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A Novel Two-Stage Scheduling Approach for a Hybrid Floating Photovoltaic-Battery-Hydropower Plant Considering Uncertainties

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Abstract

The application of floating photovoltaics (PVs) in hydropower plants has gained increasing interest in forming hybrid energy systems (HESs). It enhances the operational benefits of the existing hydropower plants. However, uncertainties of PV and load powers can present great challenges to scheduling HESs. To address these uncertainties, this paper proposes a novel two-stage optimization approach that combines distributionally robust chance-constrained (DRCC) and robust-stochastic optimization (RSO) approaches to minimize the operational cost of an HES. In the first stage, the scheduling of each device is obtained via the DRCC approach considering the PV power and load forecast errors. The second stage provides a robust near real time energy dispatch according to different scenarios of PV power and load demand. The solution of the RSO problem is obtained via a novel double-layer particle swarm optimization algorithm. The performance of the proposed approach is compared to the traditional stochastic and robust-stochastic approaches. Simulation results demonstrate the superiority of the proposed two-stage approach and its solution method in terms of operational cost and execution time.

Keywords

Distributionally Robust Chance-Constrained, Robust-Stochastic Optimization, Double-Layer Particle Swarm Optimization, Floating PV, Uncertainties, Operational Cost

1. Introduction

Hybrid energy systems (HESs), formed by hydropower units (HUs), floating photovoltaics (FPVs), and battery energy storage systems (BESSs), have received significant attention worldwide due to technological advancements and the increased use of smart control devices. However, the intermittent characteristics of renewable energies and load fluctuations introduce many uncertainties into HESs and have a significant impact on their economic performance [1]. To address this problem, researchers have optimized the energy dispatch of HESs by stochastic optimization (SO) and robust optimization (RO) methods to obtain the expected cost and worst-case cost, respectively. Works using SO methods can be found in [2]-[9], where stochastic solution strategies are developed for the optimal economic operation of HESs. The uncertainties are modeled by large scenarios to obtain a reliable solution, and this approach creates a computational burden. Consequently, scenario reduction methods are applied. The solutions obtained comprise the best and worst solutions. In contrast, an RO method derives a solution in the worst-case scenario within the uncertainty set, and this approach is more relevant in practice. Therefore, the uncertainties in HES economic dispatching can also be handled by RO methods.

Works in [10]-[15] presented robust dispatching methods to maximize economic performance, in which the uncertainty sets are constructed for all energy sources. These problems are modeled as a two-stage approach, where the first stage decision deals with the unit commitment and the second stage decision deals with the economic dispatch to adjust the output power of generation units. In this case, RO methods offer the worst scheduling plan. As the worst-case scenario is rare, the RO methods will be overly conservative. Some papers have integrated SO and RO methods into a scheduling model, such as in [16] [17]. However, SO and RO are combined considering two separate groups of uncertainty, such as the uncertainty related to power and electricity prices. Thus, both solution methods require separate implementations.

In the context of HES scheduling based on SO and RO methods, we highlight works [18] [19], in which a mathematical formulation is proposed for day-ahead (DA) scheduling that minimizes the expected and worst-case costs. The solution approach can address the stochastic DA scheduling problem and seeks to determine the optimal plan that is robust against an uncertainty set of renewable energy generation. As an alternative paradigm, a distributionally robust optimization (DRO) approach was developed in [20], which combines the SO and RO methods. The DRO provides a robust solution that cannot be obtained by SO and reduces the conservativeness of the solution given by RO [21].

There are some similarities between our paper and [18] [19], where both papers comprehensively consider the uncertainties through all possible scenarios.

Considering the advantages of RO and SO methods, papers [18] [19] formulated a two-stage optimization approach that combines RO and SO methods to reduce the conservativeness of traditional RO methods. However, the first stage decision is made before the realization of uncertainties. This is unable to provide a robust solution against any scenario. In addition, there is a need to adopt a decomposition algorithm to solve the problem. Therefore, we propose a novel two-stage approach in which the decision in the first stage takes into account the source-load forecast errors. Furthermore, we design a novel robust-stochastic approach in the second stage to address all possible source-load scenarios. The proposed two-stage approach is more robust, efficient, and tractable. The main contributions of this paper are summarized as follows

- Develop a novel two-stage approach for optimal scheduling of a hybrid HU-FPV-BESS system that combines the DA and near real time approaches using distributionally robust chance-constrained (DRCC) and robust-stochastic optimization (RSO) approaches. The two-stage approach can effectively deal with the realization of the uncertainties of PV power and load.
- To the best of the authors' knowledge, this is the first attempt to design a novel approach to schedule a hybrid HU-FPV-BESS system considering several cost parameters and operational constraints. This provides an efficient assessment tool for the feasibility study of integrating an FPV with a BESS in the existing hydropower plant.
- Propose a new solution procedure of an HES-based RSO problem via a coevolution process of a particle swarm optimization (PSO) algorithm, namely, the hybrid binary PSO-PSO (HBPSO-PSO) algorithm. This method is simple and effective for solving RSO problems.

This paper is organized as follows: Section 2 presents the mathematical model used in the studied HES, including the cost functions and operational constraints of each device. In Section 3, the problem formulation is described. Section 4 provides a solution methodology. In Section 5, numerical simulations are conducted to verify the performance of the proposed approach. Finally, the conclusion is given in Section 6.

2. System Modeling

The studied HES is shown in **Figure 1**, which is composed of five HUs, one FPV, and one BESS. The hydropower plant is mimicked from the Nam Theun 2 power plant located in Laos, in which a technical study for integrating the FPV-BESS is ongoing. Each HU has a capacity of 200 MW. The PV has a total capacity of 200 MW. The nominal capacity of the BESS is 50 MWh. PVs and BESSs have been installed after the hydropower plant to maximize operational benefits, resulting in water savings and increasing economic gains. The owner of the HES is an independent power producer (IPP) that has to sell the power to the client. Thus, the power flow is only possible in one direction.

