . \sin\theta_{xy}\right) \\ Q_t^x = U_t^x . \sum_{x \in x} U_t^y . \left(G_{xy} . \sin\theta_{xy} - B_{xy} . \cos\theta_{xy}\right) \end{cases} \quad (10)$$

(ii) Operational constraints

For a DR model, in addition to branch line flow limits, vehicle voltage constraints, and power flow constraints were added as Equation (11)

$$\begin{cases} U_{min}^x \le U_t^x \le U_{max}^x \\ P_t^{xy} \le P_{max}^{xy} \end{cases} \quad (11)$$

Where U_{min}^x and U_{max}^x indicate the upper and lower bounds of the VA of vehicles x, correspondingly:

P_t^{xy} and P_{max}^{xy} represent the TP and its maximum value, for branch xy correspondingly.Load shifting constraints

$$\begin{cases}\gamma_{min}P_t^{load} \le P_t^{out} \le \gamma_{max}P_t^{load} \\ \sigma_{min}P_t^{load} \le P_t^{in} \le \sigma_{max}P_t^{load}\end{cases} \quad (12)$$

This will presented in Equation (12), where LS out energy factor γ_{min} and γ_{max} are the upper and lower bounds respectively of time t and LS in σ_{min} and σ_{max} are the upper and lower bounds respectively.

(iii) Load balance constraints

LS out and LS in load balance is established by

$$\sum_{t=1}^{T} P_t^{out} = \sum_{t=1}^{T} P_t^{in} \quad (13)$$

3.2 Model of Energy Storage (two way) systems

This can be compared to a load while charging and discharging through links to the distribution system [17].

3.2.1 Objective function

This study examines an HES system's two-way imbalance between the power and carbon markets.

$$max f_{ES} = \sum_{t=1}^{T}\Big[(P_{out}(t)K_{out}(t)\eta_{out}) - \frac{P_{in}(t)K_{in}(t)}{\eta_{in}}\pi_t^x - c_x(P_{out}(t)+P_{in}(t))\Big].\Delta t \quad (14)$$

where $P_{in}(t)$ and $P_{out}(t)$ represent the power used by the HES system to charge and discharge during t seconds; The binary variables $K_{in}(t)$ and $K_{out}(t)$ are used to charge and discharge the HES system over time; discharging and charging efficiency of the HES system was indicated by in and out, correspondingly.

3.2.2 HES Operation constraints

(i) Binary variable constraints that charge and discharge

$K_{in}(i) \cdot K_{out}(i)=0$ (15)

Equation (15) describes the maximum capacity of an energy storage system to function simultaneously in the charging and discharging stages.

3.3 Rated capacity constraints

$$\begin{cases} 0 \le E_0 + \sum_{t'} E \le E_{max} \\ \sum_{t'} E = \sum_{t=1}^{t'}[P_{in}(t)K_{in} - P_{out}(t)K_{out}(t)].\Delta t \end{cases} \quad (16)$$

According to Equation (16), the power storage system's capacity should never be exceeded by any amount of energy. E_0 - HES system starting energy; $_{t}{'}E$ denotes the discharge and charge the HES system of moment of $_{t}{'}$; E_{max} - HES system maximum rating.

3.4 Power constraints (discharge and charge)

$P_{min} \le P_{in}(t) \le P_{max}$ (17)

$P_{min} \le P_{out}(t) \le P_{max}$ (18)

Equations (17) and (18) are the discharging and charging power inequality limitations, correspondingly, where P_{min} and P_{max} signify the lower and upper bounds of the HES system's discharging and charging PCs.

4. Scenario generation method of Wind Power Uncertainty (WPU)

To accurately depict the shifting structure of wind energy, various situations with the characteristics of that hour's Wind Power Fluctuation (WPF) are selected each time. The fundamental characteristics of the fluctuation in wind energy are correctly stated, while the computational volume required to solve the optimization methodology is adequately controlled on one extreme.

