Journal of Engineering and Technology Management 78 (2025)

Integration of Renewable energy sources with Battery Energy Storage for Line Loss Reduction in Distribution Networks using HALACBO algorithm

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***Abstract*— Line loss is a critical indicator of energy management efficiency in low-voltage power systems, with transformer areas contributing significantly to overall distribution losses. It is vital to reduce these losses to enhance efficiency, minimize wastage of energy and enable sustainable power distribution. A new hybrid optimization method, HALACBO which combines the Artificial Lemming Algorithm (ALA) with Coyote and Badger Optimization (CBO), is presented in this research. The technique emphasizes finding the most excellent location and size of distributed generation (DG) units and solving voltage profile enhancement and harmonic distortion constraints. Renewable energy sources (RES) like photovoltaic (PV) systems, wind turbines, and battery energy storage systems (BESS) are integrated in order to improve grid performance. Simulation results based on the IEEE 33-bus test system implemented in MATLAB confirm that the devised model effectively mitigates line losses, providing better results. The results validate HALACBO's capability to improve efficiency and integration of renewables. When compared to other existing algorithms the proposed technique has a low fitness value at 20 iterations.**

Keywords*— Distribution Networks, HALACBO algorithm, line loss, BESS, Solar, wind and Renewable energy sources

I. Introduction

The steadily increasing demand for power and the worldwide move toward sustainable energy solutions have transformed the operation of modern distribution networks [1]. Centralized fossil-fuel-based power generation has dominated the electricity sector, but it is associated with high greenhouse gas emissions, inefficient long-distance transmission, and considerable energy losses [2]. Line losses in distribution systems remain a significant challenge as they directly reduce the efficiency of power delivery, increase operational costs, and stress network infrastructure [3]. To improve efficiency and meet sustainability goals, RES such as PV and wind energy are increasingly being integrated into distribution networks [4]. These resources are clean, abundant, and well-suited for localized generation. The intermittent and uncertain nature introduces operational issues including voltage fluctuations, power imbalance, and reverse power flow [5]. One of the key consequences of these uncertainties is the increase in real and reactive line losses, which diminishes the benefits of renewable integration and affects overall system reliability [6]. One of the main goals of integrating RES into distribution systems is to minimize line losses [7]. A reliable method to address these challenges uses Battery Energy Storage System (BESS). Storing excess renewable power when demand is low and releasing it during peak load conditions, BESS reduces unnecessary energy circulation through distribution feeders, resulting in a notable decrease in technical line losses [8]. BESS improves load leveling, voltage stability and power quality while providing fast response to renewable variability. In existing works, several challenges still persist [9]. Many methods fail to accurately minimize line losses due to nonlinear and dynamic nature of distribution systems. Conventional optimization techniques often struggle with premature convergence, leading to suboptimal positioning and dimensions of renewable energy sources and battery storage units [10]. To achieve maximum line loss reduction, novel advanced optimization techniques are required. In recent years, metaheuristic algorithms have proven effective in handling such complexities. The major objective of this work is;

- To enhance energy efficiency, this study presents a hybrid optimization approach called HALACBO, which combines the ALA with CBO and is applied to determine DG's ideal positioning and dimensions to reduce line losses.
- To increase efficiency and decrease line losses of distribution networks, RES like solar PV and wind, when integrated with BESS can be effectively utilized.

Remaining section of this paper is structured follows; section 2 describes the literature survey based on line loss minimization. Proposed methodology for integration of RES and minimization of line losses is explained in section 3.The results and discussion for evaluating the performance of proposed approach is provided in section 4. Last section of this paper explained in section 5.

II. LITERATURE SURVEY

Some of the authors explained for the minimization of line loss in the distribution system and it is given as;

Lu et al. [11] described a distributed optimum control technique based on projected gradient descent for medium-voltage DC distribution systems with an emphasis on line loss minimization. Modifying the optimization model's optimality requirements, the projection operator made it possible to include variables with constant derivatives, like line loss, in the operation scheduling layer's objective function. A distributed control strategy was developed, where the iterative solution process was carried out using projected gradient descent through an integral controller and feedback mechanism. Routray et al. [12] explored the use of machine learning techniques to predict wind speed and minimize losses in radial distribution systems that are not balanced. An efficient optimization method, teaching Learning Based optimization, was employed to identify the optimal placement and distributed generation unit sizing to reduce distribution line power losses. Because of its simplicity and robustness with single-step computing, the load impedance matrix approach was used for distribution system load flow analysis.