The principle of the power purchase agreement is described as follows:

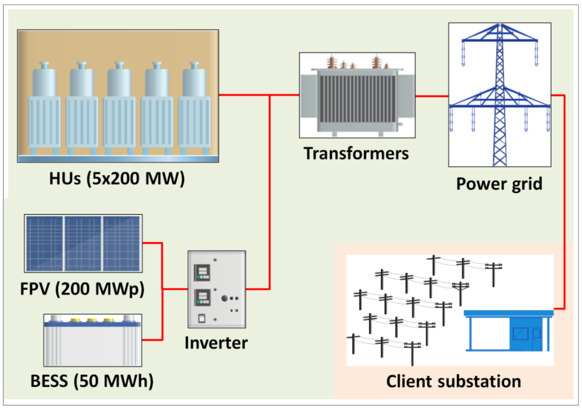


Figure 1. HES architecture.

1) The IPP submits the DA bid to the client, *i.e.*, how much energy can be produced within the next day.

2) The client will decide the time and the amount of power to be delivered.

3) The maximum load demand is related to the maximum installation power of the hydropower plant.

2.1. Cost Function

- **Cost function of the HUs**

The cost function of the HUs is made up of the startup cost (*SUC*) and the maintenance cost (*MC*).

The *SUC* is expressed as follows [1]

$$SUC_i = \begin{cases} HSUC_i & MDT_i \le T_i^{off} \le MDT_i + T_i^{cold} \\ CSUC_i & T_i^{off} \ge MDT_i + T_i^{cold} \end{cases} \tag{1}$$

where $HSUC_i$ and $CSUC_i$ are the hot/cold startup costs, respectively. T_t^{on} is the duration that the HU is ON. *MUT* is the minimum uptime. T_t^{off} is the duration that the HU is OFF. *MDT* is the minimum downtime. T_i^{cold} is the cold startup time. *i* is the index of the HU.

The *MCH* is assumed to be proportional to the HU power and is expressed by [13]

$$MCH_i(t) = K_{hu} \cdot P_{hu,i}(t) \cdot \Delta T \tag{2}$$

where K_{hu} is the maintenance cost coefficient, P_{hu} is the output power of a HU, and ΔT is the time step. The output power of the HU can be written as

$$P_{hu,i}(t) = \eta \cdot \rho \cdot g \cdot Q(t) \cdot H \cdot \Delta T \tag{3}$$

where P_{hu} is the output power (w), η is the turbine-generator efficiency (%), ρ is the water density (1000 kg/m^3), g is the acceleration due to gravity (9.81 m/s^2), Q is the water flow (m^3/s), and H is the water head (m).

- **Cost function of the FPV system**

The cost function of the FPV consists of the maintenance cost (*MCP*), which is expressed by

$$MCP(t) = K_{pv} \cdot P_{pv}(t) \cdot \Delta T \tag{4}$$

where K_{pv} is the maintenance cost coefficient and P_{pv} is the PV power.

- **Cost function of the BESS**

The total cost of a BESS (*BC*) is the summation of the operational cost (*OCB*) and maintenance cost (*MCB*).

The *OCB* of a BESS is associated with the charge and discharge powers, which is described by [13]

$$OCB(t) = C_{ch} \cdot P_{ch}(t) \cdot \eta_{ch} \cdot \Delta T - C_{disch} \cdot P_{disch}(t) \cdot \Delta T / \eta_{disch} \tag{5}$$

where C_{ch} and C_{disch} are the costs related to BESS charging and discharging, respectively. P_{ch} and P_{disch} are the battery charge and discharge powers, respectively. η_{ch} and η_{disch} are the battery charge and discharge efficiencies, respectively.

The *MCB* of a BESS is assumed to be proportional to the BESS power and is expressed by [13]

$$MCB(t) = K_{bess} \cdot \left[P_{ch}(t) \cdot \eta_{ch} \cdot \Delta T + P_{disch}(t) \cdot \Delta T / \eta_{disch} \right] \tag{6}$$

where K_{bess} is the maintenance cost coefficient.

- **Reserve cost**

The reserve cost is represented by the reserve power, which is written as

$$RC(t) = C_{res} \cdot P_{res}(t) \cdot \Delta T \tag{7}$$

where C_{res} is the cost of reserve power per MW/h and P_{res} is the reserve power.

2.2. Constraints

- Power balance

$$P_{load}(t) + P_{ch}(t) = \sum_{i=1}^{n} \left[y_i(t) \cdot P_{hu,i}(t) \right] + P_{disch}(t) + P_{pv}(t) \tag{8}$$

where P_{load} is the load demand, which also means the injected power to the grid, and y is the unit status of HUs. n is the total number of HUs ($n = 1, \cdots, 5$).

- Minimum/maximum power limits

$$P_{pv\_min} \le P_{pv}(t) \le P_{pv\_max} \tag{9}$$

$$P_{hu\_min,i} \le P_{hu,i}(t) \le P_{hu\_max,i} \tag{10}$$

$$0 \le P_{ch}(t) \le P_{ch\_max} \tag{11}$$

$$0 \le P_{disch}(t) \le P_{disch\_max} \tag{12}$$

$$P_{load\_min} \le P_{load}(t) \le P_{load\_max} \tag{13}$$

where P_{pv_min} and P_{pv_max} are the minimum and maximum powers of the PV, respectively. P_{hu_min} and P_{hu_max} are the minimum and maximum powers of the HUs, respectively. P_{ch_max} and P_{disch_max} are the maximum charge and discharge powers of the BESS, respectively. P_{load_min} and P_{load_max} are the minimum and maximum load powers, respectively.

