# Preliminary Results of Advanced Heuristic Optimization in the Risk-based Energy Scheduling Competition

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## ABSTRACT

In this paper, multiple evolutionary algorithms are applied to solve an energy resource management problem in the day-ahead context involving a risk-based analysis corresponding to the proposed 2022 competition on evolutionary computation. We test numerous evolutionary algorithms for a risk-averse day-ahead operation to show preliminary results for the competition. We use evolutionary computation to follow the competition guidelines. Results show that the HyDE algorithm obtains a better solution with lesser costs when compared to the other tested algorithm due to the minimization of worst-scenario impact.

## CCS CONCEPTS

• **Computing methodologies** → *Search methodologies*; • **Applied computing** → **Engineering**.

## KEYWORDS

Energy resource management, evolutionary computation, optimization, risk analysis

## 1 INTRODUCTION

The current goals set to decrease the carbon footprint, mainly in the European Union, which are set to reduce emissions of at least 55% by 2030 [1], encourage the integration of distributed energy resource (DER) in the smart grid paradigm. This high penetration increase poses new challenges to the correct operation of the electricity grid because of the uncertainty characteristic of these resources. The energy resource management (ERM) problem considering uncertainty is introduced here to achieve a proper operation of the energy management system.

Considering the variability and uncertainty of the considered technologies like renewable generation such as photovoltaic (PV) and wind (weather dependent), EV travel behavior, load consumption, and electricity market prices, we introduce the concept of extreme event day-ahead operation problem. As the name indicates, an extreme event is an occurrence that is of low probability because it is something improbable to occur, but that can cause a high impact on the energy management system, making the obtained solution volatile. The existence of these events creates a risk associated with the ERM problem. In this situation, we incorporate two risk measuring tools: value-at-risk (VaR) and conditional VaR (CVaR) to evaluate the risk associated with the day-ahead management solution for a given number of scenarios [2]. The CVaR measuring tool is utilized in comparison to the mean-variance tool, because the CVaR analysis is not limited to an elliptical probability distribution as referenced in [3], and a gaussian distribution can be used as we propose in this paper.

Traditional optimization algorithms have struggled to keep up with the increasing complexity in several scientific disciplines. Alternative methodologies, such as evolutionary computation (EC), are a possible choice in this circumstance [4]. Due to the complexity presented in most energy optimization problems, which involve the ERM problem, EC is a powerful tool well suited to be applied to solve this problem [5].

This paper is based on [6] which proposed a robust ERM including CVaR risk analysis. The optimization problem is mixed-integer linear programming (MILP) and was solved using evolutionary algorithms (EAs) considering risk-neutral and risk-averse approaches. This work focuses on the "Competition on Evolutionary Computation in the Energy Domain: Risk-based Energy Scheduling[1]," which only considers a total risk aversion in the optimization, and fewer scenarios are evaluated with fewer extreme events being created. Different EAs are used from the one previously, including differential evolution (DE), hybrid-adaptive DE with decay function (HyDE-DF) [7], vortex search (VS) [8], particle swarm optimization (PSO), success-history based adaptive DE (SHADE) [9], and L-SHADE [10]. These algorithms are used, because the basis of the competition is the application of EC in the energy domain. Numerous research has demonstrated the efficacy of these algorithms in addressing benchmark issues and real-world applications. The proposed ERM framework for the competition can be seen in Figure 1.

## 2 RISK-BASED METHODOLOGY

Regarding the risk-based methodology, this section presents the mathematical formulation for the ERM model present in the proposed competition considering multiple EC optimization techniques.

### 2.1 Risk formulation

The proposed day-ahead optimization problem consists in a cost minimization given by:

$$min\ Cost = z^{\text{ExCost}} + \text{CVaR}_{\alpha} \tag{1}$$

[1] http://www.gecad.isep.ipp.pt/ERM-competitions/2022-2/


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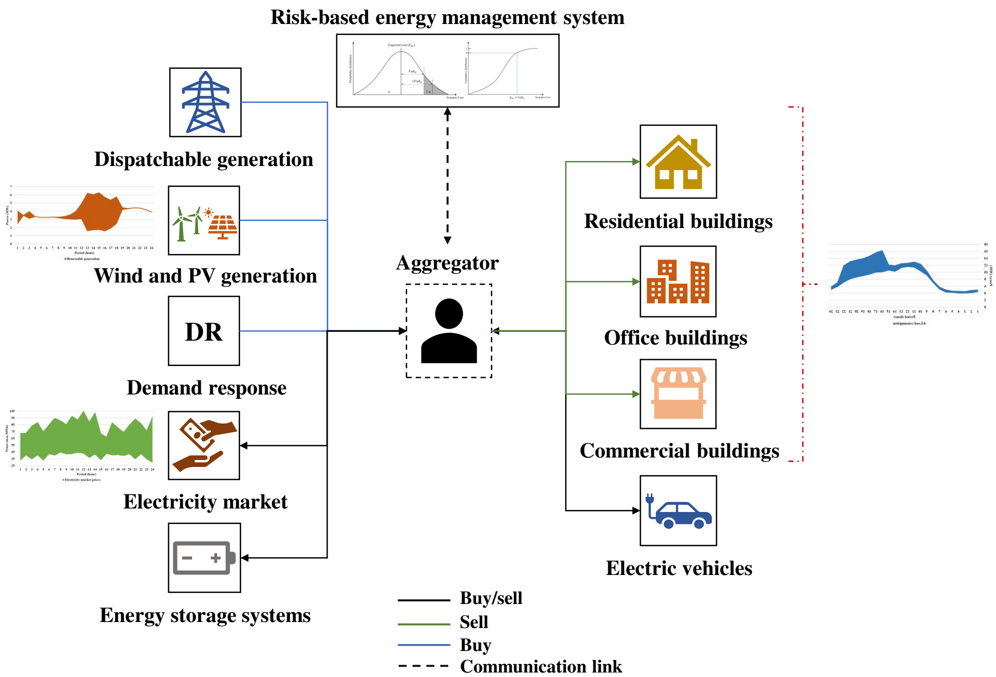


**Figure 1: Considered ERM with risk evaluation.**

where the expected cost ($z^{\text{ExCost}}$), and $\text{CVaR}_\alpha$ are given by:

$$z^{\text{ExCost}} = \sum_{s}^{N_s} z_s^{\text{Cost}} \times \rho_s \tag{2}$$

$$\text{CVaR}_\alpha(z_s^{\text{Cost}}) = \text{VaR}_\alpha(z_s^{\text{Cost}}) + \frac{1}{1-\alpha}\sum_{s=1}^{N_s} \rho_s \times \pi_s \tag{3}$$

where:

$$\text{VaR}_\alpha(z_s^{\text{Cost}}) = z - score(\alpha) * std(z_s^{\text{Cost}}) \tag{4}$$

where $z_s^{\text{Cost}}$ are the costs associated with each scenario, $\rho_s$ represents the scenario probability, $\alpha$ is the confidence level, and $\pi_s$ are the worst scenario costs. That is the costs of the scenarios that exceed the confidence level. $z - score(\alpha)$ computes the cumulative distribution function. The formulation for $z_s^{\text{Cost}}$ can be expressed as:

$$z_s^{\text{Cost}} = z_s^{\text{OC}} - z_s^{\text{MT}} + BV_s \tag{5}$$

where $z_s^{\text{OC}}$ are the operational costs of each scenario, $z_s^{\text{MT}}$ are the revenues from market transactions, and $BV_s$ is the bound violation penalty.

The remaining formulations for the operational costs, market transactions and problem constraints can be seen in [6].

A risk-averse approach analyzes the risk associated with the considered technologies' (renewables, load, market prices, etc) uncertainty. In (1-$\alpha$) of the scenarios with the highest costs that exceed the confidence level, the additional cost of $\text{CVaR}_\alpha$ is added in Eq. 1.

## 2.2 Metaheuristic optimization

To tackle the complex energy problem that is the ERM, multiple CI optimization methods were used. Each metaheuristic randomly generates an initial solution between variables' upper and lower bounds. For each of the 24 periods, each solution is comprised of a series of sequentially repeated variables.

The risk-based scheduling methodology's optimization procedure aims to reduce the costs in Eq.1 by minimizing the impact of extreme events. The fitness function represented in Figure 2 begins by importing the initial metaheuristic solution, the case study comprising all created scenarios (a total of 15 scenarios), where some contain extreme occurrences such as market price increase, load increase, and renewable generation reduction due to weather variability. In the proposed methodology, we considered a total risk aversion, so there is no need to set up a risk aversion variable that can vary from 0 to 100% as shown in [6]. The following step is the fitness evaluation that calculates all the scenario costs regarding the proposed day-ahead ERM problem formulations. After that, the function calculates all the risk measuring parameters as presented in section 2.1.

The output of this function is the fitness value which is the cost to be minimized by each metaheuristic.

The ERM under consideration includes 13,680 variables per individual, distributed across 570 variables per period, with 21 variables forming the generators' active power and 21 binary variables indicating the generators' status. A total of 500 EVs were integrated, with 25 different load types, two energy storage systems, and one wholesale electricity market.