Skunana et al. [13] analyzed how to best locate battery energy storage devices in distribution networks to improve voltage profiles and lower power losses. The cost of voltage deviations in the 16-bus Witzenberg network was minimized by optimal placement of BESS, resulting in improved dependence on renewable energy sources. The Particle Swarm Optimization (PSO) and the Genetic Algorithm (GA) were utilized to solve the optimization problem and compare the performance. The results indicated that BESS can enhance network performance and support additional generation from renewable energy sources. Norouzpour Shahrbejari et al. [14] consulted on optimized energy storage systems to improve performance of the power grid. The authors concentrated on loss reduction and voltage stability. A Multi-Objective Optimization Algorithm (MOA) was developed for strategic placement and sizing of ESS units in an IEEE 33-bus distribution network, aiming to minimize voltage deviation and power losses. The results of the simulation indicated a significant reduction in power losses and better voltage stability. The results contributed to an overall increase in robustness and economic efficiency of the power grid.

Jeon et al. [15] developed a combined optimization strategy for hybrid energy storage system deployment, sizing, and energy management in renewable power systems. The study employed a combination of Mixed-Integer Linear Programming (MILP) and the Non-Dominated Sorting Genetic Algorithm II (NSGA-II) to determine the capacity, location, and operational strategy of HESS in RES-based systems. The suggested approach produced extremely dependable results by improving cost effectiveness, stability of voltage, and line failure minimization. In existing works, line losses are relatively high, which reduces overall network efficiency. To address this, a novel optimization technique HALACBO, is proposed. This approach aims to minimize line losses considerably while enhancing the stability of voltage and overall system performance.

III. PROPOSED METHODOLOGY

In low-voltage power systems, line loss is a crucial indicator of lean management, energy conservation, and loss reduction levels. Also indicates the energy management efficiency of power supply companies. In particular, the low-voltage transformer areas' line loss makes up over half of the distribution network's total line loss, which contributes significantly to the power system's overall power loss. However, these losses are often difficult to detect and manage. Given the current challenges faced by power grids worldwide, the reduction of low voltage in the line loss distribution system presents considerable potential for improving efficiency and saving energy. Strengthening line loss management through monitoring the operational condition of low-voltage transformers can effectively minimize these losses. Simultaneously, growing environmental concerns associated with conventional energy generation have accelerated the integration of RES such as PV systems and WT, into distribution networks. To address this, the present study introduces a hybrid optimization approach named HALACBO, which combines the ALA with CBO. The proposed method optimizes the location and capacity of DG units with the primary objective of reducing line losses while considering voltage and harmonic constraints. Integrating RES such as solar PV, wind, with BESS effectively utilized to minimize line losses and enhance the efficiency of distribution networks. The model is enabling enhanced integration of RES-based DG for loss minimization.

Objective function

The optimization problem formulated in the work focuses on minimizing distribution generation losses within a power electronic distribution network [16]. This problem is treated as a planning task where both the location and DG units are determined strategically to achieve the lowest possible overall losses. The objective function is to minimize the combined transformer and line losses in the system expressed as;

$$\text{MIN } \mathrm{P}_{tot\,loss} = \text{MIN}\left(\sum \mathrm{P}_{loss(\tau)} + \sum \mathrm{P}_{loss(l)}\right) \tag{1}$$

The transformer power loss is represented by $\mathrm{P}_{loss(\tau)}$, the line power loss is denoted by $\mathrm{P}_{loss(l)}$ and the total loss in the grid is symbolized by $\mathrm{P}_{tot\,loss}$.

Constraints

Voltage regulation constraint: The voltage at each bus must be maintained within an acceptable operating variation to ensure system stability and reliability. The allowable limits require the bus voltage magnitude to stay between 0.9p.u and 1.1 p.u. The equation of the bus voltage from the nominal reference voltage should not exceed 0.05 p.u. This condition is expressed as;

$$\begin{cases} 0.9\,p.u. \le |v_{\mathrm{I}}| \le 1.1\,p.u \\ \sum\limits_{\mathrm{I}} \overline{|v_{\mathrm{I}} - v_{\gamma ef}|} \le 0.05\,\rho.u \end{cases} \tag{2}$$

The nominal reference voltage of the system is represented by $v_{\gamma ef}$.