- Ramp rate limits

$$-DR_{pv} \le P_{pv}(t) - P_{pv}(t-1) \le UR_{pv} \tag{14}$$

$$-DR_{hu} \le P_{hu,i}(t) - P_{hu,i}(t-1) \le UR_{hu,i} \tag{15}$$

where DR_{pv} and DR_{hu} are the ramp-down limits of the PV and HU, respectively. UR_{pv} and UR_{hu} are the ramp-up limits of the PV and HU, respectively.

- Minimum up/down time of the HUs

$$T_i^{on}(t) - MUT_i \ge 0 \tag{16}$$

$$T_i^{off}(t) - MDT_i \ge 0 \tag{17}$$

- Limit of the stored energy in a BESS

$$E_{min} \le E(t) \le E_{max} \tag{18}$$

where E_{min} and E_{max} are the minimum and maximum limits of the stored energy (in MWh), respectively. The stored energy of the BESS is expressed as

$$E(t+1) = E(t) + \eta_{ch,i} \cdot P_{ch}(t) \cdot \Delta T - P_{disch}(t) \cdot \Delta T / \eta_{disch,i} \tag{19}$$

- Limit of charge/discharge cycles: This constraint avoids the frequent charge/discharge cycle of the BESS, which reduces the lifetime degradation.

$$N_{cycle} \le N_{max} \tag{20}$$

where N_{cycle} is the charge/discharge cycle of the BESS and N_{max} is the maximum allowed cycle per day.

- Reserve power constraint: The reserve power is indispensable to compensate for the intermittent of PV power.

$$P_{res}(t) \ge P_{pv}(t) \tag{21}$$

where $P_{res}(t)$ is the maximum reserve power at time *t*, $P_{res}(t) = \sum_{i=1}^{n} y_i(t) \cdot \left[P_{hu\_max,i} - P_{hu,i}(t)\right] + \left[P_{b\_res}(t) - P_{disch}(t)\right]$. P_{b_res} is the maximum discharge power of a BESS, $P_{b\_res}(t) = \left[E(t) - E_{min}\right] \cdot \eta_{disch,i} / \Delta T$.

3. Problem Formulation

The two-stage scheduling approach defines the optimal operation of an HES based on the uncertainties of PV power and load forecasting. The global objective (22) is to minimize the total DA operational cost procured by the IPP. The main steps of DA scheduling include 1) forecasting and generating PV and load powers; 2) defining the optimal output power of each device; and 3) submitting the bids to the client.

$$\min_{H} e(Y) + \max_{Z} \min_{U} \sum_{1}^{n} f(X, U) \tag{22}$$

The first stage decision variables are

$$H = \left\{y, P_{hu,i}, P_{bess}, \alpha, \beta\right\} \tag{23}$$

where α and β are the participation ratios of each HU and a BESS according to uncertainties, respectively. They are bounded between 0 and 1. Note that $P_{bess}(t) = P_{disch}(t) - P_{ch}(t)$.

The second stage decision variables are

$$U=\{y,\theta\} \tag{24}$$

$$Z=\{\phi\} \tag{25}$$

where θ and ϕ are the compensation ratios of each HU and a BESS, respectively, according to the change in PV and load powers. They are bounded between 0 and 1.

3.1. DA Optimization Problem Based on a DRCC Approach

The first stage of the proposed approach minimizes the total cost of HUs, PV, and BESS, considering the PV power and load forecast errors, as follows

$$\min_{\substack{y,P_{hu},P_{bess}\\ \alpha\quad \beta}} \sum_{i=1}^{n}\left[SUC_i(t)+MCH_i(t)\right]+MCP(t)+BC(t) \tag{26}$$

Subject to constraints (8)-(21). From constraints (8) and (21), we can model the chance constraints to take into account uncertainties.

$$\begin{aligned}&P_{load}(t)+\zeta_{load}(t)+P_{ch}(t)\\&=\sum\nolimits_{i=1}^{n}y_i(t)\cdot\left[P_{hu,i}(t)+R_i(t)\right]+P_{pv}(t)+\zeta_{pv}(t)+P_{disch}(t)+S(t)\end{aligned} \tag{27}$$

$$\begin{aligned}&\sum\nolimits_{n=1}^{n}y_i^t\cdot\left[P_{hu\_max,i}-P_{hu,i}(t)+R_i(t)\right]+\left[P_{b\_res}(t)-P_{disch}(t)+S(t)\right]\\&\ge P_{pv}(t)+\zeta_{pv}(t)\end{aligned} \tag{28}$$

$$R_i(t)=\alpha_i(t)\cdot\left[\zeta_{load}(t)-\zeta_{pv}(t)\right] \tag{29}$$

$$S(t)=\beta(t)\cdot\left[\zeta_{load}(t)-\zeta_{pv}(t)\right] \tag{30}$$

$$\sum\nolimits_{i=1}^{n}\alpha_i(t)+\beta(t)=1 \tag{31}$$

$$P_{hu\_min,i}\le P_{hu,i}(t)+R_i(t)\le P_{hu\_max,i} \tag{32}$$

$$\Pr\left\{P_{hu,i}(t)+R_i(t)\le P_{hu\_max,i}\right\}\ge 1-\epsilon \tag{33}$$

$$\Pr\left\{P_{hu,i}(t)+R_i(t)\ge P_{hu\_min,i}\right\}\ge 1-\epsilon \tag{34}$$

$$\Pr\left\{P_{disch}(t)+S(t)\le P_{b\_res}(t)\right\}\ge 1-\epsilon \tag{35}$$

$$\Pr\left\{P_{disch}(t)+S(t)\ge 0\right\}\ge 1-\epsilon \tag{36}$$

where r is the joint probability distribution. ζ_{pv} and ζ_{load} denote random variables that indicate the PV power and load forecast errors, respectively. ϵ is the confidence level (=5%).

