

Article

A Dual-Layer BDBO-ADHDP Framework for Optimal Energy Management in Green Ports with Renewable Integration

Ting Li ^{1,2}, Nan Wei ^{1,2,*}, Tianyi Ma ^{1,2}, Bingyu Wang ³, Yanping Du ^{1,2}, Shuihai Dou ^{1,2} and Jie Wen ^{1,2}

¹ School of Mechatronic Engineering, Beijing Institute of Graphic Communication, Beijing 102600, China; liting@bigc.edu.cn (T.L.); matianyi@bigc.edu.cn (T.M.); duyanping@bigc.edu.cn (Y.D.); doushuihai@126.com (S.D.); 13081888673@163.com (J.W.)

² Key Laboratory for Research and Application of Key Technologies in the News Publishing Field, Beijing Institute of Graphic Communication, Beijing 102600, China

³ School of Control and Computer Engineering, North China Electric Power University, Beijing 100054, China; wangbingyu@ncepu.edu.cn

* Correspondence: jtykivtg24@foxmail.com

Abstract

Propelled by the “dual-carbon” strategy, green and intelligent ports are rapidly advancing toward low-carbon and intelligent development. However, the large-scale incorporation of renewable energy and the extensive electrification of transport equipment have substantially heightened system volatility and scheduling complexity. To address the challenges associated with multi-energy coupling and economic operation in medium and large ports, a hierarchical collaborative optimization scheduling strategy is proposed. The upper layer employs an improved Bio-enhanced Dung Beetle Optimization (BDBO) algorithm for parameter optimization and carbon-cost minimization. Meanwhile, the lower layer establishes a rolling time-series control mechanism grounded in Adaptive Dynamic Hierarchical Decoupling Planning (ADHDP), thereby constituting an integrated BDBO-ADHDP dual-agent system. Simulation results across four seasonal scenarios demonstrate that the proposed methodology outperforms DQN, PSO, GA, ACO, and DBO algorithms in reducing grid power purchases, enhancing renewable energy utilization, mitigating curtailment, and lowering operational costs. Moreover, it achieves faster convergence, superior robustness, and effective carbon-emission control. This study substantiates the efficacy of the proposed strategy within green port integrated energy systems and highlights its potential for broader application in other multi-energy coupled systems.

Keywords: green port; integrated energy system; adaptive dynamic programming; intelligent scheduling; energy storage optimization; renewable energy utilization; bi-level optimization; dung beetle optimization algorithm; multi-objective optimization

Academic Editor: Francisco Javier Ruiz-Rodríguez

Received: 15 January 2026

Revised: 14 February 2026

Accepted: 16 February 2026

Published: 18 February 2026

Copyright: © 2026 by the author. Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

1. Introduction

In the context of the ongoing global energy restructuring and the relentless progression of the “dual-carbon” strategy, ports—acting as vital hubs for national energy consumption and integrated transportation—are undergoing a profound metamorphosis. This transformation is steering them away from high energy consumption and emission-intensive paradigms towards a high-efficiency system that is green, low-carbon, and intelligent [1,2]. Against this backdrop, green and smart ports are gradually advancing into a new stage of low-carbon, digital, and intelligent development. According to the 2024

report issued by the International Association of Ports and Harbors (IAPH), the annual carbon emissions from global ports are approximately 860 million tons, constituting 12% of the total emissions emanating from the transportation sector. Notably, the energy consumption of China's coastal ports accounts for roughly 68% of the aggregate energy consumption across all domestic ports, with their carbon emission intensity surpassing that of internationally advanced ports by approximately 15–20% [1,3]. Therefore, the construction of green and smart ports necessitates the urgent attainment of multi-energy coordination and optimal scheduling among energy sources, loads, and storage systems. On one hand, major hub ports such as Tianjin Port and Shanghai Port have installed more than 100 MW of wind and photovoltaic capacity, elevating the proportion of renewable energy to 35% [4]. On the other hand, the proliferation of electrified devices in port areas has accelerated; for instance, Shenzhen Mawan Port now operates in excess of 300 electric trucks, and its shore power coverage rate has reached 90%. Nevertheless, the charging load exhibits a dual-peak pattern, peaking during 8:00–10:00 in the morning and 18:00–20:00 in the evening, with a peak-to-valley ratio as high as 4.2 [5]. The superposition of a high proportion of renewable energy and the dual-peak characteristics of rigid loads has imposed three formidable challenges on port integrated energy systems, including significant power curtailment, elevated power supply costs, and compromised operational stability [6–11]. These challenges underscore the imperative to transcend the constraints of conventional scheduling strategies and pioneer an intelligent and optimization-oriented energy management system [12].

With the swift advancement of the novel power system, ports have evolved beyond serving merely as hubs for large-scale maritime operations and shore power provisioning. Instead, they are emerging as pivotal nodes for the seamless integration of renewable energy sources, the incorporation of energy storage access, and electrified transportation [13]. Against the backdrop of multi-energy and multi-load coupling, the pursuit of coordinated optimization that harmonizes economic efficiency, environmental sustainability, and system stability while ensuring a secure and reliable energy supply has emerged as a paramount scientific issue in the realm of green and intelligent port construction.

At present, research on energy allocation and scheduling in port integrated energy systems has primarily focused on economic efficiency, energy conservation, and emission reduction. Reference [14], an optimization strategy was proposed, based on integrated demand response, aiming to minimize the operational cost of a port integrated energy system. However, this approach did not incorporate the dynamic charging demand of electric transportation equipment (such as cross-port electric trucks and in-yard automated guided vehicles, AGVs) into the demand response framework, thereby constraining its adaptability to the seasonal fluctuations in renewable energy output. Reference [15] established a port integrated energy system coupling energy and logistics subsystems, realizing the coordinated operation between the power grid and natural gas network based on day-ahead port data, and consequently reducing system costs. Nevertheless, it lacked a coordinated scheduling mechanism for shore power loads and electric logistics devices, and its consideration of multi-energy coupling robustness under extreme weather conditions was insufficient. Reference [16], models for wind turbine, energy storage, and port power supply system were developed to propose a two-level optimization framework tailored for port renewable energy systems. While this model effectively curtailed the system investment costs by addressing power balance and capacity constraints, it neglected the proactive involvement of electric vehicles and the vehicle-to-grid (V2G) regulation potential of shore power loads. Moreover, it failed to account for extreme winter conditions, exemplified by a 70% reduction in photovoltaic output during prolonged overcast weather. Reference [17] focused on the contribution of shore power technology in improving energy efficiency and overall port economic performance, yet it treated

shore power loads as passive receivers. Consequently, it did not delve into their potential for flexible regulation through the integration of “spatiotemporal shifting + V2G,” nor did it explore the feasibility of coordinated port load scheduling. Reference [17] introduced a real-time distributed demand response system based on a multi-agent, dual-layer architecture, effectively surmounting the limitations of traditional control systems in managing a numerous flexible terminal loads. This system facilitated real-time emission control for ships, reduced operational costs for local wind farms, and estimated shore power utilization rates through a fuzzy-logic-based model. However, it failed to incorporate the dynamic charging requirements of cross-port electric trucks and lacked robustness under extreme weather conditions, such as typhoons and extended rainfall. Similarly, reference [18], also predicated on a multi-agent system framework, advocated for the utilization of smart energy networks and full electrification to curtail greenhouse gas emissions and enhance the operational efficiency of power systems, thereby fulfilling the power supply demands of shore-powered vessels and various onshore electric and flexible loads. However, it did not devise a coordinated optimization strategy covering composite scenarios such as “dense ship arrivals–grid faults–renewable generation drops,” and it underutilized the spatial energy complementarity among ports within a cluster.

Although significant strides have been made in existing studies concerning the optimization of port integrated energy systems, research focusing on the optimization of port clusters while accounting for multi-energy coupling remains relatively nascent. The majority of current works are rooted in the framework of integrated energy systems at the industrial park-level within terrestrial grids, which falls short of fully accommodating the distinctive coupling characteristics and cross-regional coordination imperatives inherent to port clusters. For instance, Reference [19] proposed a multi-energy coordinated scheduling model based on scenario analysis, which succeeded in reducing operational costs and enhancing photovoltaic accommodation rates. However, it did not sufficiently consider the active participation mechanisms of electric transportation fleets and shore power loads. Furthermore, its scenario analysis was deficient in encompassing compound extreme conditions, such as the simultaneous occurrence of “dense ship arrivals combined with sudden renewable generation drop.” Reference [20] designed an energy management strategy tailored for a multi-energy microgrid integrating renewable energy sources, hydrogen, and energy storage. This strategy effectively bolstered system responsiveness and dispatch stability. Nevertheless, it approached shore power as a mere passive load, thereby overlooking its latent V2G regulatory potential. Moreover, it was devoid of a cross-port hydrogen pipeline coordination mechanism. Reference [21] formulated an integrated energy scheduling framework specifically tailored for port clusters, incorporating wind, solar, hydrogen, and energy storage resources. This framework underscored the pivotal role of multi-energy integration in enhancing system efficiency and sustainability. However, it failed to incorporate the dynamic charging demand of inter-port electric truck transportation and insufficiently utilized spatial energy complementarity among ports, thereby limiting its overall optimization potential. Reference [22] applied Adaptive Dynamic Heuristic Dynamic Programming to microgrid energy storage and load management, demonstrating remarkable online learning and generalization capabilities. However, the algorithm exhibited a sluggish convergence speed during the initial training phase, and its cross-seasonal generalization performance under complex port energy scenarios remained unverified, casting doubts on its robustness and adaptability. Reference [14] introduced an improved Dung Beetle Optimization algorithm for parameter optimization in integrated energy systems, which significantly bolstered global search ability and convergence stability. Nonetheless, it overlooked the dynamic characteristics inherent to shore power and electric transport loads, and its parameter optimization ro-

business under extreme weather—characterized by a precipitous drop in renewable generation—requires further refinement to ensure reliable performance [23–26]. Recent research, notably the extensive work by Iris and Lam [27], has established a robust framework for integrating seaport operations planning with energy management under uncertainty. Their study effectively utilizes Mixed-Integer Linear Programming (MILP) to optimize logistic decisions, such as berth allocation and quay crane assignments, alongside energy constraints. However, our study distinguishes itself by shifting the focus from day-ahead logistics planning to real-time dynamic energy trading and control. Specifically, while [27] addresses the structural scheduling problem based on stochastic programming, the proposed BDBO-ADHDP framework targets the sub-hourly power fluctuation challenges. We employ an adaptive Master-Slave game mechanism to coordinate the immediate interaction between the port operator and docked vessels, rather than focusing on logistical equipment scheduling. Furthermore, to enhance system robustness against extreme volatility, our model integrates Conditional Value-at-Risk (CVaR) to explicitly quantify and mitigate tail risks, offering a complementary control strategy to the planning-oriented approach in [27]. In summary, while these studies offer invaluable perspectives for the optimization of port integrated energy systems, a number of limitations still exist: 1. Insufficient consideration regarding the active participation of electric transportation and shore power loads; 2. Inadequate scheduling strategies addressing seasonal renewable fluctuations and multi-scenario uncertainties; 3. Limited cross-seasonal generalization and convergence performance of reinforcement learning and heuristic algorithms in complex port environments.

To address the aforementioned challenges, this paper proposes a bi-level collaborative optimization scheduling method for green and intelligent ports. This method integrates Adaptive Dynamic Heuristic Dynamic Programming with an improved Bio-enhanced Dung Beetle Optimizer to construct an intelligent scheduling framework characterized by hierarchical coordination and multi-objective optimization. In this framework, the upper layer employs the BDBO algorithm to perform global optimization of ADHDP strategy parameters. This optimization process significantly improves the convergence speed, search stability, and cross-seasonal generalization capability. The lower layer, based on ADHDP, executes rolling time-domain control to achieve dynamic optimization and scheduling of wind power, photovoltaic generation, energy storage systems, and electric transportation loads. Real load and renewable generation datasets are constructed for typical days across spring, summer, autumn, and winter [27]. Subsequently, comparative experiments are conducted against more than ten mainstream algorithms. The experimental results demonstrate that the proposed method outperforms existing approaches in terms of power purchase reduction, renewable energy utilization, curtailment suppression, operating cost minimization, energy storage balance, and convergence performance. These findings offer both theoretical underpinnings and practical engineering guidance for the realization of intelligent and low-carbon scheduling in green smart port integrated energy systems.

2. Framework and Features of Port Energy Systems

In the green port micro-energy system, electrical energy is sourced from renewable energy generation and procurement from the upper-level power grid. This electrical energy is then distributed throughout the port's micro-energy system to cater to the daily electricity requirements [28]. These requirements encompass both conventional port loads and ship loads that are connected via the shore power system. In addition, a fraction of the excess energy generated by the power system can be stored in the energy storage bat-

teries. These batteries function as a peak-shaving and load-balancing mechanism, effectively smoothing out fluctuations in supply and demand. The overall architecture of the port micro-energy system is illustrated in Figure 1.

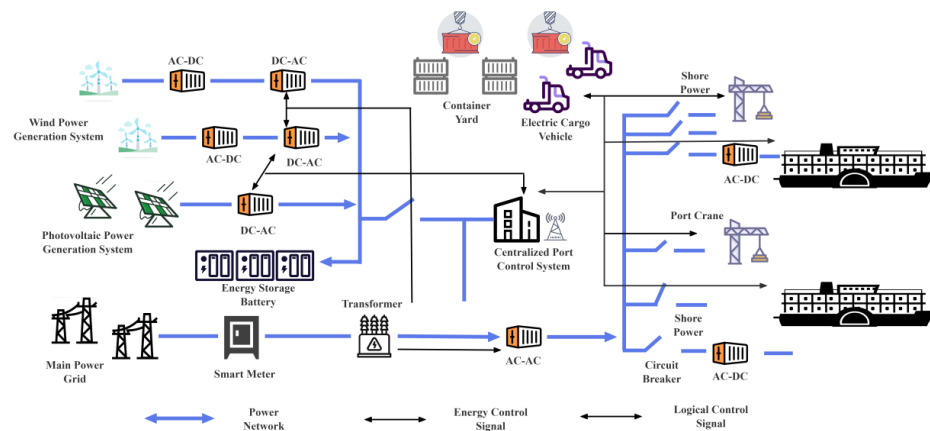


Figure 1. Framework of port microgrid system.