Harmonic Distortion constraint: To maintain acceptable power quality, the total harmonic distortion

(THD) at each bus is restricted to a maximum of 5%. The THD is determined by the ratio of the root-mean-square value of all harmonic voltage components to the fundamental voltage component. It is expressed as:

$$\left\{ \begin{array}{c} \mathrm{TH}D_{\mathrm{I}} = \dfrac{\sqrt{\sum_{m=2}^{\mathrm{M}} \left(\nu_{\mathrm{I}}^{(m)}\right)^2}}{\nu_{\mathrm{I}}^{(1)}} \\ \mathrm{TH}D_{\mathrm{I}} \le 5\% \end{array} \right. \tag{3}$$

From the above equation, $\nu_{\mathrm{I}}^{(m)}$ is the m^{th} order harmonic voltage at bus I and $\nu_{\mathrm{I}}^{(1)}$ represents the fundamental component.

Modeling of solar PV, wind and BESS

The fundamental component of a PV module is a solar PV cell, which is basically a P-N junction device [17]. To get the required voltage and current levels, many cells are connected in parallel and series. A PV cell's output current can be calculated theoretically using;

$$\mathrm{I}_{\mathrm{P}\nu} = \mathrm{I}_{\mathrm{P}h} - \mathrm{I}_{\delta}\left(e^{q(\nu_{\mathrm{P}\nu} + \mathrm{I}_{\mathrm{P}\nu} * \Re_{\delta})/\eta\kappa\mathrm{T}} - 1\right) - \left(\nu_{\mathrm{P}\nu} + \mathrm{I}_{\mathrm{P}\nu} * \Re_{\delta}\right) / \Re_{\delta H} \tag{4}$$

Where $\mathrm{I}_{\mathrm{P}h}$ the light-generated is current, I_{δ} is the diode saturation current, q is the electron charge, κ is Boltzmann's constant, η is the ideality factor and T is the absolute temperature. A wind turbine is the central element of a wind energy conversion system and its behavior mathematically described using aerodynamic principles [18]. The mechanical output power is expressed as;

$$\mathrm{P_M} = 0.5\rho\pi\Re^2 \mathrm{E}_{\rho}(\beta, \gamma)\nu^3 \tag{5}$$

Where, ρ is the air density, ν is the wind velocity, E_{ρ} is the power coefficient dependent on the tip speed ratio β and pitch angle γ . The tip speed ratio is defined as;

$$\beta = \frac{\omega\Re}{\nu} \tag{6}$$

The wind turbine's angular velocity is ω and the rotor radius is denoted by $\Re$ .Performance of a lead-acid battery can be represented using Peukert's law, which relates its capacity to the discharge current [19]. The expression is given as;

$$\mathrm{E}_{\rho} = \mathrm{I}^{\kappa} * \tau \tag{7}$$

From the above equation, E_{ρ} is the rated capacity in ampere-hours, I is the discharge current, κ is the Peukert constant and τ denotes the discharge time in hours. The terminal DC voltage can be written as;

$$u_{dc} = u_{MAX} * (\delta OC) + u_{MIN}(1 - \delta OC) - \mathrm{I} * \mathrm{Z_I} \tag{8}$$

Where u_{MAX} and u_{MIN} correspond to the fully charged and fully discharged cell voltages, δOC is the state of charge, $\mathrm{Z_I}$ is the internal impedance and I is the discharge current.

Proposed HALACBO framework

A new hybrid optimization framework called HALACBO is proposed by integrating ALA with CBO. This technique is used to determine the best places and dimensions for DG units with the goal of reducing line losses while preserving voltage stability and managing harmonic distortions. The ALA begins by forming an initial set of solutions, each representing possible configurations to minimize the line losses in the distribution system. These solutions are structured in a matrix of size $\mathrm{N} \times \partial im$, where N the population size is and ∂im is the number of decision variables (e.g., DG location, capacity or operating settings). Each candidate solution is generated randomly within the lower and upper bounds of the problem. The best solution is identified as the configuration that yields the lowest line losses.