4.1 WPF scenario

- Historical information was categorized and analyzed to establish the division of WP over time.
- The Monte Carlo stochastic (MCS) modeling approach was utilized to produce *N* randomly selected arrays for each time depending on the WP probability curves. It is also possible to obtain the corresponding N T sets of randomly selected arrays.
- In each scenario, the WP of T times could be described by a random sequence; the WP sequence in scenario s could be defined as P^S=$P^1(s)$,$P^2(s)$,...,$P^T(s)$. The wind power output sequence

This result was produced using an MCS simulation that accurately depicts the unpredictability of WP. The preceding methods could be used to construct N×T sample matrices, i.e., N WP random scenarios.

The preceding processes create beginning possibilities for wind power with random probabilities that were impractical and unreasonable to execute computed scenarios. As a result, some scenarios must be eliminated or merged to generate a restricted number of typical situation groups to assure calculating speed and accuracy. Thus, the sample characteristics are preserved to the greatest extent possible, and the performance of the scenario description was enhanced. We apply a quick scenario-reducing strategy based on likelihood distance in this paper to decrease the initial ten scenarios to 2000 scenarios.

4.2 Case studies

Case description

This study used an altered PJM-5 bus system as a model instance. The time phase is equal to one hour, and the optimization period is 24 hours long. Figure 1 depicts its framework. The components of this model example consist of five buses, five generating units, three load buses, two active power-constrained branches and four unconstrained branches. The carbon tax is $50 per tonne, the overall active load was 1000 j328.69 MVA. The optimization methods are created in MATLAB 2021b utilizing MATPOWER and YALMIP shown in Table 1.

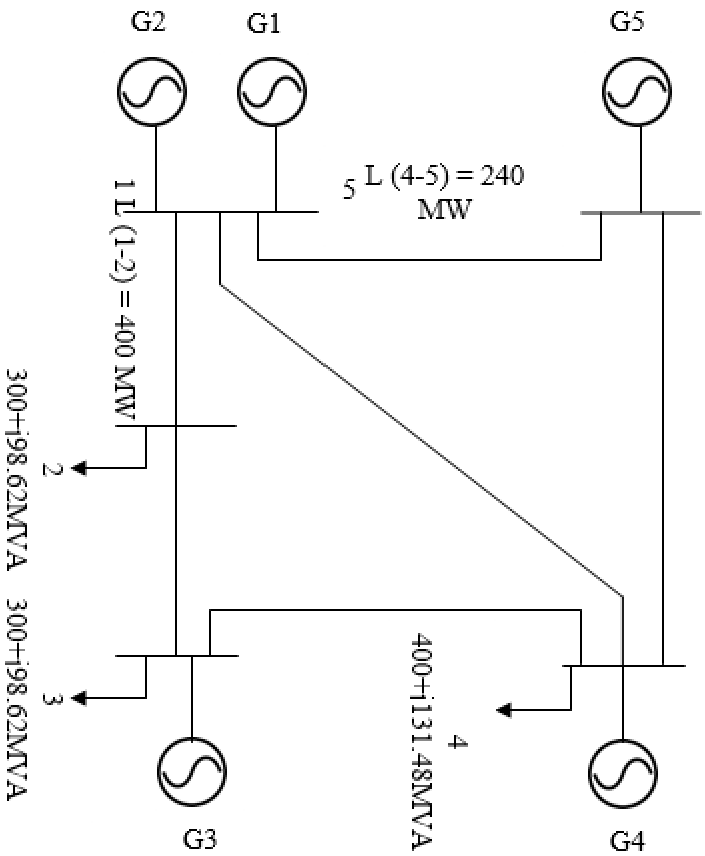

Fig 1: The diagram of bus system PJM-5

Table 1: Data

Gen No.	Bus Number	Type of turbines	Cost ($/MWh)	CEI rate	Limit (MW)	Limit (MVar)
1	1	Wind	15	0	42	±31.0
2	2	Wind	17	0	169	±128.2
3	3	Gas	31	0.4	522	±392.0
4	4	Gas	42	0.4	210	±149.0
5	5	Coal-fired	22	0.10	605	±451.3

To test the reliability of the research, 4 typical situations were presented in the study for comparison.