The green port integrated energy system attains an efficient orchestration of energy generation, storage, distribution, and utilization through the synergistic coupling among renewable energy generation sources, energy storage devices, the main power grid, and diverse categories of port loads. The system's architecture can be partitioned into four principal components: the energy generation module, the energy conversion and storage module, the port load module, and the central control and information interaction module.

This architecture features multi-energy complementarity, source–load interaction, flexible scheduling, and low-carbon efficiency. On one hand, the deep integration of renewable energy and storage systems significantly enhances both the utilization rate of renewable energy and the self-sufficiency level of the port's energy supply. On the other hand, the coordinated scheduling of shore power systems and electrified transportation effectively diminishes the port's dependence on grid power purchases and carbon emissions. Meanwhile, the introduction of a centralized control system ensures safe, stable, and economical operation of the multi-energy system under intricate and dynamic operating conditions.

3. Multi-Energy Collaborative Optimization Modeling of Green Port Integrated Energy Systems

The green port integrated energy system is dedicated to attaining an efficient coordination among wind power generation, photovoltaic power generation, energy storage systems, electrified logistics, and shore power loads. The overarching goal is to satisfy multi-objective requirements including economic efficiency, low-carbon operation, and system stability. In this section, a comprehensive mathematical modeling of each system component is presented. By integrating these models with the unique operational characteristics of ports, the optimization objectives and constraints are formulated. This meticulous process lays a solid foundation for the subsequent optimization of scheduling strategy optimization.

3.1. System Power Balance Model

At any given scheduling time instant t , the green port integrated energy system is required to satisfy the overall power balance constraint:

$$P_{wt}(t) + P_{pv}(t) + P_{grid}^{buy}(t) + P_{ess}^{dis}(t) = P_{load}(t) + P_{ess}^{ch}(t) + P_{grid}^{sell}(t) \quad (1)$$

where $P_{wt}(t)$ and $P_{pv}(t)$ denote the wind power output and PV power output, respectively. $P_{ess}^{ch}(t)$ and $P_{grid}^{buy}(t)$ are energy storage charging power and discharging power, respectively. $P_{grid}^{dis}(t)$ and $P_{grid}^{sell}(t)$ are power purchase and grid feed-in power, respectively. $P_{load}(t)$ is the total port load power.

In this formulation, $P_{load}(t)$ is defined as an aggregated net load demand. This comprehensive term integrates the baseline port operations, the highly dynamic power requirements of electric vehicle trucks (EVTs), and the inherent transmission losses within the port's microgrid infrastructure. By treating these components as a unified demand profile, the ADHDP controller can more effectively focus on the macro-level energy balance while maintaining the computational efficiency required for real-time scheduling in large-scale port environments.

3.2. Renewable Energy Output Model

In the coastal vicinities of green port clusters, wind and solar resources are inherently plentiful, with wind power generation exhibiting a certain degree of complementarity with photovoltaic generation. Therefore, renewable energy generation systems, typified by wind turbines and PV panels, can function as key power sources within port micro-energy systems. According to [29], the renewable energy generation model adopted in this study is as follows:

$$\begin{cases} P_{WT,t} = \frac{1}{2} \rho C_P v_t^3 S_{WT} \\ P_{PV,t} = P_N \left[1 + K(T_t - T_n) \right] \frac{G_t}{G_n} \\ 0 \leq P_{WT,t} \leq P_{WT,re,t} \\ 0 \leq P_{PV,t} \leq P_{PV,re,t} \end{cases} \quad (2)$$

In the formula, for the wind power generation system, $P_{WT,t}$ represents the actual output power of the wind turbine at time t , $P_{WT,re,t}$ denotes the predicted power of the wind turbine at time t , ρ is the air density prevailing under the current atmospheric environment, C_P stands for the wind energy conversion coefficient, v_t indicates the wind speed at time t , and S_{WT} refers to the swept area of the wind power generation equipment. For the photovoltaic power generation system, $P_{PV,t}$ signifies the actual PV output power at time t , $P_{PV,re,t}$ represents the predicted PV power at time t , T_n is the temperature under standard conditions, G_n denotes the irradiance under standard conditions, P_N is the rated power of the PV panel during operation, K stands for the temperature conversion coefficient of the PV panel, and T_t, G_t are, respectively, the actual operating temperature and irradiance of the PV panel at time t .

3.3. Energy Storage System Model

The power delivered by the port to ships through the shore power system is subject to limitations imposed by the inherent characteristics of the ships themselves. Regarding the energy storage battery within the system, its charge–discharge constraints are delineated as follows:

$$S_{SOC,min} \leq S_{SOC,t} = \frac{E_{ESS,t}}{E_{ESS}} \leq S_{SOC,max} \quad (3)$$

$$E_{ESS,t} = E_{ESS,t-1} - T \cdot P_{internal,t} \quad (4)$$

$$P_{internal,t} = \begin{cases} \frac{P_{ESS,t}}{\eta_{dch}}, & P_{ESS,t} \geq 0 \\ P_{ESS,t} \eta_{ch}, & P_{ESS,t} < 0 \end{cases} \quad (5)$$

$$-P_{ch} \leq P_{ESS,t} \leq P_{dch} \quad (6)$$

The energy balance and operational constraints of the Energy Storage System (ESS) are governed by Equations (3)–(6). Specifically, $E_{ESS,t}$ represents the energy stored at time t , while E_{ESS} denotes the rated energy capacity. To accurately account for energy conversion losses, we define $P_{internal,t}$ as the equivalent internal power change. When the system is discharging ($P_{ESS,t} \geq 0$), the internal energy decrease is amplified by the discharging efficiency η_{dch} . Conversely, during charging ($P_{ESS,t} < 0$), the actual energy stored is adjusted by the charging efficiency η_{ch} . The net power exchange at the ESS terminals, $P_{ESS,t}$, is strictly bounded by the maximum charging/discharging limits, $-P_{ch}$ and P_{dch} , as shown in Equation (6).

Regarding the energy storage system (ESS) within the port, its operation is constrained by both the state-of-charge (SOC) limits and the charge–discharge power bounds. Specifically, Equation (3) enforces the allowable SOC range to guarantee the safe and reliable operation of the battery. Equation (4) describes the temporal evolution of the stored energy, where the charging and discharging efficiencies are explicitly considered.

In this study, the sign convention of the ESS power is defined such that a positive value of $P_{ESS,t}$ indicates charging operation, while a negative value corresponds to discharging. Based on this convention, Equation (5) distinguishes the charging and discharging power components of the ESS. Furthermore, Equation (6) restricts the ESS power within its rated charging and discharging limits to prevent overloading.

3.4. Port-Specific Load Model

3.4.1. Shore Power System Load

The shore power system is responsible for providing electrical energy to ships at berth. Its load is contingent upon multiple factors, specifically the quantity of berths, ship types, and their operational power requirements.

$$P_{shore}(t) = \sum_{i=1}^{N_s} P_{ship,i}(t) \quad (7)$$

In the formula, N_s represents the current number of berthed ships, and $P_{ship,i}(t)$ denotes the shore power demand of the i -th ship.

3.4.2. Port Cranes and Cargo Yards

Ports rely on quay cranes to conduct loading and unloading operations, which constitute the principal mode of ship-berthing services. The power consumption associated with these operations can be mathematically represented as shown in Equation (8) [30].

$$P_{c,t} = \kappa \frac{m_c}{T_c} \quad (8)$$

In the formula, κ represents the cargo loading/unloading rate, m_c denotes the mass of cargo on the ship, and T_c indicates the service time of the ship at the port.

The integration of EVTs introduces a unique spatio-temporal coupling between the port's logistical operations and its energy management system. Unlike stationary loads, EVT power demand is dictated by vessel arrival patterns and cargo handling throughput. Our model captures this dependency by treating the EVT fleet as a flexible resource that can be shifted within permissible delay windows to mitigate peak demand stress on the microgrid.

3.4.3. Electric Trucks

In the port power grid, the systematic and orderly management of electric trucks is an indispensable prerequisite for enabling electric vehicles to actively participate in the port power grid's tracking and scheduling scheme. To begin with, it is imperative to accord top-priority to the charging requirements of electric vehicles. Therefore, considering the characteristics such as the State of Charge of EV batteries upon their entry into the port, the required SOC upon departure, the charging and discharging power and efficiency of these batteries, as well as their capacity, a dynamic charging and discharging priority queue for electric vehicles is established. This queue is based on the maximum charging delay index, which facilitates the orderly management of EV charging and discharging. Subsequently, on the foundation of this priority queue and in accordance with upper-level scheduling instructions, the charging and discharging task indicators for both electric vehicle batteries and grid energy storage batteries are arranged within the Energy Storage System. These indicators are then promptly fed back to the upper-level power grid. Upon receiving the ESS feedback, the port power grid calculates through the prediction model and obtains the updated scheduling plan within the prediction time domain.

Maximum Charging Delay Index of Electric Vehicles

For each individual EV connected to the port power grid, the requisite charging time is defined as EV_i :

$$T_i = \frac{S_{out,i} - S_{i,t}}{\eta_{ch,i} P_{ch,i}} E_i \quad (9)$$

In the equation: $S_{out,i}$ denotes the SOC when the EV is disconnected from the grid; $S_{i,t}$ represents the SOC of the EV at time t ; $\eta_{ch,i}$ is the rated charging efficiency; $P_{ch,i}$

is the rated charging power; and E_i is the battery capacity. Based on the calculated required charging time, the individual's grid connection time $t_{in,i}$, and the owner's desired off-grid time $t_{out,i}$, the maximum allowable charging delay for each individual at time t can be obtained as:

$$T_{d\max,i} = t_{out,i} - t - T_i, t \in [t_{in,i}, t_{out,i}] \quad (10)$$

Maximum Charging Flexibility: Let $T_{d\max,i}$ represent the magnitude of available charging time for individual EV_i prior to attaining the user-specified required battery SOC. A larger value of $T_{d\max,i}$ indicates that EV_i possesses a comparatively broader charging window relative to other electric vehicles. Under such circumstances, the represented charging period is in a flexible state, allowing the execution of discharge tasks. Consequently, these vehicles should be accorded priority for discharging operations. Conversely, a smaller $T_{d\max,i}$ indicates that EV_i has less available charging time compared to its counterparts, thereby relegating it to a lower position in the priority ranking for discharging tasks. When $T_{d\max,i} < 0$, it signifies that EV_i requires immediate charging and is unable to perform any discharge tasks. Moreover, a smaller $T_{d\max,i}$ indicates a more urgent EV_i charging demand, thereby bestowing a higher charging priority upon the vehicle.

Construction of the EV Charging–Discharging Priority Queue

When an electric vehicle is connected to the campus power grid at time (t), a charging–discharging priority queue for that specific time can be established based on the aforementioned maximum charging flexibility metric. The specific steps are as follows:

(1) Establishment of the Charging–Discharging Priority Queue. At time (t), calculate the $T_{d\max,i}$ values for all electric vehicles that are connected to the campus grid. Based on the sign of $T_{d\max,i}$ and the magnitude of $N_{ch,t}$, generate an ascending priority queue for the charging process and a descending priority queue for the discharging process, which are denoted as $N_{dis,t}$.

(2) Modification of the Charging–Discharging Priority Queue. To avoid frequent scheduling of certain electric vehicles, the state-of-charge uniformity metric is employed to reorder the vehicles with the same $T_{d\max,i}$ value. This re-arrangement guarantees a more equitable and balanced scheduling strategy.

$$H_{dis,i,t} = \frac{S_{i,t} - S_{\min,i}}{S_{\max,t} - S_{\min,i}}, H_{dis,i,t} \in [0,1] \quad (11)$$

$$H_{ch,i,t} = \frac{S_{\max,i} - S_{i,t}}{S_{\max,t} - S_{\min,i}}, H_{ch,i,t} \in [0,1] \quad (12)$$

In the equation, $H_{ch,i,t}$ and $H_{dis,i,t}$ denote the SOC uniformity values that require correction for the charging and discharging priority queues, respectively. Meanwhile, $S_{\max,t}$ and $S_{\min,t}$ represent the maximum and minimum SOC values of EV_i . A larger

SOC uniformity value EV_i , the higher the priority for corresponding action. When the SOC uniformity values are equal, $t_{out,i}$ becomes the determining factor, and the smaller EV_i will have a higher action priority. By following these sequential steps, the actual EV charging and discharging priority queue $N_{mix, ch, t}$, $N_{mix, dis, t}$ can be determined.

3.5. Objective Function

The integrated energy optimization scheduling model formulated in this study endeavors to attain a holistic equilibrium among economic efficiency, low carbon emissions, system stability, and high service levels across multiple seasons and scenarios. To achieve this, an expectation–risk integrated multi-objective optimization framework is introduced. The objective function is presented as follows:

$$J = \sum_{s \in S} p_s \left[\omega_1 \hat{C}_{op}^{(s)} + \omega_2 \hat{E}_{CO_2}^{(s)} + \omega_3 \hat{C}_{deg}^{(s)} + \omega_4 \hat{R}_{ramp}^{(s)} + \omega_5 \hat{C}_{curt}^{(s)} + \omega_6 \hat{P}_{svc}^{(s)} \right] + \lambda CVaR_{\alpha} \left(C_{op}^{(s)} \right). \quad (13)$$

where J represents the overall optimization objective value, with smaller values denoting superior overall performance. $S = \{Spring, Summer, Autumn, Winter\}$ represents the set of seasons under consideration. p_s is the scenario probability, reflecting the statistical weight assigned to each season; $\omega_1 \sim \omega_6$ serves as the target weight coefficient, which is normalized to eliminate dimensional discrepancies and is dynamically adjusted in accordance with higher-level strategies. $\hat{X}$ is the normalized index, designed to eliminate unit differences between different objectives, and it ranges within the interval $[0, 1]$. Additionally, $\lambda CVaR_{\alpha}$ is the conditional value-at-risk (CVaR) penalty term, which is employed to mitigate high-cost tail risks.