3.2. Near Real Time Optimization Problem Based on an RSO Approach

In the second stage, the output power of each device is adjusted taking into account the worst scenarios of PV power and load. Inspired by the concept presented in [22] [23], we can design robust scheduling for any scenario of PV power and load. The rapid variation of PV and load powers can act on the operation of the HUs and BESS. Thus, there is a case that induces the least impact on the total operational cost; that is, in this case, the total operational cost is the lowest. Thus, the total operational cost with the least impact is formulated as follows

$$F_L(U) = \min f(U,Z) \tag{37}$$

where U represents the operational cost of the HUs under the variation of PV and load powers and Z represents the operational cost of the BESS.

Likewise, there is a case that causes the worst impact on the total operational cost, and this case corresponds to the highest total operational cost. The total operational cost with the worst impact is formulated as follows

$$F_U(U) = \max f(U,Z) \tag{38}$$

Consequently, for a certain operation of the HUs, the total operational cost is $f(U,Z) \in [F_L(U), F_U(U)]$.

For each scenario of PV power and load, we take into account the case that causes $F_U(U)$, that is, the worst impact on the total operational cost. Therefore, the optimization problem taking into account the worst impact of scenarios of PV power and load on the total operational cost of an HES is represented as follows

$$\max F_L(U) = \max\text{-}\min f(U,Z) \tag{39}$$

The max-min problem is a robust two-layer optimization problem. Each value of U is related to Z, which results in the highest total operational cost. The values of U (the optimization variables of the inner layer) have a direct impact on the values of Z (the optimization variables of the outer layer).

In the second stage, the cost of reserve power and the deviation cost of HUs, PV, and BESS operation are considered. Thus, the startup of HUs can be readjusted. The objective function of the second stage is taken from (39) and represented as follows

$$\max_{\phi} \min_{y,\theta} \sum_{i=1}^{n} \left[RC_i(t) + \Delta MCH_i(t) \right] + \Delta MCP(t) + \Delta BC(t) \tag{40}$$

Subject to constraints (8)-(21), where ΔMCH is the deviation cost of HU maintenance. ΔMCP is the deviation cost of PV maintenance. ΔBC is the deviation cost of BESS operation which includes the deviation cost of operational (ΔOCB) and maintenance (ΔMCB).

4. Solution Methodology

This section presents the solution procedure of the proposed two-stage approach for DA scheduling of an HES. The first stage consists of the DRCC approach to deal with PV power and load forecast errors, while the second stage involves an RSO approach that adjusts the first stage solution in accordance with scenarios of PV power and load. The general concept for the two-stage scheduling approach of an HES is described in **Figure 2**.

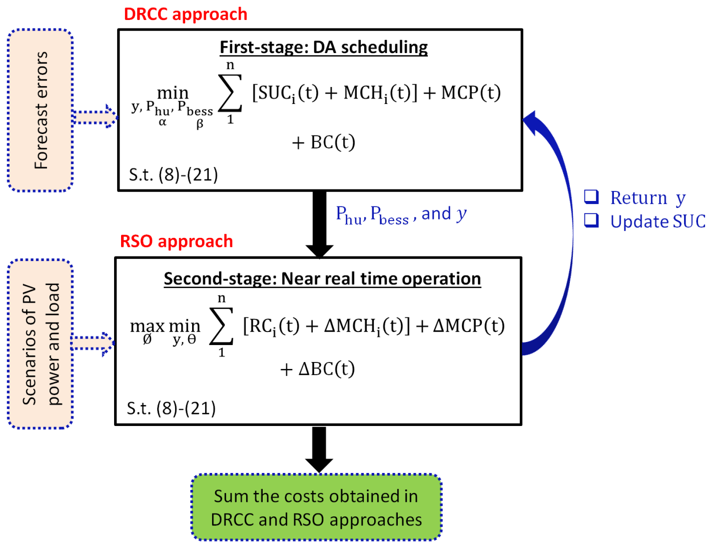


Figure 2. Structure of the two-stage scheduling approach.

4.1. First Stage Problem: DRCC Approach

The optimization problem with chance constraints (33)-(36) is nonconvex and very hard to solve. Nevertheless, there are solutions to find the convexity of the mentioned model. DRO is one of the prominent methods to solve chance-constrained optimization problems and can be used to transform the chance-constrained formulation into a DRCC formulation. The latter can be converted into a deterministic second-order cone programming (SOCP) problem.

- **Reformulation of the DRCC approach**

ζ_{pv} and ζ_{load} are assumed to follow Gaussian distributions with known means and variances; then, the chance-constrained formulation is equivalent to an SOCP problem [24] [25] [26]:

$$\sqrt{\frac{1-\epsilon}{\epsilon}}\sqrt{\alpha_i^T\sigma_{load}^2\alpha_i+\alpha_i^T\sigma_{pv}^2\alpha_i} \le P_{hu\_max,i}-P_{hu,i}-\alpha_i\mu_{load}^T-\alpha_i\mu_{pv}^T \quad (41)$$

$$\sqrt{\frac{1-\epsilon}{\epsilon}}\sqrt{\alpha_i^T\sigma_{load}^2\alpha_i+\alpha_i^T\sigma_{pv}^2\alpha_i} \le -P_{hu\_min,i}+P_{hu,i}+\alpha_i\mu_{load}^T+\alpha_i\mu_{pv}^T \quad (42)$$

$$\sqrt{\frac{1-\epsilon}{\epsilon}}\sqrt{\beta^T\sigma_{load}^2\beta+\beta^T\sigma_{pv}^2\beta} \le P_{disch\_max}-P_{disch}-\beta\mu_{load}^T-\beta\mu_{pv}^T \quad (43)$$

$$\sqrt{\frac{1-\epsilon}{\epsilon}}\sqrt{\beta^T\sigma_{load}^2\beta+\beta^T\sigma_{pv}^2\beta} \le -P_{disch\_min}+P_{disch}+\beta\mu_{load}^T+\beta\mu_{pv}^T \quad (44)$$

where μ_{pv} and σ_{pv} are the mean and variance of the PV power forecast error, respectively. μ_{load} and σ_{load} are the mean and variance of the load forecast error, respectively. Equations (41)-(44) are deterministic SOCP problems that can be efficiently solved by an optimization technique. Here, $P_{disch\_min}=0$.