Case 1: IPP case with WPU, excluding consumer HES and DR.

Case 2: The consumer employs a DR of the LME price by using scenario of power purchase.

Case 3: In scenario 2, the cost of the DR input was translated to the LME-CO2 price discussed in this study.

Case 4: Compare the benefits of the HES systems installed on different buses based on sub-cases.

Case 4-1: The second bus has the HES system fitted.

Case 4-2: The third bus fitted using the HES system.

Case 4-3: The fourth bus has the HES system fitted.

4.3 Result analysis

In this work, 10,000 historical information collections from a wind farm in Belgium were selected as examples, and the high-order curve fitting method was used to identify the fluctuation characteristics of wind power throughout various periods. Figure 2 shows the first period's wind power probability curve and the historical variation of WP data.

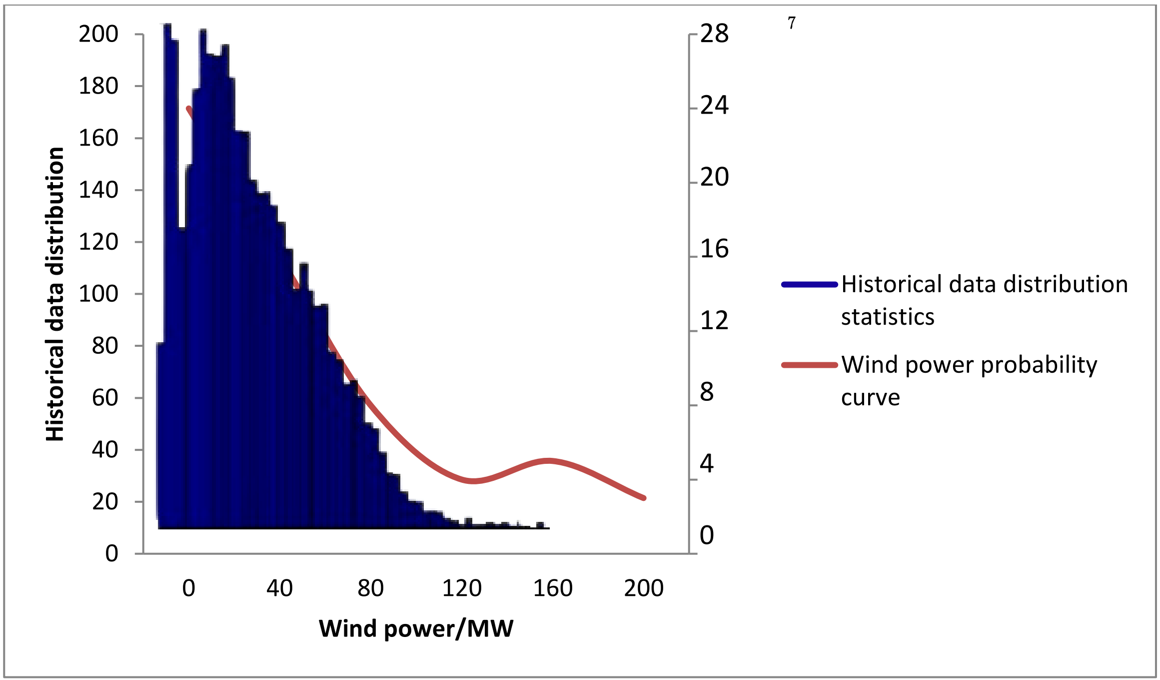

Fig 2: HD of WP curve over time

Figure 3 compares customer electricity costs, consumer carbon emissions costs, total consumer costs, and carbon emissions from Case 1 to Case 3. Consumers carbon taxes could be effectively decreased by DR with a LME-CO2 price, lowering total prices and lowering CO2 emissions from the energy system. When compared to Scenario 1, Case 3 and Case 2 cost is \$1.938×10^4 and \$2.635×10^4 respectively. Customers' power costs are reduced by \$1.354×10^4 and \$1.186×10^4, correspondingly while carbon tax costs are reduced by \$0.584×10^4 and \$1.229×10^4 correspondingly.