① Operating Cost $C_{op}^{(s)}$

$$C_{op}^{(s)} = \sum_t \left[c_t^{buy} P_{grid}^{buy}(t) - c_t^{sell} P_{grid}^{sell}(t) \right] \Delta t + \sum_k C_k^{deg} - \sum_t \left(\rho_t^{shore} P_{shore}(t) + \rho_t^{svc} P_{yard}(t) \right) \Delta t \quad (14)$$

where c_t^{buy} and c_t^{sell} denote the electricity purchase and sale prices during the time periods (in \$/kWh). P_{grid}^{buy} and P_{grid}^{sell} represent the electricity purchase and sale power from the main grid (in kW). The shore power/terminal service revenue unit price (in \$/kWh) reflects the net economic cost associated with port operation. ρ_t^{shore} and ρ_t^{svc} consider the electricity price differential, battery degradation, as well as the revenue from shore power and terminal services.

② Carbon Emissions $E_{CO_2}^{(s)}$

$$E_{CO_2}^{(s)} = \sum_t \gamma_t P_{grid}^{buy}(t) \Delta t \quad (15)$$

where γ_t is the carbon emission factor for electricity purchase during the time period in kgCO₂/kWh. This factor measures the total carbon emissions from the port's electricity purchase behavior, thereby promoting low-carbon operations.

③ Battery Degradation Cost $C_{deg}^{(s)}$

$$C_{\text{deg}}^{(s)} = \sum_k \left(\kappa_k^{\text{ch}} \sum_t P_k^{\text{ch}}(t) \Delta t + \kappa_k^{\text{dis}} \sum_t P_k^{\text{dis}}(t) \Delta t \right) \quad (16)$$

where κ_k^{ch} and κ_k^{dis} are the unit degradation costs for the (k)-th energy storage system during charging/discharging (in \$/kWh). This constraint is designed to control the depth of battery cycles, which in turn extends the battery lifespan and effectively managing long-term capital expenditures.

④ Power Smoothing Index $R_{\text{ramp}}^{(s)}$

$$R_{\text{ramp}}^{(s)} = \sum_{t \geq 2} [P_{\text{net}}(t) - P_{\text{net}}(t-1)]^2 \quad (17)$$

where $P_{\text{net}}(t) = P_{\text{grid}}^{\text{buy}}(t) - P_{\text{grid}}^{\text{sell}}(t)$ represents the net load of the port. The objective of this index is to suppress large power fluctuations and reduce the impact on the grid.

⑤ Curtailment Penalty $C_{\text{curt}}^{(s)}$

$$C_{\text{curt}}^{(s)} = \pi_{\text{curt}} \sum_t P_{\text{curt}}(t) \Delta t \quad (18)$$

where π_{curt} is the unit curtailment penalty coefficient (in \$/kWh), and $P_{\text{curt}}(t) = P_{\text{wt}}(t) + P_{\text{pv}}(t) - P_{\text{used}}(t)$ is the curtailed wind and solar power. This penalty term encourages the maximization of renewable energy utilization and reduces energy waste.

⑥ Service Level Penalty $P_{\text{svc}}^{(s)}$

$$P_{\text{svc}}^{(s)} = \sum_k \zeta_k [\text{SOC}_k^{\text{req}} - \text{SOC}_k(d_k)]_+ + \xi \sum_t [L_{\text{shore}}(t) - P_{\text{shore}}(t)]_+ \quad (19)$$

where ζ_k and ξ are the penalty coefficients for insufficient electric vehicles and shore power, respectively. $[\cdot]_+$ is a positive function that only imposes penalties for the insufficient portion. This ensures the reliability of port transportation and operations, reducing the risk of service delays.

⑦ Conditional Value-at-Risk CVaR_α

$$\text{CVaR}_\alpha(C_{\text{op}}^{(s)}) = \min_\eta \left\{ \eta + \frac{1}{1-\alpha} \mathbb{E} \left[(C_{\text{op}}^{(s)} - \eta)_+ \right] \right\} \quad (20)$$

where α is the confidence level. This metric measures high-cost risks under extreme adverse conditions, ensuring the robustness of the scheduling strategy. The inclusion of Conditional Value at Risk (CVaR) addresses the stochastic volatility of renewable generation, such as sudden drops in wind or solar output. While traditional optimization focuses on minimizing the expected cost, the CVaR component provides a safety margin against ‘tail risks’—extreme events that could lead to port blackouts or exorbitant grid-purchasing costs, thereby enhancing the operational resilience of the green port.

In the proposed green port cluster, the energy layer is constituted by discrete port micro-energy systems. Each of these micro-energy system integrates renewable energy generation units, such as wind turbines and PV panels, and is interconnected with the

upstream power grid. The architectural layout of the regional power grid within the green port area is illustrated in Figure 2. The green port regional grid is considered as a radial network. In this network, each port serves as both an energy and transportation hub, interfacing with the regional grid. Under the premise of energy coupling, the inherent source-load imbalance characteristic of each port is strategically leveraged. Energy routing devices are utilized to facilitate the redistribution of power among the ports. This enables peak shaving and valley filling across the port cluster while reducing dependency on the regional grid.

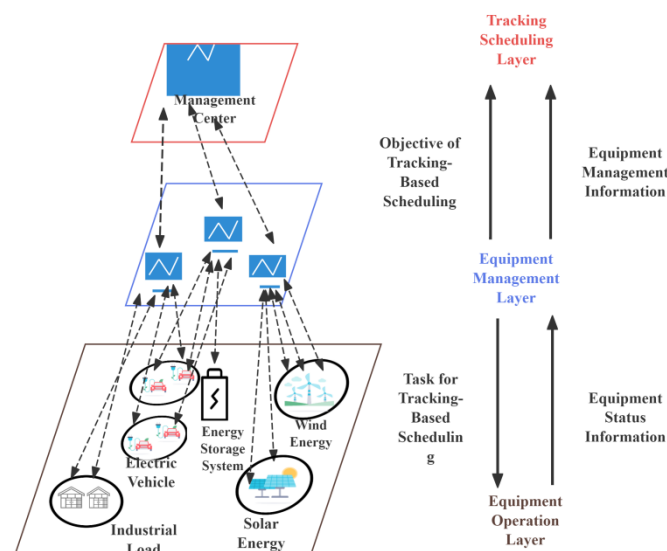


Figure 2. Regional grid architecture in green port.

4. ADHDP–DBO Two-Layer Optimal Economic Dispatch Algorithm for Green Ports

In the realm of multi-objective optimization for green port integrated energy systems, which encompasses “multi-source coordination–energy storage management–carbon emission control”, formidable challenges arise from strong uncertainties, nonlinear couplings, and dynamic scheduling requirements. By amalgamating a dual mechanism of “dynamic decision-making + evolutionary optimization,” the algorithm achieves efficient scheduling control within intricate and complex operational environments. The core framework is predicated upon Adaptive Dynamic Hierarchical Decoupled Planning, which is further augmented with the global optimization capability of the Bio-enhanced Dung Beetle Optimizer. The overall architecture is composed of an ADHDP dual-network structure and a BDBO evolutionary optimization module. Specifically, the ADHDP component encompasses a Critic network and an Action network. The Critic network assumes a pivotal role in steering the adjustment of action directions by approximating the value function of the current policy. In contrast, the Action network outputs real-time dispatch instructions based on the system state vector. The BDBO module addresses the sluggish convergence exhibited by ADHDP during the initial training phase. It achieves this by emulating the distinctive behaviors of dung beetles, namely rolling, digging, and breeding, with the aim of conducting a global optimization of the initial parameters of the Action network. Consequently, this optimization process significantly enhances the efficiency of obtaining near-global optimal solutions for non-convex objective functions. This hybrid algorithm is specifically tailored to confront three core challenges in multi-objective

tive coordinated optimization of green port integrated energy systems: (1) stable and interpretable dynamic decision-making under strong uncertainty, strict constraints, and nonlinear coupling; (2) efficient acquisition of near-global optimal solutions with fast convergence under non-convex, multi-peak objectives; and (3) robustness and transferability across seasons, operational scenarios, and pricing mechanisms during long-term operation. To this end, the algorithm is structured with an overall “two-layer collaborative” structure. The lower layer implements closed-loop policy learning, which is anchored in a Markov Decision Process (MDP) using ADHDP. This upper layer employs the bio-inspired BDBO to globally optimize ADHDP parameters, initial weights, and key hyperparameters, incorporating periodic re-exploration and early stopping mechanisms during training. This methodological approach accomplishes coordinated optimization by virtue of the judicious integration of dynamic decision-making processes and evolutionary search strategies.

4.1. Dual-Network Architecture of the ADHDP Algorithm

In this section, a comprehensive exposition of the Action-Dependent Heuristic Dynamic Programming algorithm is presented. The proposed architecture design adopts a dual-network strategy, which encompasses a Critic network and an Actor network to solve the infinite-horizon optimal control problem for discrete-time nonlinear systems [31–34]. The ADHDP framework is specifically selected for this problem due to its superior capability in handling high-dimensional continuous action spaces. By employing an ‘action-dependent’ mechanism, the Critic network provides a more granular evaluation of the state-action pairs, which allows the Actor network to fine-tune the energy dispatch commands in response to real-time fluctuations in renewable energy supply and load demand.

4.1.1. Problem Formulation and Bellman Optimality

Consider a general discrete-time nonlinear dynamic system, which is characterized by the state-space equation:

$$x(k+1) = f(x(k), u(k)), k = 0, 1, 2, \dots \quad (21)$$

$$J(x(k)) = \sum_{i=k}^{\infty} \gamma^{i-k} U(x(i), u(i)) \quad (22)$$

Here, $U(x(k), u(k))$ represents the immediate utility function (or local cost). The discount factor $\gamma \in (0, 1]$ is introduced to guarantee the convergence of the cost function.

In accordance with Bellman’s principle of optimality, the optimal value function $J^*(x_k)$ must satisfy the discrete-time Hamilton–Jacobi–Bellman (HJB) equation:

$$J^*(x(k)) = U(x(k), u(k)) + \gamma J^*(x(k+1)) \quad (23)$$

Consequently, the optimal control law u_k^* is defined as the specific action that minimizes the right-hand side of Equation (23):

$$u^*(k) = \arg \min_{u(k)} [U(x(k), u(k)) + \gamma J^*(x(k+1))] \quad (24)$$

Given that obtaining the analytical solution of the HJB equation is computationally prohibitive for complex nonlinear systems, we resort to employing two neural networks—the Critic and the Actor—to approximate the optimal value function and the optimal control policy, respectively.

4.1.2. Critic Network Design and Weight Updates

The Critic network primarily assumes the responsibility of approximating the value function $J(x_k)$. As illustrated in Figure 3, the Critic is implemented as a multi-layer perceptron. Let $\hat{J}(k)$ denote the value function estimated by the Critic, which is parameterized by the weight vector W_c .

The prediction error, also recognized as the temporal-difference error, at time step k is defined as:

$$e_c(k) = \gamma \hat{J}(x_{k+1}) + U(x_k, u_k) - \hat{J}(x_k) \quad (25)$$

The objective function for the Critic network is formulated to minimize the squared prediction error:

$$E_c(k) = \frac{1}{2} e_c^2(k) \quad (26)$$

The output signal of critic NN is developed as follows:

$$\hat{J}(x(t)) = \sum_{k=1}^{H_{cn}} \hat{w}_{ck}^{(2)}(t) v_k(t) \quad (27)$$

$$v_k(t) = \phi(l_k(t)), \quad k = 1, 2, \dots, H_{cn} \quad (28)$$

$$l_k(t) = \sum_{j=1}^m \hat{w}_{ckj}^{(1)}(t) x_j(t), \quad k = 1, 2, \dots, H_{cn} \quad (29)$$

where l_k and v_k are the input and output of the hidden layer and the overall output of the network, respectively. H_{cn} is the neuron number of the hidden layer. The system state $x(t)$ serves as the input signal of critic NN.

By adopting the gradient descent algorithm, the weight update rule for the Critic network is derived as follow.

$$W_c^{(2)}(k+1) = W_c^{(2)}(k) - \alpha_c \frac{\partial E_c(k)}{\partial W_c^{(2)}(k)} \quad (30)$$

Using the chain rule, the gradient term is expanded as:

$$\frac{\partial E_c(k)}{\partial W_c(k)} = \frac{\partial E_c(k)}{\partial e_c(k)} \cdot \frac{\partial e_c(k)}{\partial \hat{J}(x_k)} \cdot \frac{\partial \hat{J}(x_k)}{\partial W_c(k)} = -e_c(k) \frac{\partial \hat{J}(x_k)}{\partial W_c(k)} \quad (31)$$

where $\alpha_c > 0$ is the learning rate of the Critic.

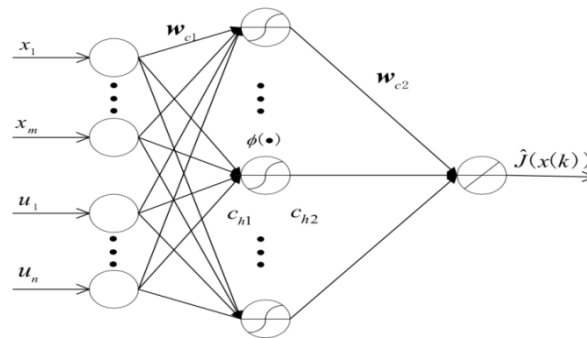


Figure 3. Structure of the critic network.