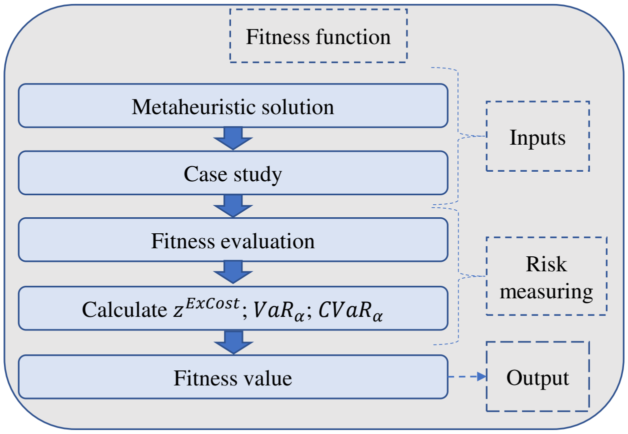


**Figure 2: Fitness function framework.**

## 3 RESULTS

This section presents the case study and obtained results regarding the risk-based results in terms of aggregator's costs and algorithm performance of each EA for the proposed methodology.

### 3.1 Case Study

This case study was conducted on a distribution network of a smart grid located in the BISITE laboratory at the University of Salamanca, Spain [11], where an external supplier (30MVA substation) is situated at bus 1. A 27% renewable generation was considered with a 24% wind and 3% PV penetration. This network includes 25 different loads in terms of consumption, including residential and office buildings, as well as some service buildings such as an hospital, fire station, and shopping mall.

High integration of electric vehicles (EVs) was considered with a total of 500 EVs, where EV uncertainty was modeled using an EV travel behavior simulator tool proposed in [12]. Multiple classes of vehicles were employed, with two types of EVs: battery EVs and plug-in hybrid EVs, each with its own set of features, as described in [13].

A total of 5000 scenarios were initially generated using the Monte Carlo Simulation, but were reduced to 15 scenarios to reduce computation time and effort. The risk scenarios generated by the aggregator's variable inputs exhibit much variation. In this setting, variations in load demand and renewable generation can be observed. Figure 3 shows the total variation in electricity market, and external supplier prices. Due to the multiple extreme scenarios that consider an increase in market costs, there is a significant variation in market prices. Period 12 has a maximum value of 104.61 m.u., with a lowest value of 43.36 m.u., indicating a significant rise of 61.25 m.u. External supplier costs have only two values fixed at 50 m.u. during off-peak hours (lower energy costs) and 90 m.u. during peak hours (higher energy costs).

The aggregator's total load demand and renewable generation are represented in Figure 4. From the extreme events generated, significant variance in load can be seen from periods 16 to 22, with the highest value of 16.20 MW in period 16. Since some extreme events

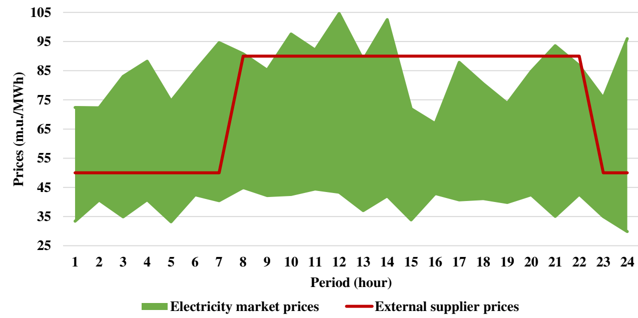


**Figure 3: Wholesale electricity market and external supplier prices variation curves.**

generated involve a reduction in renewable generation, mainly PV, the variations are modest in some periods, while a higher fluctuation may be seen in periods 13 to 18, where still PV generation is the highest.

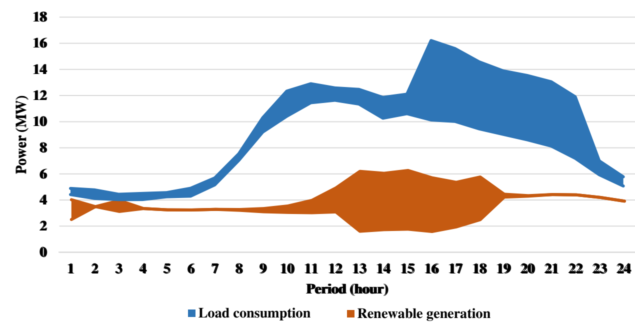


**Figure 4: Load consumption and renewable generation variation curves.**

Numerous metaheuristics were applied to solve the proposed ERM model considering risk analysis, and Table 1 illustrates the parameters used for each considering the competition rules of a total of 5,000 function evaluations (FEs). Therefore, we set the maximum generation (GEN) number and population size (NP) to 500 and 10, respectively. For the PSO algorithm, multiple parameters are needed as the personal cognitive coefficient (c1), the global cognitive coefficient (c2), minimum and maximum inertia weights (Wmin and Wmax), and particle velocity factor (V) to establish velocity limits. The scaling factor (F) and crossover probability (Cr) are set for the algorithms based on DE.