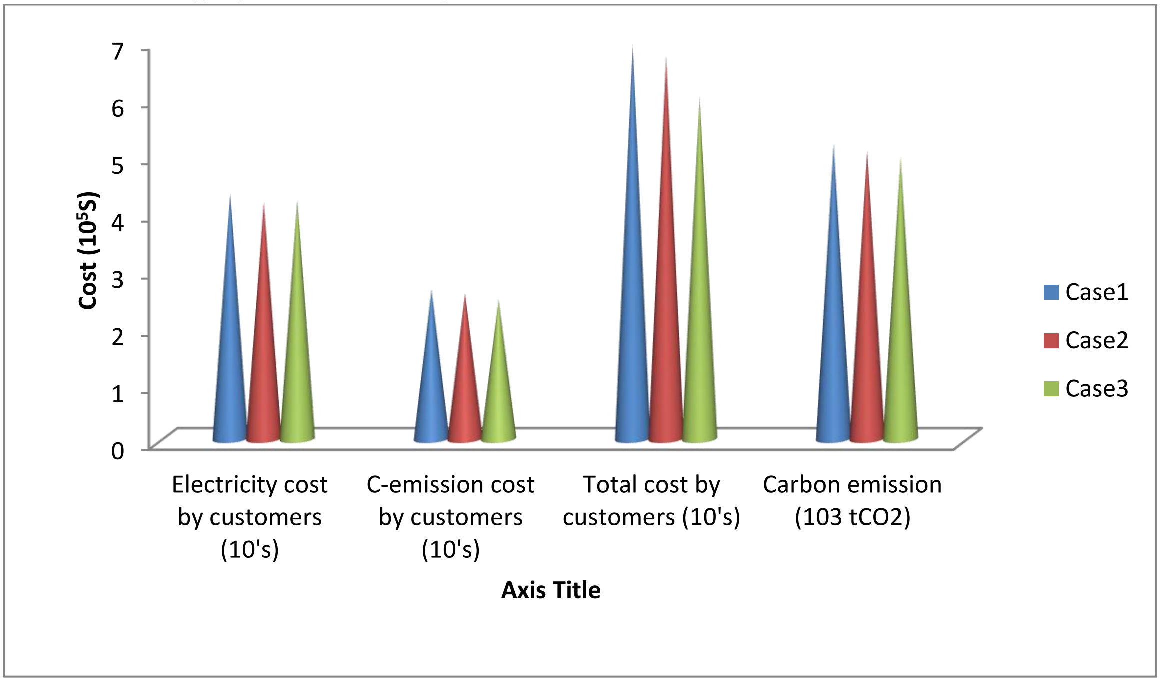

Fig 3: Several sorts of consumer costs and carbon emissions from power systems in various scenarios

Case 3 provides comparable lower customer CO2 T expenses than Case 2, resulting in LTC and CO2 emissions compared to Case 2, but having slightly higher consumer electricity costs than Case 2. The LME-CO2 price includes the CO2 emission variable while the standard DR approach does not and only looks at the cost of power. The CO2 tax element and the power price element are both considered in the DR that was suggested in this study. Figure 4 depicts the CEI and power usage for bus 3 after and before moving the load at various period points using the LME-CO2 price DR.