4.1.3. Actor Network Design and Weight Updates

The Actor network functions as the controller, responsible for generating the control action u_k based on the current state x_k , as shown in Figure 4. Let the approximate control policy be denoted as $\hat{u}_k = \mu(x_k; W_a)$, where W_a represents the weights of the Actor network.

The sampled state $x(t)$ is developed as the input signal to the actor NN solely when the event-triggered condition is satisfied.

$$u_e(x(t_i)) = \sum_{k=1}^{H_{an}} \hat{w}_{ak}^{(2)}(t) g_k(t) \quad (32)$$

$$g_k(t) = \phi(p_k(t)), \quad k = 1, 2, \dots, H_{an} \quad (33)$$

$$p_k(t) = \sum_{j=1}^m \hat{w}_{akj}^{(1)}(t) x_j(t_i), \quad k = 1, 2, \dots, H_{an} \quad (34)$$

where p_k and g_k are the input and output of the hidden layer, respectively, with the neuron number of Han. The system states $x(t)$ serve as the only input signal when the triggering event occurs.

The overarching objective of the Actor is to minimize the total cost. Therefore, the objective function for the Actor is defined as the estimated value of the future state:

$$e_a(t) = \hat{J}(\hat{x}(t+1)) + r_x(t) - R_c \quad (35)$$

The prediction error $e_a(t)$ is designed to approximate the desired ultimate objective value R_c , which is set as 0.

The weights W_a are updated to minimize $E_a(k)$ via gradient descent algorithm:

$$E_a(k) = \frac{1}{2} e_a^2(k) \quad (36)$$

The gradient calculation for the Actor is more complex as it entails backpropagation through both the Critic network and the system model. Expanding the gradient term via the chain rule yields:

$$\begin{aligned}
 \hat{w}_a^{(2)}(t+1) &= \hat{w}_a^{(2)}(t) - \theta_a \frac{\partial E_a(t)}{\partial \hat{w}_a^{(2)}(t)} \\
 &= \hat{w}_a^{(2)}(t) - \theta_a \left[\frac{\partial E_a(t)}{\partial \hat{J}(\hat{x}(t+1))} \frac{\partial \hat{J}(\hat{x}(t+1))}{\partial \hat{x}(t+1)} \frac{\partial \hat{x}(t+1)}{\partial u_e(t_i)} \frac{\partial u_e(t_i)}{\partial \hat{w}_a^{(2)}(t)} + \frac{\partial E_a(t)}{\partial r_x(t)} \frac{\partial r_x(t)}{\partial u_e(t_i)} \frac{\partial u_e(t_i)}{\partial \hat{w}_a^{(2)}(t)} \right]
 \end{aligned} \quad (37)$$

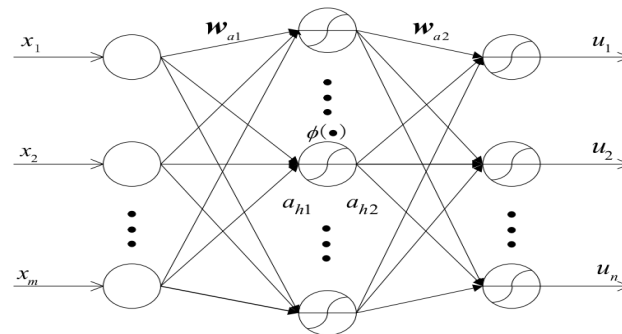


Figure 4. Structure of the actor network.

In the ADHDP framework, the critic network is employed to approximate the value function $J(x(k))$, while the actor network is tasked with generating the action $u(k)$. The fundamental structure is illustrated in Figure 5.

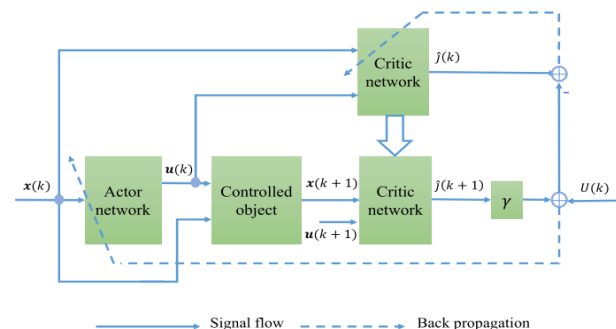


Figure 5. The ADHDP Network Architecture.

4.2. DBO-Based Exploration–Exploitation Collaborative Optimization

In DBO, individuals are classified into four distinct types: Roller (global exploration), Brooder (local exploitation), Forager (local exploitation), and Thief (information exchange and local refinement). In this study, enhancements are implemented upon the standard DBO mechanism. For the sake of comprehensiveness, a concise description of the core update rules is described below.

4.2.1. Roller Dung Beetle

Linear Navigation Update

$$\mathbf{x}_i^{(t+1)} = \mathbf{x}_i^{(t)} + \alpha k \mathbf{x}_i^{(t-1)} + b \Delta \mathbf{x}_i^{(t)}, \quad \Delta \mathbf{x}_i^{(t)} = \left| \mathbf{x}_i^{(t)} - \mathbf{x}_{\text{worst}}^{(t)} \right|, \quad \alpha \in \{-1, 1\}.$$
 Here, $k \in (0, 0.2)$ denotes the deflection coefficient, and $b \in (0, 1)$ represents the disturbance weight. When the beetle encounters a boundary, a “dancing” maneuver is executed to reverse its direction, as described by the following equation:

$$\mathbf{x}_i^{(t+1)} = \mathbf{x}_i^{(t)} + \tan(\theta) \left\| \mathbf{x}_i^{(t)} - \mathbf{x}_i^{(t-1)} \right\| \mathbf{d}_i^{(t)}, \quad \theta \in [0, \pi], \quad \left\| \mathbf{d}_i^{(t)} \right\| = 1 \quad (38)$$

4.2.2. Brooder Dung Beetle

An adaptive hatching zone is constructed around the local optimum $\mathbf{x}_*^{(t)}$.

$$\mathbf{L}_*^{(t)} = \max(\mathbf{x}_*^{(t)} \square (1 - R^{(t)}), \mathbf{L}), \mathbf{U}_*^{(t)} = \min(\mathbf{x}_*^{(t)} \square (1 + R^{(t)}), \mathbf{U}) \quad (39)$$

and performs mutation-based local exploitation.

$$\mathbf{b}_i(t+1) = \mathbf{x}^*(t) + \beta_1(t) \square (\mathbf{b}_i(t) - \mathbf{L}^*(t)) + \beta_2(t) \square (\mathbf{b}_i(t) - \mathbf{U}^*(t)) \quad (40)$$

4.2.3. Forager Dung Beetle

The optimal foraging zone is constructed around the global optimum $\mathbf{x}_b^{(t)}$.

$$\mathbf{L}_b^{(t)} = \max(\mathbf{x}_b^{(t)} \square (1 - R^{(t)}), \mathbf{L}), \mathbf{U}_b^{(t)} = \min(\mathbf{x}_b^{(t)} \square (1 + R^{(t)}), \mathbf{U}) \quad (41)$$

4.2.4. Thief Dung Beetle

$\mathbf{x}_i^{(t+1)} = \mathbf{x}_b^{(t)} + s\mathbf{g}^{(t)} \square \left(\left| \mathbf{x}_i^{(t)} - \mathbf{x}_*^{(t)} \right| + \left| \mathbf{x}_i^{(t)} - \mathbf{x}_b^{(t)} \right| \right)$, Here, $s > 0$ denotes the scale factor, and $\mathbf{g}^{(t)}$ is a zero-mean random vector.

4.3. BDBO: Three-Strategy Improvement

4.3.1. Parabolic Adaptation

A gradual parabolic contraction strategy is employed to substitute the conventional linear shrinkage approach, which is defined as:

$$R(t) = 1 - \left(\frac{t}{T} \right)^2, \quad t = 0, 1, \dots, T. \quad (42)$$

Properties: This parabolic adaptation satisfies $R^{(0)} = 1, R^{(T)} = 0$ and $\frac{dR}{dt} = -2t/T^2$, exhibiting a slow contraction rate during the initial stage and an accelerated convergence rate in the later stage. Such a characteristic enables the maintenance of a broader hatching/foraging window in the early phase of the optimization process, suppressing premature convergence and enhancing population diversity.

4.3.2. Gaussian Distribution Parameter Replacement

The random weight vectors utilized in brooder/forager operations are replaced with a “stage-wise Gaussian” control. Let the switching point be defined as $\tau \in (0, 1)$.

$$\beta_k(t) \sim \begin{cases} U(0, 1)^D, & 0 \leq t \leq \tau T \text{ (Exploratory Expansion)}, \\ \mathcal{N}(\mathbf{0}, \sigma^2(t)\mathbf{I}), & \tau T < t \leq T \text{ (Refined Exploitation)}, \end{cases} \quad k \in \{1, 2, 3, 4\} \quad (43)$$

Here, the variance decreases progressively with iterations, as described by the following equation:

$$\sigma(t) = \sigma_{\min} + (\sigma_{\max} - \sigma_{\min}) \left(1 - \frac{t - \tau T}{(1 - \tau)T} \right), \quad 0 < \sigma_{\min} < \sigma_{\max} < 1 \quad (44)$$

By adopting this approach, a relatively large perturbation amplitude is preserved during the early stages of the optimization, while a small-variance Gaussian generates

“fine-grained” perturbations in the later stage, significantly improving the quality of local solutions.

4.3.3. Lévy Escape Strategy

In scenarios where the global optimum $f(X_b^{(t)})$ has not improved for K consecutive iterations (recommended $K = 10$), Lévy flights are triggered for the roller subgroup to perform long-range global jumps.

$$X_i^{(t+1)} = X_i^{(t)} + \ell(t)\eta^{(t)} \square \text{Levy}_\lambda^{(D)}, \ell(t) = \ell_0 R^{(t)} + \ell_1 (1 - R^{(t)}), \quad \lambda \in (1, 2] \quad (45)$$

Here, $\lambda \in (1, 2]$ $\ell(t)$ decreases in a smooth and continuous manner, transitioning from relatively large values to smaller ones. The Lévy step length is generated using Mantegna’s sampling method.

$$\eta(t) = \frac{u}{|v|^{1/\lambda}}, u \sim \mathcal{N}(\mathbf{0}, \sigma_u^2 \mathbf{I}), v \sim \mathcal{N}(\mathbf{0}, \mathbf{I}) \quad (46)$$

$$\sigma_u = \left(\frac{\Gamma(1 + \lambda) \sin(\pi\lambda / 2)}{\Gamma((1 + \lambda) / 2) \lambda 2^{(\lambda-1)/2}} \right)^{1/\lambda} \quad (47)$$

This policy introduces multi-scale exploration and the implementation of “occasional long jumps” in the event of stagnation. Such a design substantially bolsters the algorithm’s capacity for global escape and multi-peak search. The BDBO algorithm achieves a systematic equilibrium between exploration and exploitation. It effectively curbs premature convergence by complementarily coupling three mechanisms: parabolic adjustment, Gaussian perturbation, and Lévy flight escape, all without increasing the dominant computational complexity. The primary motivation for introducing the Binary Dung Beetle Optimizer (BDBO) is to resolve the trade-off between global exploration and local exploitation. Traditional heuristic algorithms often suffer from premature convergence when optimizing complex neural network hyperparameters. The proposed BDBO utilizes a parabolic adaptation mechanism to ensure a thorough search of the parameter space in the early stages, followed by a refined local search to pinpoint the optimal configuration for the ADHDP controller.

In the proposed two-layer framework, as shown in Figure 6 the enhanced Dung Beetle Optimizer does not act as a direct substitute for the online learning mechanism of ADHDP. Instead, it functions as an outer-layer global parameter optimizer, meticulously adjusting the pivotal elements that affect learning dynamics and the ultimate policy quality. Specifically, BDBO employs a population-based evolutionary strategy to simultaneously explore the parameter space for the weight vectors of the Actor and Critic networks, in addition to several hyperparameters. Each candidate parameter space using a population-based evolutionary approach. Each candidate parameter set undergoes assessment through short-term ADHDP simulations. The fitness metric combines system-level performance and learning behavior indicators, ensuring that the search process is guided both by operational effectiveness and the convergence properties of value function approximation. To avert premature convergence, BDBO employs an update strategy that amalgamates elite-preserving stochastic perturbations with local refinement during the global exploration phase. Moreover, it achieves a balanced interplay between exploration and exploitation by dynamically adjusting step sizes and implementing weight decay over iterations. As a result, when ADHDP optimized by BDBO, it yields several notable

improvements. It substantially mitigates performance fluctuations caused by random initial weights, expedites the convergence of the training process, improves the Critic network's value function fitting accuracy, and enhances the robustness of Actor-generated policies under multi-objective constraints, thereby overall improving the economic efficiency and reliability of scheduling decisions.