4.2. Second Stage Problem: RSO Approach

The objective of the second stage is to determine solutions against the worst-case realizations of PV power and load. As part of our paper, we propose a formulation and solution procedure of an RO approach aimed at minimizing the total operational cost of an HES according to scenarios of PV power and load. The proposed approach was developed via the coevolution of HBPSO and PSO algorithms, namely, the HBPSO-PSO algorithm.

The intergeneration projection genetic algorithm (IP-GA) was proposed in [22] to solve a nonlinear optimization model considering an uncertain parameter. The authors of [23] were inspired by the concept of [22] and proposed the intergeneration projection evolutionary algorithm (IP-EA) for optimal scheduling of household appliances, aiming to minimize the cost of electricity. In this paper, we adopt the HBPSO-PSO algorithm to solve the RSO problem for HES scheduling. The IP-GA is composed of an inner genetic algorithm (GA) and outer GA, while the IP-EA is composed of an inner GA and outer PSO algorithm. Our proposed algorithm is composed of an inner HBPSO algorithm and an outer PSO algorithm. The main advantage of the two-level structure of the mentioned algorithms is that an optimization problem can be solved directly without decomposition of the original problem [23].

$$\max_{\phi} \min_{y,\theta} \sum_{i=1}^{n} \left[RC_i(t) + \Delta MCH_i(t) \right] + \Delta MCP(t) + \Delta BC(t) \tag{45}$$

where

$$\Delta MCH_i(t) = K_{hu} \cdot \Delta P_{hu,i}(t) \cdot \Delta T \tag{46}$$

$$\Delta MCP(t) = K_{pv} \cdot \Delta P_{pv}(t) \cdot \Delta T \tag{47}$$

$$\Delta BC(t) = \Delta OCB(t) + \Delta MCB(t) \tag{48}$$

$$\Delta OCB(t) = C_{ch} \cdot \Delta P_{ch}(t) \cdot \eta_{ch} \cdot \Delta T - C_{disch} \cdot \Delta P_{disch}(t) \cdot \Delta T / \eta_{disch} \tag{49}$$

$$\Delta MCB(t) = K_{bess} \cdot \left[\Delta P_{ch}(t) \cdot \eta_{ch} \cdot \Delta T + \Delta P_{disch}(t) \cdot \Delta T / \eta_{disch} \right] \tag{50}$$

Subject to constraints (8)-(21).

The new equations of power balance (8) and reserve power (21) are expressed as

$$\begin{aligned} & P_{load}(t) + \Delta P_{load}(t) + P_{ch}(t) \\ & = \sum_{i=1}^{n} y_i(t) \cdot \left[P_{hu,i}(t) + \Delta P_{hu,i}(t) \right] + P_{pv}(t) + \Delta P_{pv}(t) + P_{disch}(t) + \Delta P_{disch}(t) \end{aligned} \tag{51}$$

$$P_{res}(t) \geq P_{pv}(t) + \Delta P_{pv}(t) \tag{52}$$

$$\begin{aligned} & \textstyle\sum_{i=1}^{n} y_i(t) \cdot \left[P_{hu\_max,i} - P_{hu,i}(t) + \Delta P_{hu,i}(t) \right] + \left[P_{b\_res}(t) - P_{disch}(t) + \Delta P_{disch}(t) \right] \\ & \geq P_{pv}(t) + \Delta P_{pv}(t) \end{aligned} \tag{53}$$

$$P_{s\_load}(t) = P_{load}(t) + \Delta P_{load}(t) \tag{54}$$

$$P_{s\_pv}(t) = P_{pv}(t) + \Delta P_{pv}(t) \tag{55}$$

$$P_{s\_ch}(t) = P_{ch}(t) + \Delta P_{ch}(t) \tag{56}$$

$$P_{s\_disch}(t) = P_{disch}(t) + \Delta P_{disch}(t) \tag{57}$$

$$\Delta P_{hu,i}(t) = \theta_i(t) \cdot \left[\Delta P_{load}(t) - \Delta P_{pv}(t) \right] \tag{58}$$

$$\Delta P_{bess}(t) = \phi(t) \cdot \left[\Delta P_{load}(t) - \Delta P_{pv}(t) \right] \tag{59}$$

$$\sum_{i=1}^{n} \theta_i(t) + \phi(t) = 1 \tag{60}$$

where ΔP_{pv} and ΔP_{load} are the variations in PV and load powers, respectively, compared to the forecast values. ΔP_{hu} and ΔP_{bess} are the amount of compensated powers of HUs and a BESS in accordance with the variations of PV and load powers, respectively. ΔP can be a negative or positive value. P_{s_pv} and P_{s_load} are the scenarios of PV power and load, respectively. P_{s_ch} and P_{s_disch} are the charge and discharge powers of a BESS with respect to scenarios of PV power and load, respectively. Note that $\Delta P_{bess}(t) = \Delta P_{disch}(t) - \Delta P_{ch}(t)$. Here, we consider $\Delta P_{ch}(t) = 0$.

- **Scenario generation and reduction of PV power and load demand**

To better model the change in PV and load powers, a large number of scenarios should be generated. However, this requires a high computational time to resolve the problem. Therefore, a scenario reduction technique is used to reduce the total number of scenarios by omitting repetitive or low-probability scenarios. The scenario reduction method can maintain a good approximation of the uncertain behavior of the system. In this work, an autoregressive moving average method [27] [28] is used to generate 100 scenarios of PV and load powers. Then, a forward selection method [29] is used to reduce them to 20 scenarios.