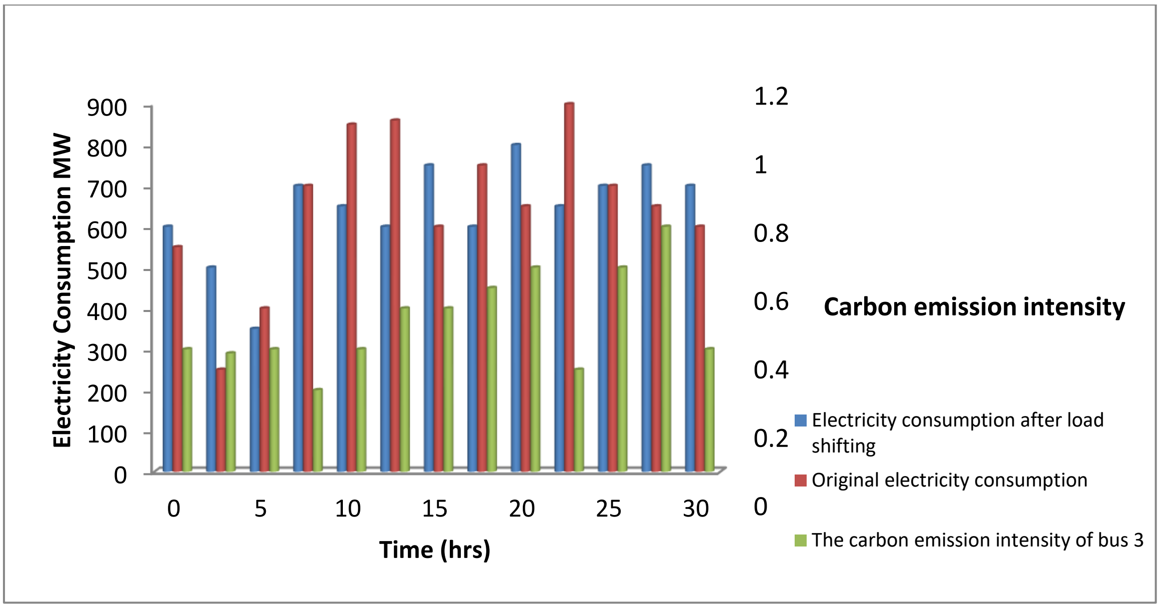

Fig 4: CEI and electrical usage of bus 3 after and before LS at various period intervals

Following the implementation of the LME-CO2 price DR, certain load power usage was transferred from periods of greater CEI (15-17, 10-11, 19-21) to times with lesser CEI. Figure 5 depicts the impact of moving the HES system's installation position on its arbitrage.