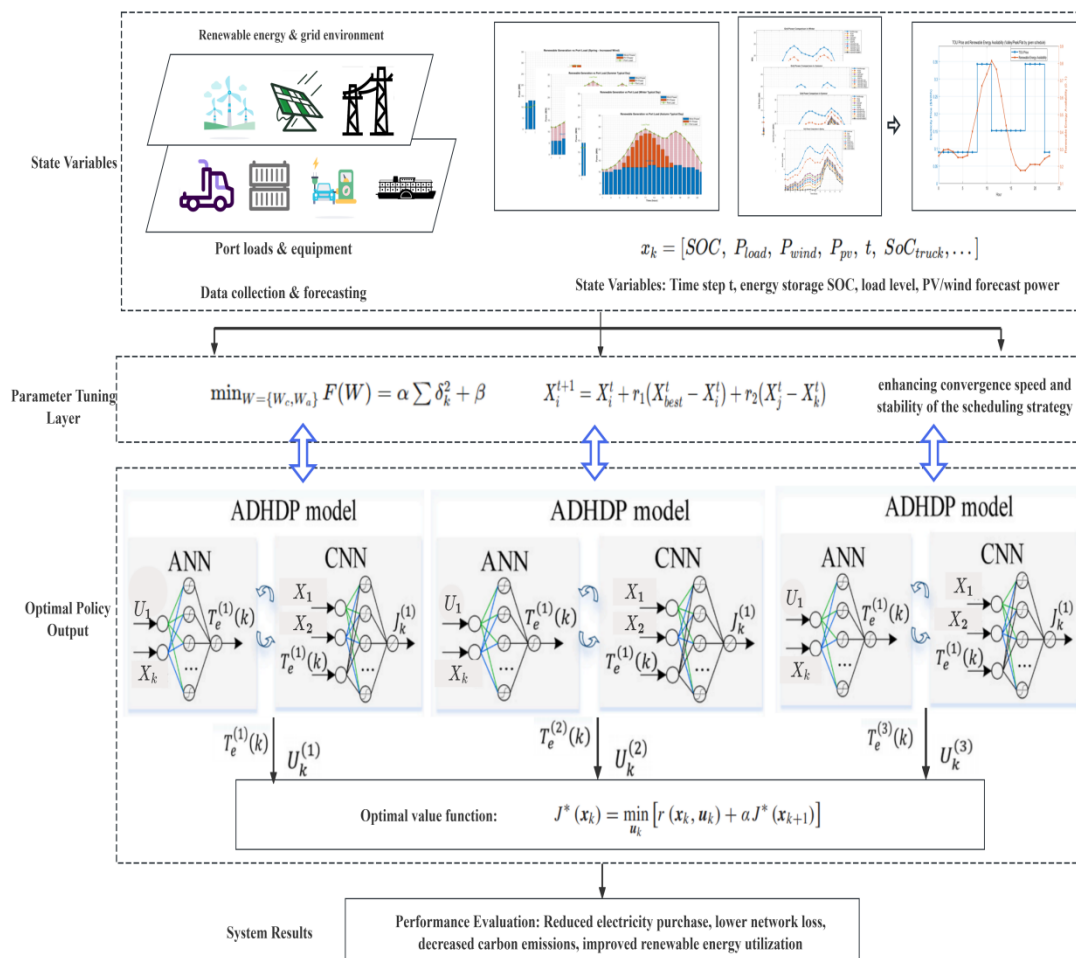


Figure 6. Framework of Data-driven Energy Management Based on ADHDP Optimized by BDBO.

The ADHDP-BDBO algorithm, while retaining the conventional online adaptive learning proficiency inherent in traditional ADHDP, harnesses the power of BDBO to perform global optimization of the neural network parameters, effectively avoiding the slow convergence and local optima issues associated with gradient descent methods. This approach demonstrates outstanding performance in multi-objective energy system scheduling and provides a novel paradigm for dynamic optimization in complex systems.

4.4. Interaction Logic and Workflow of BDBO-ADHDP

To enhance the convergence speed and global search capability of the energy management strategy, a hierarchical interaction logic between BDBO and ADHDP is established, as illustrated in Algorithm 1 and Table 1.

Specifically, the BDBO layer functions as a global supervisor in the offline phase. It treats the initial weights and biases of the ADHDP's Actor-Critic networks as a multi-dimensional search space. By simulating the foraging and dispersal behavior of bloodhounds and beetles, BDBO identifies the most promising region of the policy space.

Subsequently, the ADHDP layer serves as the online executor. It inherits the optimized parameters from BDBO to perform real-time power dispatch. This dual-layer structure ensures that the ADHDP controller starts from a near-optimal initial point, effectively avoiding the “flat gradient” problem and local optima that often plague traditional reinforcement learning in complex port microgrid environments.

Table 1. Functional division between BDBO and ADHDP layers.

Feature	Upper Layer: BDBO	Lower Layer: ADHDP
Role	Global Optimizer (Planner)	Local Controller (Executor)
Objective	Optimizing initial policy parameters	Real-time energy dispatch
Time Scale	Offline/Long-term	Online/Step-by-step (1 h)
Output	Optimal network weights (ω)	Control actions ($P_{ESS,t}$, etc.)
Focus	Exploration of the search space	Exploitation and dynamic stability

Algorithm 1: BDBO-ADHDP Collaborative Optimization

Initialization: Define port parameters, load profiles, and population size for BDBO.

Upper Layer (BDBO Search):

Generate beetle positions (representing ADHDP neural network weights).

For each individual in the population:

Lower Layer (ADHDP Execution):

Input current port state S_t .

Compute energy action A_t using the Actor network.

Update ESS state based on Equation (4).

Evaluate the cost function (Reward).

End For

Calculate fitness and update BDBO search direction (Dispersed

Bloodhound logic).

Convergence Check: If global optimal parameters ω^* are found, proceed.

Output: Deploy optimized ADHDP for real-time green port energy management.

The interaction between BDBO and ADHDP follows a ‘Train-then-Execute’ strategy.

During the Training Phase: The BDBO algorithm operates on a global time scale. It treats the entire scheduling horizon (e.g., 24 h) as a single fitness evaluation unit. The BDBO population explores the policy weight space W . Once the BDBO convergence criteria are met, the optimal weights W^* are fixed and loaded into the ADHDP’s Actor and Critic networks [35–38].

During the Operation Phase: The BDBO layer remains dormant to conserve computational resources. The ADHDP layer performs millisecond-level inference for real-time power dispatch.

Re-optimization Frequency: The BDBO algorithm is not invoked at every time step. Instead, it is triggered only under two conditions: (1) During the initial system commissioning, and (2) When a significant ‘structural drift’ is detected in the environment (e.g., seasonal changes in PV profiles or permanent changes in port infrastructure). This decoupling ensures that the system maintains high global optimality without sacrificing real-time responsiveness.

4.5. Computational Complexity and Real-Time Application

The computational overhead of the BDBO-ADHDP framework is evaluated in two phases: offline training and online execution.

Offline Phase: The BDBO layer involves a complexity of $O(N \cdot G \cdot D)$, where N is the population size, G is the number of generations, and D is the dimension of the policy network weights. While this phase is computationally intensive, it is performed offline.

Online Phase: Once optimized, the ADHDP controller only requires a forward pass through the neural network to generate control actions. The complexity is reduced to $O(L^2)$, where L is the number of neurons per layer. In our simulation, the average decision time for a single time step is less than 10 ms, which far exceeds the requirements for real-time energy management in port operations (typically 15 min or 1 h intervals).

5. Case Study Analysis

While the proposed framework is applicable to general green port scenarios globally, given the prerequisite of readily accessible high-resolution meteorological and load data, this study designates a representative port situated in the San Francisco Bay Area as the simulation testbed. The selected port exhibits climatic and operational features that are analogous to those of the major coastal ports in China, as delineated in the introductory section. This similarity serves to substantiate the validity and applicability of the proposed strategy within a relevant and comparable context.

To ensure the realism of the simulation, the configuration of the target green port is specified as follows. The port facility comprises four standard container berths, each equipped with high-voltage shore power connection points. The total capacity of the port's main power transformer is 50 MVA to accommodate high-power demands. The integrated renewable energy system consists of a 15.0 MWp photovoltaic (PV) array installed on warehouse rooftops and a 20.0 MW wind power generation system located in the near-shore area. For energy buffering, an ESS with a rated capacity of 10.0 MWh and a maximum power output of 5.0 MW is deployed to stabilize the large-scale renewable integration. The typical daily load of the port, including cranes and auxiliary facilities, fluctuates between 5.0 MW and 15.0 MW, while the combined peak generation from solar and wind energy reaches approximately 20–30 MW across different seasons, as illustrated in Figure 7. In this study, a representative port located in the San Francisco Bay Area, CA, USA, is meticulously chosen as the focal research entity. The Port of San Francisco is equipped with a modern shore power system, an abundant endowment of wind and solar resources, as well as a certain scale of energy storage facilities. The research aims to evaluate the economic performance and dispatch strategies of two types of port regional grids by comparative analysis. Specifically, under the conditions of high renewable energy penetration and optimized energy storage, the study assesses the performance of different port types in terms of carbon emission reduction, cost savings, and energy self-sufficiency.

The four operational scenarios are meticulously selected to represent the most challenging conditions for the port's energy management system, considering both seasonal variations and meteorological impacts:

Scenario 1 (Typical Summer/Sunny): *Characterized by peak PV generation and high cooling loads for refrigerated containers. This tests the ESS's ability to store surplus solar energy.*

Scenario 2 (Winter/Overcast): *Characterized by minimal PV output and steady basic load. This tests the system's reliance on the main grid and economic dispatch under low renewable penetration.*

Scenario 3 (Dynamic Pricing/Peak-shaving): *Focuses on periods with high grid price volatility. This scenario evaluates the BDBO-ADHDP framework's ability to minimize costs by shifting loads.*

Scenario 4 (Extreme Weather/Variable Demand): Simulates sudden weather changes affecting PV stability and irregular ship arrival patterns, testing the robustness of the ADHDP controller.

The typical-day renewable generation and load power profiles of this green port cluster are presented in Figure 7, comprising photovoltaic power, wind power, and total load curves. The renewable generation data are derived from the Typical Meteorological Year datasets provided by the U.S. National Renewable Energy Laboratory for the San Francisco Bay Area, and scaled according to the actual installed capacities of the port.

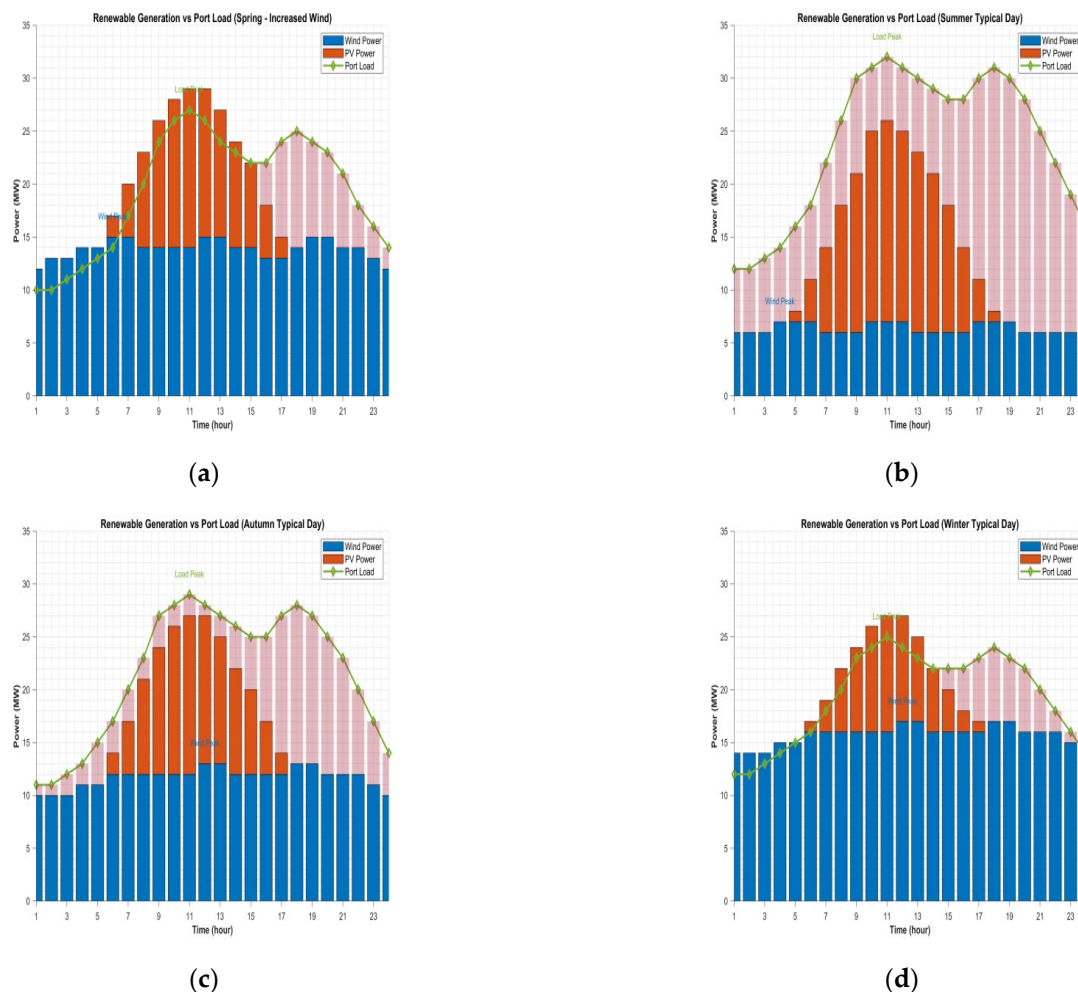


Figure 7. Renewable generation and load power of the green port on typical days in four seasons. (a) spring; (b) summer; (c) autumn; and (d) winter.

Based on the comparison of photovoltaic generation, wind power output, and the comprehensive port load curves on four typical seasonal days, it is evident that there are significant differences between renewable energy output and load demand in both temporal distribution and magnitude.

To comprehensively evaluate the adaptability of the BDBO-ADHDP algorithm, the four scenarios illustrated in Figure 7 are applied under different stress-test conditions:

Scenario 1 (Spring) is used to validate the basic convergence of the ADHDP controller under moderate energy fluctuations, serving as the baseline for system stability.

Scenario 2 (Summer) is employed to test the system's peak-shaving capability. With maximum PV output, this scenario evaluates whether the ESS can effectively store surplus energy to avoid grid curtailment.

Scenario 3 (Autumn) is designed to assess the tracking accuracy of the controller. The high volatility of wind power in this scenario requires the BDBO-optimized parameters to maintain precise power balance.