Since the flowchart of PSO has already been presented in many research studies, therefore, we emphasize the implications of binary and continuous (standard) versions of PSO in problem-solving, as shown in **Table 1**. By using the combination of these two versions, we can obtain the hybrid version, namely HBPSO. In this study, all versions of PSO include the modification in velocity updating where the time-varying inertia weight with a constriction coefficient is inserted.

The solving procedure of problem (45) is illustrated in **Figure 3**, based on the HBPSO-PSO algorithm. The inner HBPSO algorithm achieves the optimal operation of the HUs, while the outer PSO algorithm finds the operation of the BESS under the worst impact on the total operational cost. More precisely, the worst case is obtained via the outer PSO algorithm. Then, we can obtain the worst cost under the change in PV and load powers.

5. Simulation Results

In this section, the simulation results of the two-stage approach are presented. It is worth mentioning that the DRCC formulation in the first stage is converted to a deterministic SOCP problem. Thus, it is suitable to solve the problem using a standard PSO algorithm. The simulations are implemented in MATLAB, installed on a PC with an Intel Core i5 processor running at 2.5 GHz with 8 GB of RAM. The forecasted PV and load powers and their scenarios are shown in **Figure 4(a)**, **Figure 4(b)**. The black line represents the forecast values, and the green lines represent their scenarios. The water in the hydro reservoir is assumed to always be satisfied to produce energy.

To demonstrate the effectiveness of the proposed two-stage approach, different simulation cases are conducted. First, the cost derived by the proposed two-stage approach is compared with SO and RSO approaches. Second, a sensitivity analysis is carried out to study the impact of forecast errors on the operational cost. Third, the performance of an FPV-BESS system is analyzed. Finally, the comparison of the HBPSO-PSO algorithm with another algorithm is performed.

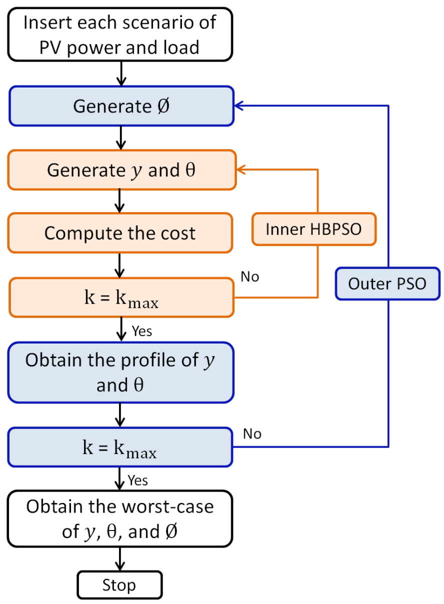
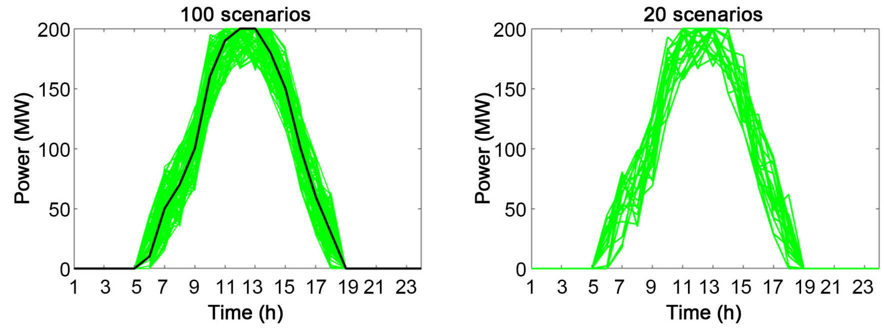


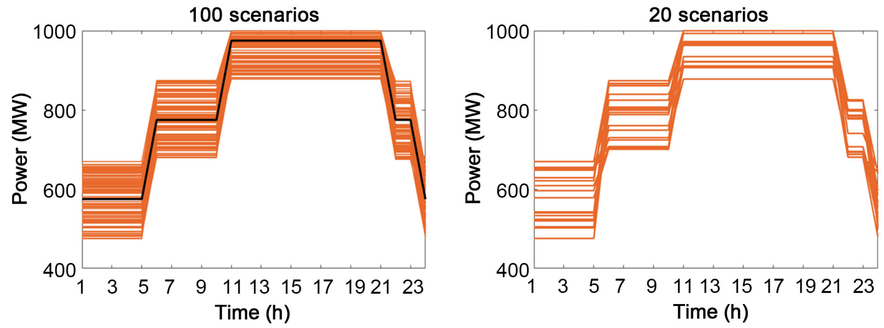
Figure 3. Flowchart of the HBPSO-PSO algorithm.

Table 1. PSO implementation.

	Binary variable	Continuous variable
Particle position	$x^{*}=\{y\}$	First stage: $x=\{P_{hu},P_{bess},\alpha,\beta\}$ Second stage: $x=\{\theta,\phi\}$
Velocity update	$V_i^{k+1}=\phi\cdot w^k\cdot v_i^k+c_1\cdot r_1\cdot\left(P_{best}-x_i^k\right)+c_2\cdot r_2\cdot\left(G_{best}-x_i^k\right)$ where k is the iteration number. i is the particle number. x is the particle position. v is the particle velocity. P_{bess} and G_{best} are the personal and global bests, respectively. c_1 and c_2 are the acceleration coefficients. r_1 and r_2 are the random numbers between 0 and 1. The time-varying inertia weight is $w^k=w_{max}-k\dfrac{w_{max}-w_{min}}{k_{max}}$ and $\phi=\dfrac{2}{\left\|2-C_0-\sqrt{C_0^2-4C_0}\right\|}$. where w_{min} and w_{max} are the minimum and maximum values of the inertia weight, respectively. k_{max} is the maximum iteration. C_0 is a constant coefficient, where $C_0=c_1+c_2$ and $C_0>4$.	
Particle update	$x_{ij}^k=\begin{cases}1 & \text{if } u_{ij}^k<s_{ij}^k\\ 0 & \text{if } u_{ij}^k\geq s_{ij}^k\end{cases}$ where u_{ij}^k is a random number between 0 and 1, and s_{ij}^k is the sigmoid function ($s_{ij}^k=\dfrac{1}{1+e^{-v_{ij}^k}}$).	$x_i^{k+1}=x_i^k+v_i^{k+1}$



(a) PV power: forecasted value (black line) and generated scenarios (green lines)



(b) Load demand: forecasted value (black line) and generated scenarios (orange lines)

Figure 4. PV power and load profiles.