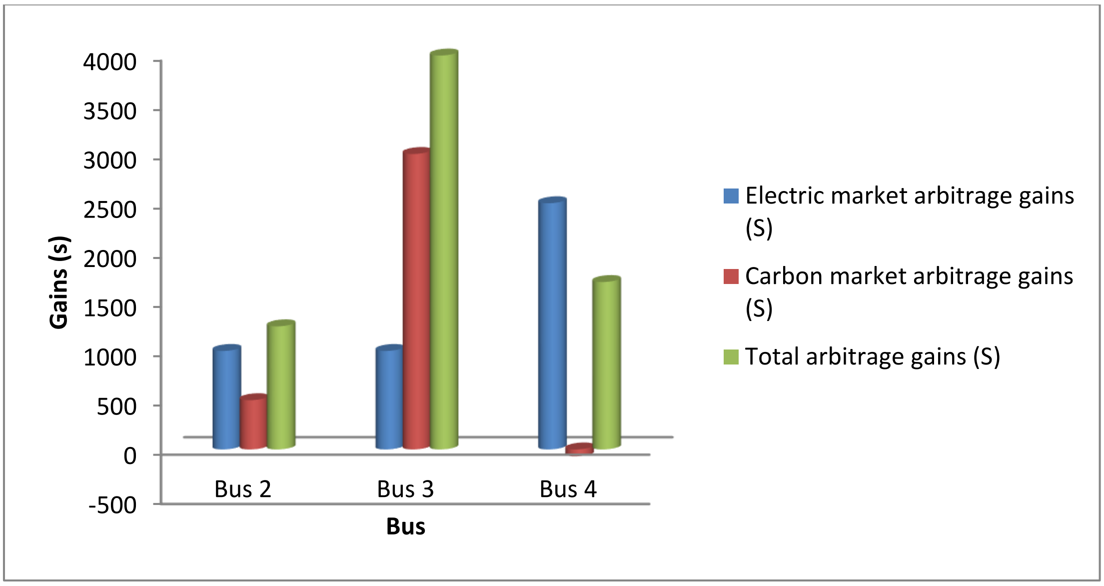

Fig 5: HES system arbitrage at various vehicles

This is due to differences in the ME and CO2 prices at various buses. According to the aforementioned findings, it is obvious that putting the HES system in bus mode provides the best advantage for this research. Figure 6 depicts the MP of buses 2, 3, and 4. The marginal power price for buses 2, 3, and 4 in periods 1 through 7 are all \$20/MWh. Bus 3's marginal carbon price varies more than the prices of the other two buses, hence when the storage device is placed on this bus as opposed to the 2 buses the arbitrage from the CO2 market was significantly larger.

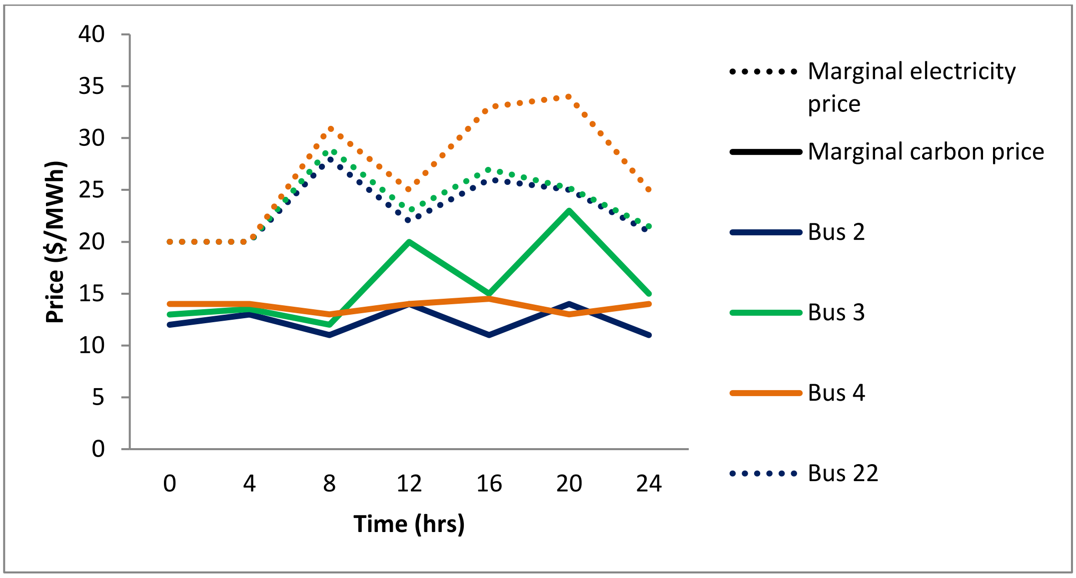

Fig 6: Cost of LME and the LMP at various buses

5. Conclusion

Conventional DR simply evaluates the variation in electricity prices to direct load usage, but it is unable to direct load variations brought on by changes in CEI on the power consumption side. The arithmetic analysis yields the following results:

(1) LME-CO2 price DR and carbon emissions in the PS were successfully decreased by lowering the price of energy purchase and the CO2 T for customers. In the meantime, the LME-CO2 price was utilized to compute the HES system's discharging and charging state.

(2) When the carbon emission component is included in the DR, the demand not only tends to react to changes in the price of electricity but also tends to follow changes in the CEI of the power system. It is more equitable for the load to change from a low CEI time to a high time.

(3) The most advantageous position for HES system installation was discovered by evaluating the variations in the advantage of putting HES systems on various vehicles.

A method presented in this paper could be used in future studies of the IES. To further reduce CO2 emissions, the methods for carbon capture and trading might be increased.

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