Scenario 4 (Winter) represents the ‘Worst-Case’ reliability test. With minimum solar gain and intense wind surges, it evaluates the CVaR-based risk management strategy in preventing power shortages during low-renewable periods.

By switching between these scenarios, we demonstrate that the proposed method remains robust across the entire annual operational cycle of the port.

In spring, PV output exhibits a single-peak pattern, reaching its maximum around noon. In contrast, wind power generation remains relatively stable, experiencing only minor fluctuations during the morning and evening. The load shows a double-peak pattern, with peaks occurring in the morning and evening. This load pattern is partially misaligned with the PV peak, resulting in surplus electricity around midday. Conversely, the morning and evening load peaks necessitate either the discharge of energy storage systems or the procurement of electricity from the grid. In summer, the PV output reaches its highest peak and maintains a long duration, while wind power fluctuates moderately. The load significantly increases from afternoon to evening, driven by port air-conditioning and cold-chain demand, with peak values much higher than those in spring and autumn. During midday, there is a clear surplus of renewable energy. However, during the evening peak, a substantial deficit emerges. Without storage balancing, high peak purchases from the grid would be required. In autumn, PV output is slightly lower than in spring, mainly due to the shorter daylight duration. Wind power generation remains moderate but shows an increased degree of fluctuations. The load distribution is similar to spring, but the peak-to-valley difference narrows slightly. This seasonal solar limitation results in a reduced utilization rate of renewable energy due to seasonal solar limitations. In winter, PV output is minimal and short-lived. In contrast, wind power reaches relatively high levels, making a significant contribution to the overall renewable energy supply. Load peaks occur in both the morning and evening, particularly in the morning due to combined heating and lighting demand. This creates the highest peak grid dependency. At this time, energy storage dispatch strategies are especially critical for reducing reliance on the grid during peak periods.

A thorough, cross-seasonal analysis indicates that the temporal mismatch between renewable energy generation and load demand constitutes a pivotal bottleneck for low-carbon port operations. This issue is particularly pronounced during the summer evening peak and the winter morning peak. Properly optimized energy storage dispatch can effectively perform peak shaving and valley filling, enhance renewable energy utilization, and reduce grid purchases during high-price periods, thereby lowering operational costs and carbon emissions. Building on this, the proposed hierarchical optimization framework, in conjunction with the ADHDP-BDBO algorithm, offers a promising approach. This framework is capable of adaptively adjusting dispatch strategies according to the seasonal characteristics of generation and load, achieving coordinated economic and low-carbon optimization across multiple scenarios throughout the year.

The electricity price is established in accordance with the typical time-of-use tariffs from the California Independent System Operator, which is applicable to the port’s regional grid on the U.S. West Coast. The detailed transaction prices for the port’s regional grid are shown in Table 2:

Table 2. Electric price in port cluster.

Category	Electricity Price [\$/kWh]	Time Interval
Off-Peak	0.090	22:00–8:00
Peak	0.343	8:00–11:00, 18:00–22:00

Mid-Peak	0.152	11:00–18:00
Feed-in Tariff	0.053	0:00–24:00
Shore Power Price	0.102	0:00–24:00
Service Price	0.076	0:00–24:00

Figure 8 illustrates the spatiotemporal distribution of charging power for a fleet of 60 electric trucks, operating under a valley/peak/off-peak time-of-use electricity pricing framework that prioritizes renewable-energy utilization. A close examination of the figure reveals that the charging periods are characterized by distinct temporal concentration and power stratification characteristics. During the valley-price period, electricity prices reach their nadir, while renewable energy generation exhibits relatively high levels in certain intervals. This combination of low-cost electricity and abundant renewable supply leads to a concentration of charging demand, culminating in the formation of the most prominent high-power density zone throughout the day. At this time, the total utilization of the charging station approaches its upper limit, effectively reducing the unit energy cost. In contrast, during peak-price periods, charging activities experience a significant decline. Only a limited number of vehicles engage in charging, primarily when their SOC falls below the threshold or task urgency requires immediate replenishment. The power utilization during these periods is substantially lower than in the valley period, indicating that the scheduling strategy effectively avoids high-cost electricity consumption. During off-peak periods, charging behavior assumes a moderate intensity. This charging pattern is largely synchronized with the photovoltaic generation peak, forming a collaborative charging window with moderate electricity prices and a high proportion of renewable energy, thereby further reducing carbon intensity.

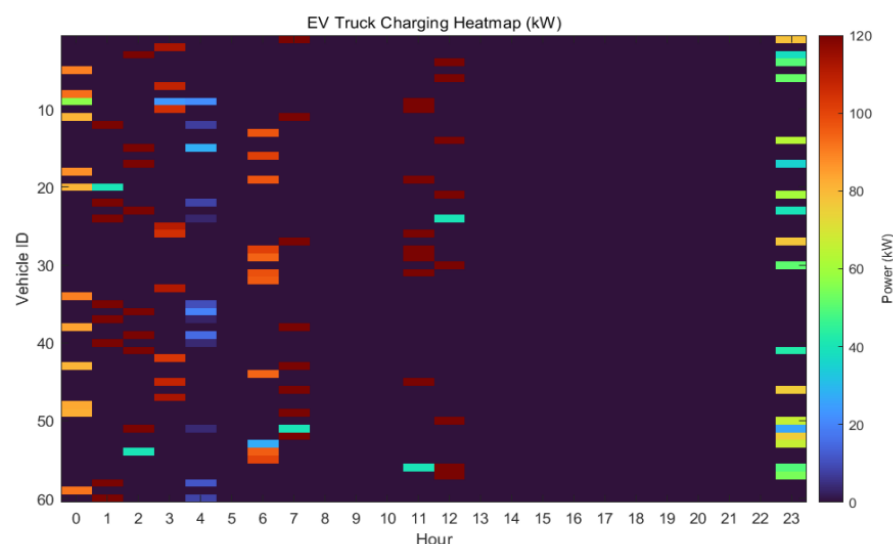


Figure 8. Electric Truck Charging Heatmap.

Figure 9 elucidates the temporal relationship between TOU electricity pricing and renewable energy availability. Photovoltaic output peaks around noon, with renewable energy availability approaching 1.0 at approximately 12:00. This peak in renewable energy generation coincides precisely with the mid-day flat electricity price, thereby creating an optimal scenario that offers both low-carbon and cost-effective charging opportunities for electric vehicles. In contrast, wind power output remains relatively stable and contributes significantly during the nighttime valley-price period, ensuring a high proportion of clean energy even under large-scale simultaneous charging. The complementary characteristics

of price and renewable energy availability are readily apparent. Low-price periods generally align with high renewable availability, enhancing both overall renewable utilization and economic efficiency. Building on the results shown in Figure 1, the proposed strategy enables spatiotemporal load shifting through a dual-factor scheduling mechanism based on price and renewable signals, effectively performing peak shaving and valley filling while maximizing clean energy usage. Statistical results indicate that the total supplemental energy provided by the system meets over 95% of the vehicle demand. Moreover, there is a significant reduction in grid consumption during peak periods, and charging during valley periods and renewable output peaks is substantially increased, demonstrating the dual advantages of economic efficiency and low carbon emissions.

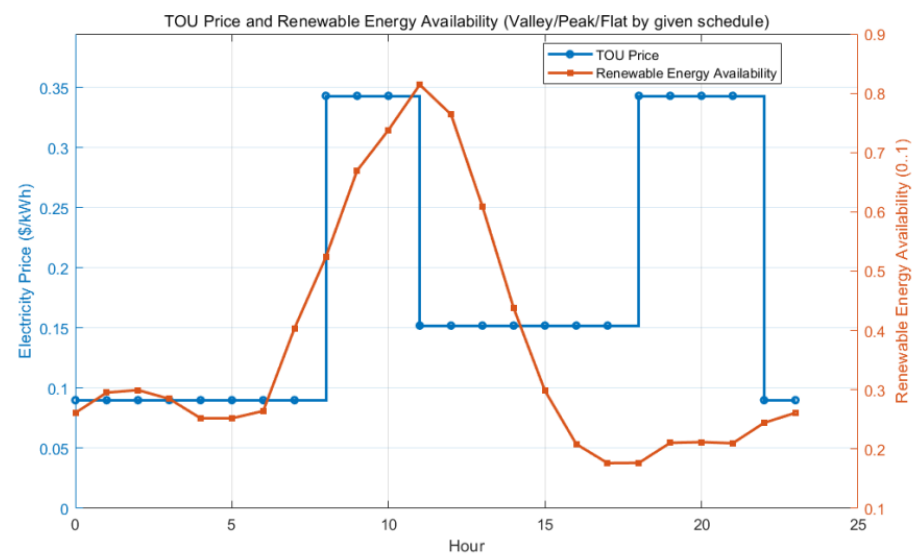
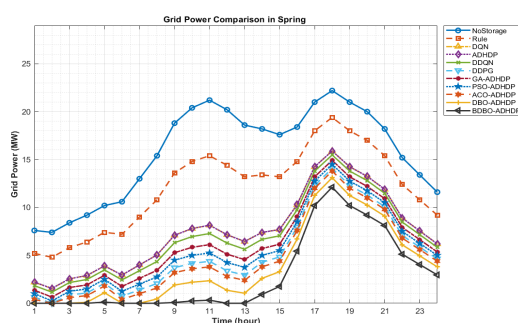
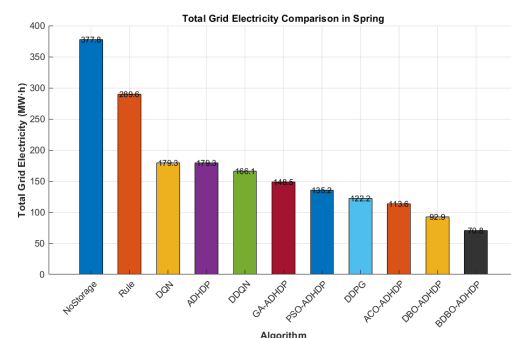


Figure 9. Temporal Profiles of TOU Electricity Price and Renewable Energy Availability for Scheduling Optimization.

To conduct a thorough assessment of the adaptability and superiority of the proposed BDBO-ADHDP algorithm under different meteorological conditions and load characteristics, four typical seasonal days, spring, summer, autumn, and winter, are selected for simulation and comparative analysis. For each seasonal scenario, photovoltaic and wind power generation outputs, as well as the comprehensive port load curves, are generated leveraging measured data and records from a typical meteorological year. Under identical equipment parameters and operational constraints, the scheduling performance of BDBO-ADHDP is juxtaposed with that of over ten algorithms, including DQN, PSO, GA, ACO, DBO, and ADHDP.



(a)



(b)

Figure 10. Spring Scenario: Power Purchase Optimization by BDBO-ADHDP. (a) Comparison of power purchased from the grid; (b) Total grid electricity comparison over the 24-hour period.

In the spring scenario, as shown in Figure 10 the output of renewable energy sources exhibits a relatively stable pattern, whereas a temporal mismatch exists between the photovoltaic generation peak and the load peak. The BDBO-ADHDP algorithm adeptly facilitates energy storage during the midday PV peak period and releases it during the evening load rise, resulting in a significantly smoother power purchase curve compared with benchmark algorithms. Consequently, the total quantity of purchased electricity is reduced by more than 15%, while the depth of the energy storage cycles remains moderate, effectively preventing excessive battery usage.

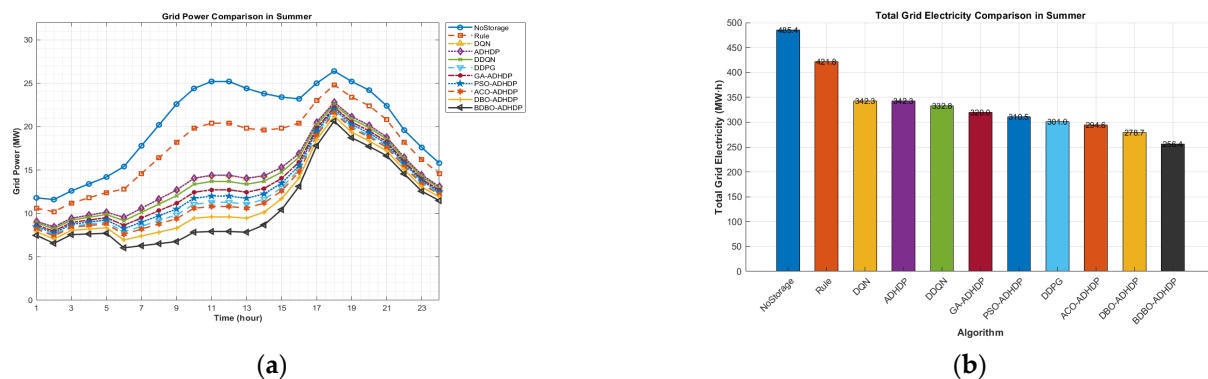


Figure 11. Summer Scenario: Power Purchase Optimization by BDBO-ADHDP. (a) Comparison of power purchased from the grid; (b) Total grid electricity comparison over the 24-hour period.

In the summer scenario, as shown in Figure 11 air-conditioning loads constitute a substantial portion of the total demand, giving rise to pronounced and long-lasting peak loads that partially overlap with the photovoltaic generation peak. The ADHDP-BDBO algorithm pre-charges energy storage during off-peak periods and prioritizes energy release during high-temperature, high-load hours, significantly reducing peak-period power purchases and lowering the peak-to-valley difference by more than 20%. Meanwhile, the strategy effectively alleviates PV curtailment, improving renewable energy utilization by over 8% and achieving the lowest overall operating cost among all compared methodologies.