The parameters used for PSO are as follows: N is 5000; w_{min} and w_{max} are 0.4 and 0.9, respectively; c_1 and c_2 are 2.05 and 2.05, respectively; and k_{max} is 20. The error mean and standard deviation are given as follows: μ_{pv} and μ_{load} are 28 MW and 86 MW, respectively. σ_{pv} and σ_{load} are 9 MW and 23 MW, respectively. The characteristics of each device are given in **Appendix A**. The initial status of all HUs is assumed to be three (3), which means that the HUs are already committed (ON) for three hours before the simulation window (period).

5.1. Performance Analysis of the Proposed Two-Stage Approach

As mentioned previously, the proposed approach is a combination of DRCC and RSO approaches to schedule an HES. To demonstrate the relevance of the proposed approach, the profiles obtained by the worst-case scenario of the proposed approach are illustrated in **Figure 5**. We can notice that the output power of HUs obtained by the proposed approach is reduced during the daytime despite the increase in load demand.

On the other hand, the BESS discharges between 9 - 15 h, which leads to the diminution of the stored energy, as shown in **Figure 6**. Thus, the results given by the proposed approach provide insight for operators and planners to deal with forecast errors and all possible scenarios of PV and load powers. In addition, this approach can help to improve the system's resiliency and enhance the efficient use of available energy resources.

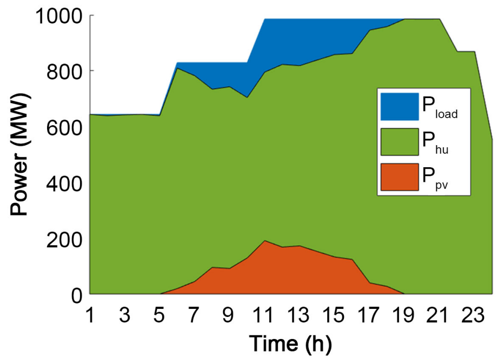
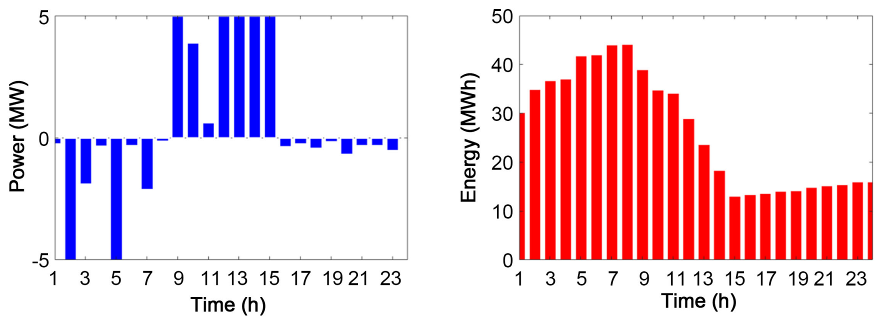


Figure 5. Load, hydropower, and FPV power profiles (third scenario).



(a) Battery power (b) Stored energy

Figure 6. Battery power and stored energy (third scenario).

Table 2 gives the average operational costs of SO, RSO, and the proposed approach under 20 scenarios of PV power and load (over 10 optimization runs). The two-stage approach takes into account the forecast errors of PV power and load in the first stage and their scenarios in the second stage. Note that the SO and RSO approaches did not include the forecast errors of PV power and load. Thus, the optimization problem is formulated under a one-stage problem where the same cost functions are used.

First, the SO approach derives the best solution among all the approaches, *i.e.*, it yields the lowest operational cost among the best- and worst-case approaches. Second, the cost obtained by the RSO approach is the highest since it takes into consideration the worst-case operation of HUs and a BESS under the worst impact of scenarios of PV power and load. By this fact, the proposed two-stage approach provides the cost between that obtained by the SO and RSO approaches. The reason is that the proposed approach has considered the forecast errors, so it is more practical to adjust the output power of HUs and a BESS against the change in PV power and load compared to the traditional RSO approach.

5.2. Sensitivity Analysis of the Proposed Approach

The PV power and load forecast errors (in the first stage) can influence the total operational cost. Therefore, we investigated the operational costs under the variation of the forecast errors, as depicted in Table 3. We used the variable λ to represent the variation factor of the forecast errors. If the mean errors of the PV power and load forecasts are equal to the initial (real) values given by historical data, then $\lambda = 1$. If the mean errors of the PV power and load forecasts are opposite to the initial values, then $\lambda = -1$. If the mean errors of the PV power and load forecasts are nil, then $\lambda = 0$. Note that $\lambda = 0$ and $\lambda = -1$ indicate that the considered mean errors are diverted from the real values. We can see that the decrease in λ can cause an expansion in the total operational cost. This can be explained by the fact that the uncertainties can be better handled if we have sufficient knowledge of the error means of forecast values.