$$\vec{\mathrm{Y}} = \begin{bmatrix} y_{1,1} & y_{1,2} & \cdots & y_{1,Dim-1} & y_{1,Dim} \\ y_{2,1} & y_{2,2} & \cdots & y_{2,Dim-1} & y_{2,Dim} \\ \cdots & \cdots & y_{j,k} & \cdots & \cdots \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ y_{\mathrm{N}-1,1} & y_{\mathrm{N}-1,2} & \cdots & y_{\mathrm{N}-1,Dim-1} & y_{\mathrm{N}-1,Dim} \\ y_{\mathrm{N},1} & y_{\mathrm{N},2} & \cdots & y_{\mathrm{N},Dim-1} & y_{\mathrm{N},Dim} \end{bmatrix} \tag{9}$$

$$y_{j,k} = lb_k + \Re and \times (ub_k - lb_k),\ j = 1,2,\ldots,\mathrm{N},\ k = 1,2,\ldots.,Dim \tag{10}$$

From the above equations, lb_k and ub_k represent the bounds of k^{th} variable, while $\Re and$ is a uniformly distributed random number in [0, 1]. Best solution iterations correspond to the configuration producing the minimum line losses.

Exploration phase

To search for solutions that further reduce line losses, the lemmings long-distance migration behavior is modeled [20]. Here, each agent updates its position based on the best solution and other randomly chosen solutions, which helps in exploring new areas of the search space. This mechanism prevents premature convergence and enhances the chance of discovering configurations that yield lower line losses.

$$\vec{\mathrm{Y}}_j(\tau+1) = \vec{\mathrm{Y}}_{BEST}(\tau) + \mathrm{E} \times \overrightarrow{\mathrm{BM}} \times \left(\vec{\Re} \times \left(\vec{\mathrm{Y}}_{BEST}(\tau) - \vec{\mathrm{Y}}_j(\tau)\right) + \left(1 - \vec{\Re}\right) \times \left(\vec{\mathrm{Y}}_j(\tau) - \vec{\mathrm{Y}}_b(\tau)\right)\right) \tag{11}$$

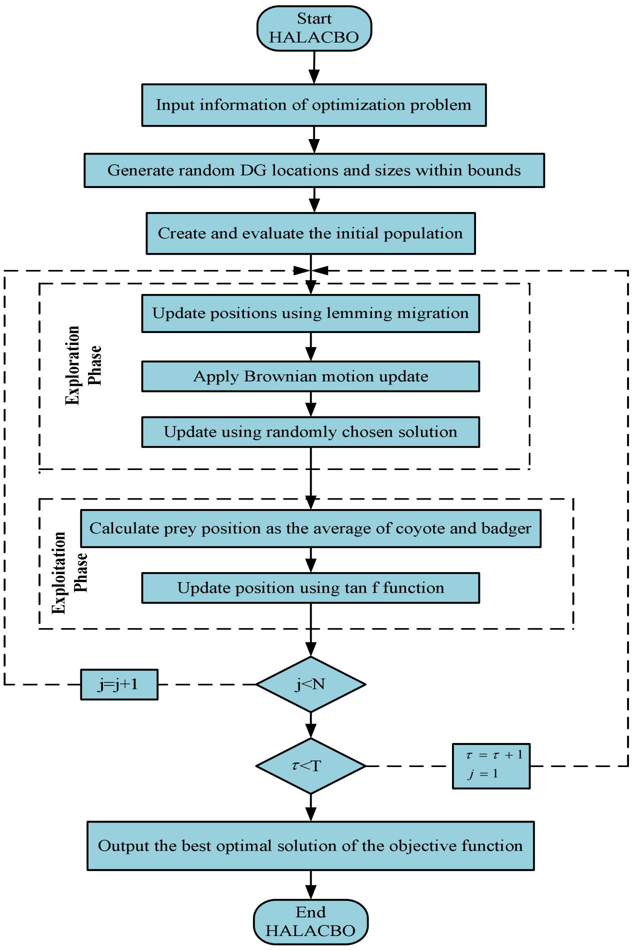

Fig. 1. Flowchart of HALACBO

From the above equation, $\vec{Y}_j(\tau+1)$ is a new position of agent j, $\vec{Y}_{BEST}(\tau)$ is current best solution and $\vec{Y}_b(\tau)$ is a randomly chosen solution as well as $\overrightarrow{BM}$ represents the Brownian motion. The direction Flag E is:

$$E = \begin{cases} 1 & if \lfloor 2\times \Re and + 1 \rfloor = 1 \\ -1 & if \lfloor 2\times \Re and + 1 \rfloor = 2 \end{cases} \tag{12}$$