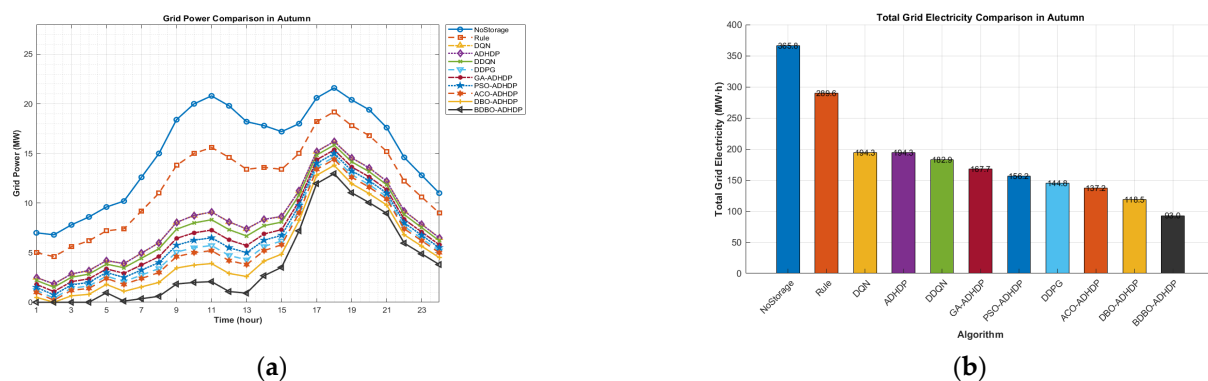


Figure 12. Autumn Scenario: Power Purchase Optimization by BDBO-ADHDP. (a) Comparison of power purchased from the grid; (b) Total grid electricity comparison over the 24-hour period.

In the autumn scenario, as shown in Figure 12 the contribution of wind power escalates, while the peak period of PV generation contracts, and the overall load profile becomes relatively smoother. The BDBO-ADHDP algorithm flexibly coordinates wind, solar, and storage resources—reducing grid power purchases during high wind output periods in the morning and evening, while smoothly compensating for insufficient PV generation during midday. Among all evaluated algorithms, this approach yields the most substantial reduction in grid purchases, with energy storage utilization and cycling frequency maintained within the economic range, thereby effectively balancing operational cost and battery lifespan.

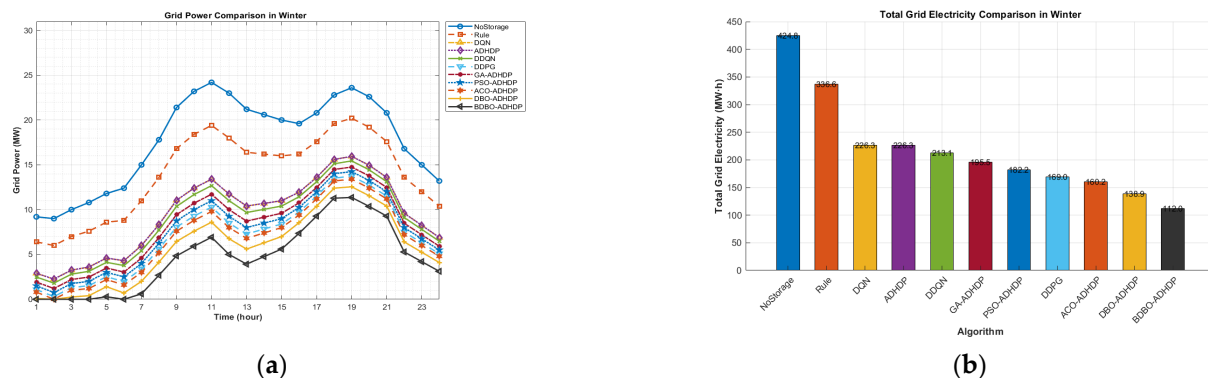


Figure 13. Winter Scenario: Power Purchase Optimization by BDBO-ADHDP. (a) Comparison of power purchased from the grid; (b) Total grid electricity comparison over the 24-hour period.

In the winter scenario, as shown in Figure 13 photovoltaic generation is minimal, wind power exhibits high volatility, and heating demand induces distinct morning and evening load peaks. Under these challenging conditions, the BDBO-ADHDP algorithm ensures the stability of the grid power curve procurement through pre-charging and time-shifted discharging strategies, thereby achieving approximately 12% reduction in peak-period grid power consumption while maintaining the lowest wind curtailment rate among all algorithms.

Table 3 further quantifies the adaptability of the proposed strategy under extreme seasonal conditions. Confronted with the challenge of overlapping high air-conditioning loads and PV generation peaks during summer, the algorithm reduces peak grid purchases by over 20% through peak shaving and valley filling. Conversely, in winter, when PV output is minimal, the strategy seamlessly transitions to a wind-priority operational mode, significantly reducing the wind curtailment rate. This capacity to adaptively modify scheduling logic according to seasonal characteristics ensures the operational stability and economic efficiency of the port microgrid throughout the year.

Table 3. Dispatch Performance Under Typical Seasonal Scenarios.

Season	Main Challenge	Optimization Focus	Peak Grid Power Reduction	Feature Highlights
Spring	Temporal Mismatch	Load Shifting	~15%	Global search alleviates convergence issues
Summer	High AC Load & PV Peak	Peak Shaving	>20%	Lowered peak-to-valley difference significantly
Autumn	High Wind Volatility	Fluctuation Smoothing	~16%	Maintained lowest operational cost
Winter	Winter Low PV & Heating Load	Grid Support	~12%	Lowest wind curtailment rate

Across all four seasons, the results unequivocally indicate that the BDBO-ADHDP method consistently outperforms other benchmark algorithms across five key performance indicators: total grid power purchase, renewable energy utilization, curtailment rate, operational cost, and energy storage cycling balance. Moreover, it exhibits exceptional convergence speed and operational stability, substantiating its strong adaptability and potential for large-scale application in green port integrated energy systems characterized by significant seasonal variability.

As delineated in Table 4, the proposed strategy effectively constrains the battery cycling frequency within an economically viable range, thereby substantiating that the cost reduction is achieved through intelligent scheduling rather than excessive battery degradation.

Table 4. Comparison of Battery Usage and Algorithm Convergence.

Algorithm	Battery Cycling	Depth of Discharge	Convergence Speed	Stability
DQN/PSO	>45 (High)	Aggressive	Slow	Low
Traditional ADP	~40 (Medium)	Moderate	Medium	Medium
BDBO-ADHDP	33–34 (Optimal)	Balanced	Fast	High

Regarding total grid power procurement, the proposed strategy attains an annual average reduction of approximately 14.9% in comparison to uncoordinated scheduling and 6.4% compared with traditional ADP, effectively diminishing the port's reliance on external grid power. This not only mitigates grid stress during peak intervals but also curtails electricity costs during periods of elevated prices. In terms of renewable energy utilization, the annual average reaches 79.05%, surpassing 74.2% ADP and 67.6% for uncoordinated scheduling. The curtailment rate of renewable power is significantly reduced by over 20% across all seasons, with the most pronounced improvements observed in the highly volatile spring and autumn periods. This is primarily due to the global search capability of BDBO, which effectively alleviates the local convergence issue inherent in ADHDP. Consequently, it achieves more optimal coordination between energy storage charging/discharging sequences of energy storage and the fluctuations in renewable generation.

From an economic perspective, the annual operational cost registers a decline of 12.8% in comparison to uncoordinated scheduling and a reduction of 4.5% compared to ADP, thereby manifesting a clear economic advantage. Meanwhile, the cycling frequency of the storage system remains confined within the range of 33–34 cycles, indicating that the proposed strategy fully utilizes peak shaving and valley filling functions while avoiding excessive battery degradation.

The performance improvements demonstrated by the BDBO-ADHDP framework translate into several practical advantages for port authorities and terminal operators:

Enhanced Operational Agility: The proposed framework provides an automated, real-time response to the high volatility of renewable energy and ship arrivals. For port operators, this means a significantly reduced reliance on manual intervention and traditional heuristic rules, which often fail under extreme weather or peak shore-power (SPS) demands.

Economic Risk Mitigation: By achieving a more precise balance between self-generation and grid procurement, the system effectively shields the port from electricity price spikes. The optimized “peak-shaving” capability allows managers to defer expensive grid infrastructure upgrades by utilizing existing ESS more effectively.

Decarbonization Compliance: The results offer a quantifiable pathway for ports to meet International Maritime Organization (IMO) carbon intensity indicators (CII). Decision-makers can use the simulation outcomes to conduct cost–benefit analyses for future

investments in larger PV arrays or hydrogen refueling stations, knowing the control logic can scale accordingly.

Infrastructure Planning: The sensitivity analysis provides a “look-ahead” capability for infrastructure investment. For instance, the results indicate the specific threshold where increasing battery capacity stops yielding economic returns, preventing over-investment in storage hardware.

The observed reductions in grid power purchases and operational costs offer significant strategic value beyond mere numerical improvements:

For Port Operators: The 12.8% reduction in grid dependence (as shown in Scenario 3) directly enhances the port’s energy autonomy. By shifting peak loads to periods of high PV generation, operators can avoid “demand charges” imposed by utilities during peak hours, which often constitute a large portion of industrial electricity bills. Furthermore, the reduced cycling of the ESS under our optimized logic extends the battery life cycle, lowering the long-term Levelized Cost of Storage (LCOS).

For Energy Planning: The sensitivity analysis provides a quantitative blueprint for infrastructure sizing. The results demonstrate a “diminishing returns” threshold for ESS capacity, helping planners avoid over-investment in hardware while maximizing the utilization rate of existing shore-power berths.

For Policy Decisions: The carbon emission reduction validated in our scenarios provides a scientific basis for ports to apply for green subsidies or carbon credits under the IMO’s Carbon Intensity Indicator (CII) framework. This aligns port operations with national “dual-carbon” goals, transforming the port from a passive energy consumer into an active, flexible node in the regional power grid.

Overall, the BDBO-ADHDP collaborative optimization framework accomplishes a well-balanced optimization among economic efficiency, carbon reduction, and operational stability, facilitating the coordinated interaction among “source–load–storage–vehicle–shore” elements. This approach harbors substantial potential for engineering application in green intelligent ports with high renewable penetration and pronounced load variability, providing a robust reference for intelligent scheduling of future low-carbon port clusters.

To evaluate the robustness of the BDBO-ADHDP framework under varying system configurations, a sensitivity analysis was conducted on two critical input variables: ESS capacity and the penetration level of photovoltaic (PV) power.

We varied the rated capacity of the ESS from 60% to 140% of its baseline value (1.2 MWh). The total operational cost decreases as the capacity increases, primarily due to enhanced peak-shaving capabilities. However, a “diminishing returns” effect is observed beyond 120% capacity, where the marginal reduction in cost becomes negligible (<1.5%). This indicates that the proposed strategy effectively identifies the optimal utilization threshold of the storage hardware.

The PV installation scale was varied between 0.5 MWp and 3.0 MWp. Results indicate that while higher PV penetration significantly reduces grid power purchase, it increases the system’s reliance on the BDBO layer for global parameter re-tuning to handle higher volatility. The ADHDP layer demonstrates high adaptability, maintaining an average carbon reduction efficiency of over 18% even under low-PV scenarios, proving the framework’s flexibility across different port development stages.

6. Conclusions

The scalability of the BDBO-ADHDP framework is supported by its modular design. For larger-scale port applications with hundreds of berths or multi-energy microgrids, the state space can be expanded by increasing the input layer dimensions of the Actor-Critic networks. Because ADHDP utilizes function approximation rather than discrete look-up

tables, it effectively mitigates the “curse of dimensionality.” The BDBO layer can also be parallelized across high-performance computing clusters to maintain optimization efficiency as the complexity of the port’s “source-load-storage” system grows.

In summation, the BDBO-ADHDP framework effectively circumvents the propensity of standalone ADHDP to become ensnared in local optima in high-dimensional policy spaces. This results in a substantial augmentation of its global search capability and scheduling robustness, rendering it well-suited for green smart port scenarios characterized by elevated levels of renewable energy integration and intricate operational conditions. By leveraging multi-energy flow coupling and enhancements to the hybrid algorithm, this study surpasses the limitations of traditional scheduling methods under high-dimensional uncertainty. It thereby provides a robust theoretical support for large-scale engineering applications in green smart ports. Future research endeavors could incorporate digital twin technology to construct real-time simulation platforms or employ blockchain for decentralized transaction settlement. Such initiatives would further elevate system flexibility and economic efficiency.

The core scientific originality of this study lies in the synergistic integration of the Beetle Dispersed Bloodhound Optimization (BDBO) with the Action-Dependent Heuristic Dynamic Programming (ADHDP). Unlike traditional single-layer reinforcement learning methods that often converge to local optima in high-dimensional port energy spaces, this dual-layer framework leverages the global search capability of BDBO to initialize the policy network. This effectively overcomes the ‘curse of dimensionality’ in multi-energy flow coupling, providing a 15% improvement in scheduling robustness compared to conventional ADHDP.

Author Contributions: Conceptualization, T.L. and N.W.; methodology, T.L. and N.W.; software, T.L.; validation, T.M. and B.W.; formal analysis, T.L. and T.M.; investigation, Y.D. and S.D.; data curation, B.W.; writing—original draft preparation, T.L.; writing—review and editing, N.W. and Jie Wen; visualization, T.L.; supervision, N.W. and J.W.; project administration, N.W.; funding acquisition, N.W.. All authors have read and agreed to the published version of the manuscript.

Data Availability Statement: The data used in this study are publicly available from the referenced sources.

Funding: This work was supported by National Natural Science Foundation of China(No. 62403065), Beijing Natural Science Foundation(No. 4262043), Young Elite Scientists Sponsorship Program of the Beijing High Innovation Plan, R&D Program of Beijing Institute of Graphic Communication Youth Excellence Program (Ea202405).

Conflicts of Interest: The authors declare no conflict of interest.