5.3. Performance Analysis of an FPV-BESS System Using the Two-Stage Approach

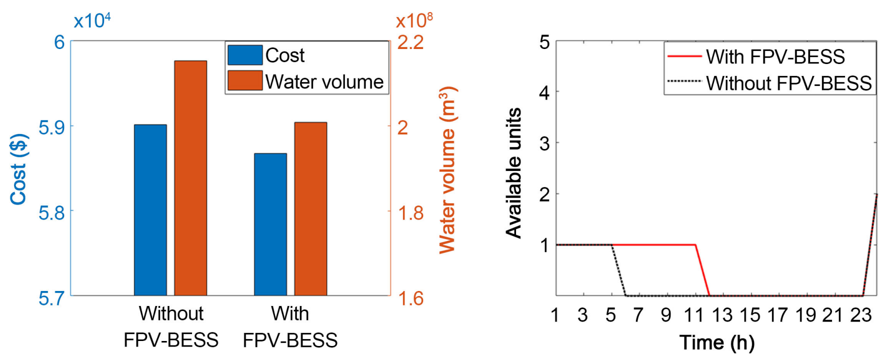
Figure 7 explores the benefit of an integrated FPV-BESS system in a hydropower plant. As we can observe in Figure 7(a), the operational cost is slightly reduced by considering the PV-BESS system. Furthermore, the water volume required by HUs is obviously decreased since the output power of the HUs is compensated by the PV power to satisfy the load. Moreover, Figure 7(b) shows that the available time of the HU is more appropriate when integrating an FPV-BESS, resulting in the reduction of the running time of the HU.

Table 2. Operational cost given by 20 PV power scenarios.

	SO		RSO		Proposed approach	
	Best	Worst	Best	Worst	Best	Worst
Cost ($)	56,101	58,077	58,115	60,064	56,519	58,674

Table 3. Costs given by the proposed approach with respect to the variation of λ (over 10 optimization runs).

	$\lambda = -1$		$\lambda = 0$		$\lambda = 1$	
	Best	Worst	Best	Worst	Best	Worst
Cost ($)	57,993	59,713	57,337	59,027	56,519	58,674



(a) Operational cost and water volume (b) Number of available HUs

Figure 7. Comparison between hydropower with and without FPV-BESS system (third scenario).

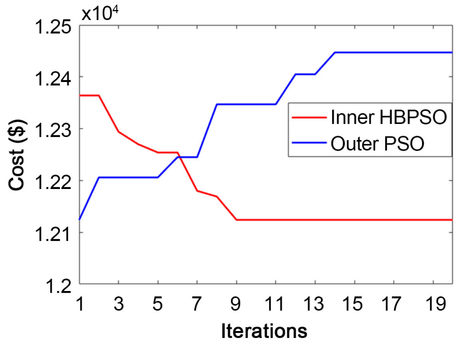


Figure 8. Convergence characteristics of the HBPSO-PSO algorithm (third scenario).

Table 4. Comparison between HBPSO-PSO and HBGA-GA.

	Cost ($)	Time (s)
HBPSO-PSO	12,469	205.9
HBGA-GA	12,949	247.2

5.4. Performance Analysis of the HBPSO-PSO Algorithm

In this subsection, we analyzed the computational efficiency of the second stage. The convergence characteristics of the inner and outer layers of PSO are shown in Figure 8. Both layers exhibit the ability to converge toward optimal values. However, the inner layer has a higher convergence speed than the outer layer. This difference can be explained by the fact that the decision variables of the outer layer are influenced by those of the inner layer. Note that Figure 8 only depicts the cost obtained in the second stage, while the operational cost procured by the first stage is $46,205.

Table 4 is dedicated to comparing the computational efficiency of HBPSO-PSO with that of the hybrid binary GA-GA (HBGA-GA) algorithm. We set the same population size and the maximum number of iterations for both algorithms. The presented results consist of the average values over 10 optimization runs. We can see that HBPSO-PSO derives a cost of $12,469 within 205.9 s, which is better than that of HBGA-GA.

6. Conclusions

In this paper, a two-stage approach is proposed for optimal DA scheduling to minimize the operational cost of an HES. The optimization in the first stage provides a solution based on the DRCC approach considering the PV power and load forecast errors. By using the DRCC approach, we can obtain a deterministic SOCP form, which can be effectively solved by a PSO algorithm. The second stage derives a robust near real time solution for each scenario of PV power and load based on the setpoint from the first stage.

The key findings can be summarized as follows: 1) Numerical results show that the proposed approach enhances the scheduling of an HES, leading to a diminution of the operational cost compared to that of traditional RSO. 2) The proposed approach provides robust scheduling of an HES against all possible scenarios of PV power and load. 3) The interaction between the first and second stages enables the readjustment of the ON/OFF status of the HUs that minimizes the SUC and RC. 4) The proposed HBPSO-PSO algorithm can effectively solve RSO problems and is very simple to implement compared to the methods found in the literature.

This paper has focused on finding the lowest operating cost without taking into account the tradeoff between cost and running time. Future works can be focused on the implementation of the tradeoff strategy of the proposed method, especially in a large power system. Also, the network stability criteria should also be further included.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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Appendix A. Simulation Parameters of the Devices

Parameter	Value
$HSUC$; $CSUC$	300$; 400$
MUT; MDT	3 h; 2 h
T^{cold}	2 h
k_{hu}	2.45$/MWh
$UR_{hu} = DR_{hu}$	100 MW/min
P_{hu_min} ; P_{hu_max}	80 MW; 200 MW
k_{bess}	0.3$/MWh
$\eta_{ch} = \eta_{disch}$	95%
$c_{ch} = c_{disch}$	60$/MWh
E_{min} ; E_{max}	5 MWh; 45 MWh
$P_{ch\_max} = P_{disch\_max}$	10 MW
$UR_{pv} = DR_{pv}$	50 MW/min
N_{max}	5
k_{pv}	0.26$/MWh
P_{pv_min} ; P_{pv_max}	0; 200 MW
C_{res}	2$/MWh
P_{load_min}	80 MW
P_{load_max}	1000 MW