Brownian motion is expressed as;

$$e_{BM}(z;0,1) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{z^2}{2}\right) \tag{13}$$

The random vector is defined by;

$$\Re = 2\times \Re and(1, Dim) - 1 \tag{14}$$

This phase enhances exploration by testing diverse candidate solutions that can potentially reduce system line losses. This stage simulates digging burrows, allowing the search agents to focus near promising configurations with already reduced line losses. The update mechanism is given as;

$$\vec{Y}_j(\tau+1) = \vec{Y}_j(\tau) + E\times\Gamma\times\left(\vec{Y}_{BEST}(\tau) - \vec{Y}_c(\tau)\right) \tag{15}$$

Where $\vec{Y}_c(\tau)$ is a randomly selected individual and Γ is factor controlling search intensity, expressed as;

$$\Gamma = \Re and\left(1 + \sin\left(\frac{\tau}{2}\right)\right) \tag{16}$$

This exploitation step fine-tunes solutions, ensuring that the placement and sizing of DG units are optimized minimum line losses while maintaining system voltage quality.

Exploitation phase

In the exploitation phase of CBO, search agents focus on refining their positions around promising regions to minimize line losses in the distribution network [21]. The prey position calculated as the average of the coyote and badger positions represents the candidate operating point for loss reduction. During each iteration, the agents update their positions toward the prey using:

$$\overrightarrow{yd^{j+1}} = \overrightarrow{yd^{j}}.\left(1 + \gamma_1 . \tan f\left(\overrightarrow{y\rho^{j}}\right)\right) \tag{17}$$

$$\overrightarrow{yc^{j+1}} = \overrightarrow{yc^{j}}.\left(1 + \gamma_2 . \tan f\left(\overrightarrow{y\rho^{j}}\right)\right) \tag{18}$$

Where, γ_1 and γ_2 are adaptive factors representing sight and smell. The $\tan f$ function constrains updates within a bounded range, preventing extreme variations and ensuring stable convergence. If any parameter exceeds the allowable operating limits, it is restricted to the boundary values to maintain system feasibility. Through this controlled exploitation process, the algorithm progressively steers the search toward configurations that achieve minimum power losses, accelerating convergence to the global optimum while avoiding unnecessary divergence. Fig. 1depicts the Flowchart of HALACBO.

IV. RESULT AND DISCUSSION

The Proposed HALACBO was approach evaluated on a standard 33-bus test system through the MATLAB/Simulink tool. The outcomes demonstrate how well the suggested approach with harmonic limitations lowers the absolute loss of lines. Determining the optimal placement and sizing of DG units significantly enhances distribution network efficiency. Simulations highlight the strength of advanced optimization frameworks in improving power flow management. Integration of distributed energy resources further contributes to minimizing losses and supporting voltage stability. These outcomes demonstrate that combining DERs with an intelligent optimization technique strengthens overall system reliability. The proposed method also ensures better utilization of renewable-based DG units in the grid. Hence, HALACBO offers a robust and sustainable pathway for modern distribution networks.

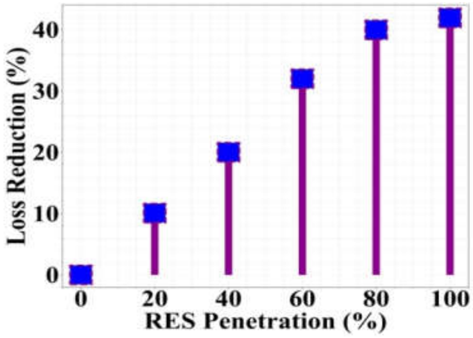

Fig. 2. Analysis of loss reduction

Fig. 2 illustrates the impact of RES penetration on loss reduction. The X-axis symbolizes share RES, and the Y-axis indicates the percentage loss reduction. A consistent upward trend is observed, where higher RES penetration corresponds to greater loss reduction. At 20% RES, the reduction is around 10%, which increases to more than 40% at full penetration. This indicates that greater integration of renewables significantly improves system efficiency by reducing losses.