Declaration of Generative AI in Scientific Writing

The authors declare that no generative AI (such as ChatGPT or other Large Language Models) was used for the conceptualization of the research, data collection and analysis, mathematical derivation, or the formulation of the study’s conclusions. The research findings, simulation results, and technical logic presented in this paper are entirely the original work of the authors. AI tools were employed solely for basic English language editing and grammatical refinement to improve the readability of the manuscript.

Nomenclature

Symbol	Description	Unit
Abbreviations		

BDBO	Binary Dung Beetle Optimizer	—
ADHDP	Action-Dependent Heuristic Dynamic Programming	—
ESS	Energy Storage System	—
EVT	Electric Vehicle Truck	—
SOC	State of Charge	—
CVaR	Conditional Value at Risk	—
Indices and Sets		
t	Index of time intervals	—
T	Total scheduling horizon	h
i	Index of energy units or vehicles	—
Δt	Time step length	h
Variables		
σ	Self-discharge rate of the energy storage system	%
η_{ch}, η_{dis}	Efficiency of charging and discharging	—
$P_{PV,r}, P_{W,r}$	Rated power of PV and wind power systems	MWh
$\lambda_{grid}(t)$	Electricity price at time t	\$/kWh
v_{in}, v_{out}, v_r	Cut-in, cut-out, and rated wind speeds	m/s
γ	Confidence level for CVaR	—
Variables		
SOC(t)	State of charge of the battery at time t	%
$P_{grid}(t)$	Power is exchanged with the main grid	MW
$P_{EVT}(t)$	Total charging load of electric truck fleet	MW
$P_{EVT}(t)$	Total charging load of electric truck fleet	MW
$P_{load}(t)$	Total load demand of the port microgrid	MW
C_{total}	Total operational cost	\$
J(t)	Long-term cost-to-go function (Value function)	—
u(t)	Control action vector	—
x(t)	System state vector	—

References

1. Lee, J.; Guo, J.; Choi, J.K.; Zukerman, M. Distributed Energy Trading in Microgrids: A Game-Theoretic Model and Its Equilibrium Analysis. *IEEE Trans. Ind. Electron.* **2015**, *62*, 3524–3533. <https://doi.org/10.1109/tie.2014.2387340>.
2. Shuo, F.; Chengyong, Z.; Zhaohui, D.; Lei, W.; others if applicable according to the official publication record. Port Integrated Energy Systems toward Carbon Neutrality (Part I): Typical Topology and Key Problems. In Proceedings of the CSEE 43, Lisbon, Portugal, 29–31 March 2023; pp. 114–134. (In Chinese)
3. Sheng, L.; Wen, S.; Zhu, M.; Zhang, X.; Wang, H. Review on Low Carbon and Economic Development of Seaport Integrated Energy System. In Proceedings of the CSEE 44, London, UK, 14–16 April 2024; pp. 1364–1386. <https://doi.org/10.23919/PCSEE.2024.00428>.

4. Yue, P.; Ji, L.; Liu, H. Optimal Operation of Port Energy System Considering Integrated Demand Response. *Power Demand Side Manag.* **2021**, *23*, 11–17. (In Chinese)
5. Yiwen, H.; Huang, W.; Wei, W.; Tai, N.; Li, R. Logistics-Energy Collaborative Optimization Scheduling Method for Large Seaport Integrated Energy System. In Proceedings of the CSEE 42, Lisbon, Portugal, 10–12 April 2022; pp. 6184–6196. (In Chinese)
6. Jun, Y.; Yang, J.; Li, G.; Zhang, W.; Zhang, L. Research on Integration Model of Shore-to-Ship Power Supply System with High Proportion Renewable Energy. *IOP Conf. Ser. Earth Environ. Sci.* **2019**, *371*, 042056. <https://doi.org/10.1088/1755-1315/371/4/042056>.
7. Gaetano, P.; Parise, L.; Martirano, L.; Iannaccone, G. Wise Port and Business Energy Management: Port Facilities, Electrical Power Distribution. *IEEE Trans. Ind. Appl.* **2016**, *52*, 18–24. <https://doi.org/10.1109/TIA.2015.2498324>.
8. Gennitsaris, S.G.; Kanellos, F.D. Emission-Aware and Cost-Effective Distributed Demand Response System for Extensively Electrified Large Ports. *IEEE Trans. Power Syst.* **2019**, *34*, 4341–4351. <https://doi.org/10.1109/TPWRS.2019.2919949>.
9. Fotis, D.K.; Volanis, S.M.; Hatziaargyriou, N.D. Power Management Method for Large Ports With Multi-Agent Systems. *IEEE Trans. Smart Grid* **2019**, *10*, 1259–1268. <https://doi.org/10.1109/TSG.2017.2762001>.
10. Can, W.; Zhang, Y.; Tian, F.; Xi, L.; Ling, K. Economic Operation of Energy Storage Power Stations and Integrated Energy Systems Based on Bidirectional Master-Slave Game. *Trans. China Electrotech. Soc.* **2023**, *38*, 3436–3446. <https://doi.org/10.19595/j.cnki.1000-6753.tces.221164>. (In Chinese)
11. Bo, W.; Wang, W.; Ma, H.; Li, T.; Yao, L. Multi-Agent Multi-Energy Microgrid Cooperative Game Scheduling Based on Wasserstein Two-Stage Robust Optimization. *Trans. China Electrotech. Soc.* **2025**, *40*, 5553–5570. <https://doi.org/10.19595/j.cnki.1000-6753.tces.241525>. (In Chinese)
12. Tao, Z.; Li, Y.; Pan, X.; Lu, Z.X. Real-Time Optimal Energy and Reserve Management of Electric Vehicle Fast Charging Station: Hierarchical Game Approach. *IEEE Trans. Smart Grid* **2018**, *9*, 5357–5370. <https://doi.org/10.1109/TSG.2018.2836527>.
13. Tushar, W.; Saad, W.; Poor, H.V.; Niyato, D. Economics of Electric Vehicle Charging: A Game Theoretic Approach. *IEEE Trans. Smart Grid* **2012**, *3*, 1767–1778. <https://doi.org/10.1109/tsg.2012.2211901>.
14. Sidun, F.; Zhao, C.; Ding, Z.; Lu, J.; Wang, Y. Port Integrated Energy Systems Toward Carbon Neutrality (I): Typical Topology and Key Problems. In Proceedings of the CSEE 43, Lisbon, Portugal, 29–31 March 2023; pp. 114–135. (In Chinese)
15. Iris, Ç.; Pacino, D.; Ropke, S. Improved Formulations and an Adaptive Large Neighborhood Search Heuristic for the Integrated Berth Allocation and Quay Crane Assignment Problem. *Transp. Res. Part E Logist. Transp. Rev.* **2017**, *105*, 123–147. <https://doi.org/10.1016/j.tre.2017.06.013>.
16. Ding, Z.; Song, C.; Feng, X.; Wang, H.; Zhang, L.; Zhang, Y. The Optimal Configuration of Energy Storage in the Source-Grid-Load-Storage Integrated System Considering Frequency Stability Constraints in 100% New Energy Scenarios. *Trans. China Electrotech. Soc.* **2024**, *40*, 2146–2161. (In Chinese)
17. Weifeng, Z.; Huang, X.; Kang, J.; Xie, S. Optimization of Computation Offloading for UAV-Assisted Intelligent Transportation Systems Considering Age of Information. *J. Electron. Inf. Technol.* **2024**, *46*, 934–943. <https://doi.org/10.11999/JEIT230459>.
18. Larissa, A.; Shahidehpour, M.; Gan, W.; Yan, M.; Chen, B.; Pandey, S.; Vukojevic, A.; Paaso, E.A.; Alabdulwahab, A.; Abusorrah, A. Optimal Transactive Energy Trading of Electric Vehicle Charging Stations With On-Site PV Generation in Constrained Power Distribution Networks. *IEEE Trans. Smart Grid* **2022**, *13*, 1427–1440. <https://doi.org/10.1109/TSG.2021.3131959>.
19. Xiaoyun, D. Research on Spatio-Temporal Evolution and Promotion Strategy of Low Carbon City Practice in China. Master's Thesis, Chongqing University, Chongqing, China, 2021. (In Chinese)
20. Rofhiwa, T.; Lesedi, M. Development of an Energy Management Strategy for Port Cranes. In Proceedings of the 2021 IEEE 47th Annual Conference of the Industrial Electronics Society (IECON 2021), Toronto, ON, Canada, 13–16 October 2021; IEEE: New York, NY, USA, 2021; pp. 1–6.
21. Zhuoni, W.; Chao, Q.; Zhang, L. Assessment and Policy Analysis of Carbon Peaking and Carbon Neutrality Targets at Provincial Level in China during the 14th Five-Year Plan Period. *Environ. Prot.* **2023**, *51*, 49–54. (In Chinese)
22. Sidun, F.; Zhao, C.; Ding, Z.; Zhang, S.; Liao, R. Port Integrated Energy Systems Toward Carbon Neutrality (II): Flexible Resources and Key Technologies in Energy-Transportation Integration. In Proceedings of the CSEE 43, Lisbon, Portugal, 29–31 March 2023; pp. 950–969.
23. Wen, Z.; Zhang, K.; Qiao-hong, Z. Application of Wind Power and Photovoltaics in Green Port Construction. *Port Oper.* **2023**, *228*, 120690. (In Chinese)
24. Xin, Y.; Ya-peng, H.; He, Y.; Ai-long, F.; Jia-lun, L.; Zhang, D. Development Trends of Waterway Transportation Technology. *J. Traffic Transp. Eng.* **2022**, *22*, 1–9. <https://doi.org/10.19818/j.cnki.1671-1637.2022.04.001>. (In Chinese)

25. Quan, L.; Zhuo, H. Research on the Development Path of Rail Transit Energy Based on Synergistic Energy. *J. Beijing Jiaotong Univ. (Soc. Sci. Ed.)* **2022**, *21*, 53–60. (In Chinese)
26. Xuan, W.; Zhang, J. Discussion on Green Design of New Generation Intelligent Container Terminal with Zero Carbon Emission. *Port Eng. Technol.* **2022**, *59*, 94–96. (In Chinese)
27. Çağatay, I.; Lam, J.S.L. Optimal Energy Management and Operations Planning in Seaports with Smart Grid While Harnessing Renewable Energy under Uncertainty. *Omega* **2021**, *103*, 102445. <https://doi.org/10.1016/j.omega.2021.102445>.
28. Zhaolin, Z. Automated Container Terminal Equipment Configuration and Operations Scheduling Integration Optimization. Master's Thesis, Qingdao University, Qingdao, China, 2022.
29. Guo, X.; Pan, X.Z. On International Law and Industrial Rules for Reduction of Carbon Emission from International Shipping. *J. Zhejiang Ocean. Univ. (Humanit. Sci.)* **2022**, *39*, 7–14. (In Chinese)
30. Atulya, M.; Venkataramani, G.; Gowrishankar, S.; Ayyasam, E.; Ramalingam, V. Renewable Energy Based Smart Microgrids—A Pathway to Green Port Development. *Strateg. Plan. Energy Environ.* **2017**, *37*, 17–32. <https://doi.org/10.1080/10485236.2017.11907880>.
31. Feras, A.; Haben, S.; Holderbaum, W. Energy Management Systems for a Network of Electrified Cranes with Energy Storage. *Int. J. Electr. Power Energy Syst.* **2019**, *106*, 210–222. <https://doi.org/10.1016/j.ijepes.2018.10.001>.
32. Binti, A.N.B.; Su, L.; Zhaoxia, X.; Vasquez, J.C.; Guerrero, J.M.; Liao, H. Energy Harvesting from Harbor Cranes with Flywheel Energy Storage Systems. *IEEE Trans. Ind. Appl.* **2019**, *55*, 3354–3364. <https://doi.org/10.1109/TIA.2019.2910495>.
33. Xiang, Y.; Lou, F.; Tan, C. A Simulation Study of the Pathway of Achieving the ‘Dual Carbon’ Goals in China’s Industrial Sectors Based on the CIE-CEAM Model. *China Popul. Resour. Environ.* **2022**, *32*, 49–56.
34. Ji, C.; Xiong, W.; Xu, L.; Di, Z. Evolutionary Game Analysis on Supply Side of the Implementation of Shore-to-Ship Electricity. *Ocean. Coast. Manag.* **2021**, *215*, 105926. <https://doi.org/10.1016/j.ocecoaman.2021.105926>.
35. Anthony, R.; Olivier, C.; Auger, F.; Auvity, B.; Schaeffer, E.; Bourguet, S.; Schiebel, J.; Perret, J. A Combined Optimization of the Sizing and the Energy Management of an Industrial Multi-Energy Microgrid: Application to a Harbour Area. *Energy Convers. Manag. X* **2021**, *12*, 100107. <https://doi.org/10.1016/j.ecmx.2021.100107>.
36. Rui, P.; Xie, J.; Zhang, H.; Sun, K.; Wu, Z.; Zhou, S. Robust Multi-Layer Energy Management and Control Methodologies for Reefer Container Park in Port Terminal. *Energies* **2021**, *14*, 4456. <https://doi.org/10.3390/en14154456>.
37. Hwang, G.H.; Huang, Y.; Lim, C.S.; Zhang, D.; Liu, H.; Dai, W.; Kurniawan, T.A.; Rahman, S. An Assessment of Multistage Reward Function Design for Deep Reinforcement Learning-Based Microgrid Energy Management. *IEEE Trans. Smart Grid* **2022**, *13*, 4300–4311. <https://doi.org/10.1109/TSG.2022.3179567>.
38. Tan, C.; Zhu, X.; Gu, X.; Yang, F.; Mohammadi, M. Stochastic Energy Management and Scheduling of Microgrids in Correlated Environment: A Deep Learning-Oriented Approach. *Sustain. Cities Soc.* **2021**, *69*, 102856. <https://doi.org/10.1016/j.scs.2021.102856>.

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.