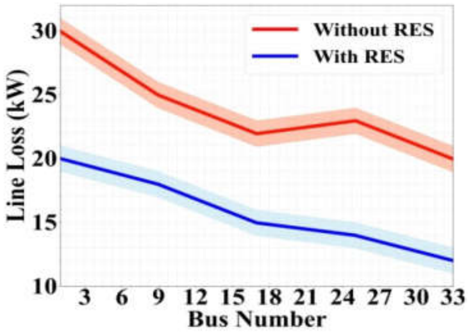

Fig. 3. IEEE 33-Bus system voltage profile

Fig. 3 presents a comparison of line losses, measured in kilowatts, for an IEEE 33-Bus system with and without the integration of RES. The data show that, in the absence of RES, line losses remain relatively high across all bus numbers, starting near 30 kW and gradually decreasing to about 20kW. When RES is incorporated, there is a marked reduction in losses, beginning around 20 kW and declining to approximately 12 kW by the final bus. This trend highlights that integrating RES into the system effectively enhances efficiency by reducing energy losses along the network.

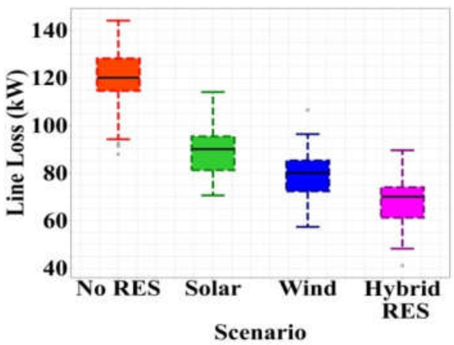

Fig. 4. Line loss reduction with RES integration

Fig. 4 depicts the impact of RES integration on line losses. In the absence of any RES, line losses are at their peak, averaging roughly 120kW. Incorporating a single type of energy from renewable sources like wind and solar noticeably lowers these losses, with wind performing slightly better than solar. The most significant reduction is observed when multiple renewable sources are combined in a hybrid RES system, bringing the average line loss down to approximately 65 kW. This clearly indicates that utilizing a combination of RES is the most effective strategy for minimizing line losses.

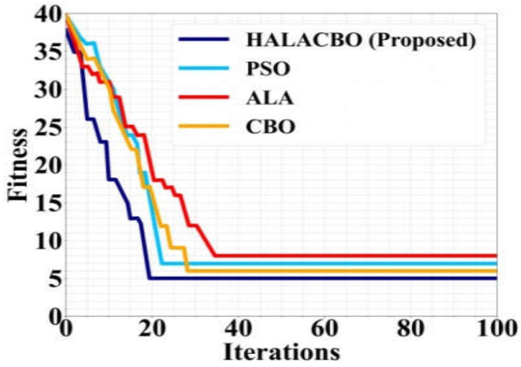

Fig. 5. Analysis of fitness curve

Fig. 5 illustrates the comparative analysis of the fitness curve. The proposed algorithm delivers the best performance among the tested methods. It rapidly converges to the lowest fitness value, reaching an optimal solution within just 20 iterations. In contrast, PSO stabilizes at around 22 iterations, CBO requires about 30, and ALA takes nearly 35 iterations. This demonstrates that while all algorithms improve over time, their final solutions remain less efficient than HALACBO. Overall, HALACBO proves to be the fastest and most effective optimization strategy in achieving superior results.

V. CONCLUSION

The proposed HALACBO framework has proven highly effective in placing and designing distributed generating units optimally to minimize line losses and enhance voltage stability in distribution networks. By integrating PV, wind, and BESS within a hybrid optimization model, the proposed method enhances energy efficiency and ensures reliable utilization of renewable-based DG units. Comparative results confirm that HALACBO outperforms conventional algorithms in terms of faster convergence and superior solution quality. Analysis further emphasizes that higher RES penetration leads to greater loss reduction, reinforcing the role of renewable integration in sustainable grid operation. Moreover, this research can be extended by applying HALACBO to larger and more complex real-world networks to assess scalability and adaptability. Incorporating dynamic load variations, demand response strategies, and advanced smart grid technologies can further strengthen performance.

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