### 3.2 Risk-based results

The average results obtained by the applied EAs for the ERM problem considering CVaR risk measuring are described in Table 2 for a total of 20 trials. The table shows the average fitness values obtained for each EA, which in this case corresponds to the objective function costs, where HyDE presents the lowest values compared to the other algorithms because of the worst scenario and penalty cost reduction. HyDE was able to reduce 30.30% of worst scenario costs compared to the next best algorithm (HyDE-DF), corresponding to

**Table 1: Parameter of each EA.**

| EA | GEN | NP | c1 | c2 | Wmin | Wmax | V | F | Cr |
|---|---|---|---|---|---|---|---|---|---|
| **PSO** | | | 1.5 | 2 | 0.4 | 0.9 | 0.1 | - | - |
| **DE** | | | | | | | | | |
| **HyDE** | | | | | | | | 0.3 | 0.5 |
| **HyDE-DF** | 500 | 10 | | | - | | | | |
| **VS** | | | | | | | | - | - |
| **SHADE** | | | | | | | | 0.5 | 0.5 |
| **L-SHADE** | | | | | | | | | |

a 28.73% in costs/fitness reduction. PSO was the fastest algorithm regarding the optimization time, followed by DE.

For a total of 15 scenarios generated for the case study Table 3 shows the average and standard deviation scenario costs, demonstrating the discrepancy between all the scenarios. Since HyDE obtained the best fitness value due to the worst scenario cost reduction, it was expected that this algorithm also obtained the lowest scenario costs, as the table shows. When it comes to the average scenario costs HyDE reduced 3,547 m.u. compared to HyDE-DF, which was the following algorithm with the lowest costs.

The average risk measuring costs given by the CVaR variable are presented in Figure 5. It can be seen that HyDE, HyDE-DF, and VS are the only algorithms that offer a lesser value than the average CVaR, with the remaining showing greater values. That is, the remaining algorithms give a more volatile solution with the costs associated with the worst scenarios being elevated (Table 2) due to the extreme events. This situation means that these EAs fail to minimize these events' impact on the ERM solution. For example, HyDE reduced 81.59% of CVaR costs compared to the average value, and SHADE presented 37.59% of higher CVaR costs from the average value.

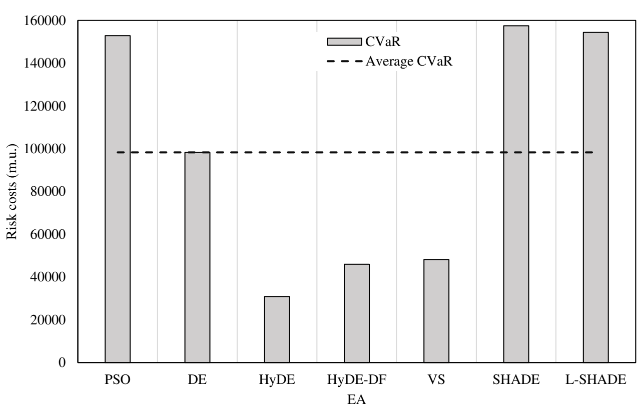


**Figure 5: CVaR costs achieved by each tested EA.**

## 3.3 Algorithm Performance

For the proposed optimization model, the EAs' performance was assessed for a total of 20 runs. The convergence of each algorithm is shown in Figure 6. From all the tested algorithms, it can be seen that HyDE presents the best performance achieving the lowest fitness value, with HyDE-DF and VS following. PSO, SHADE, and L-SHADE present similar convergences, with SHADE presenting the worst fitness values and are most likely stuck in local minima due to the fast convergence.

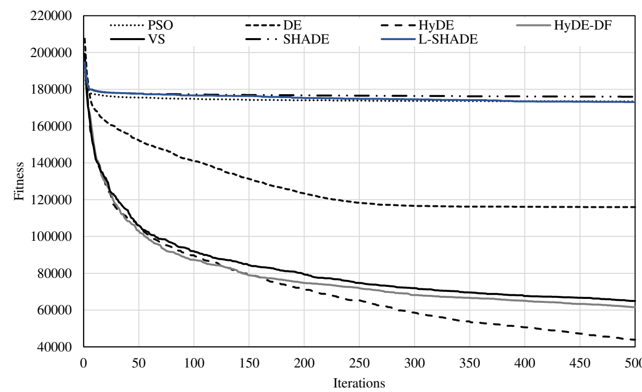


**Figure 6: Convergence of the tested EAs.**

A Wilcoxon test was performed on the risk-based results obtained with a significance level of 5%. As HyDE presented the best cost results, the statistical test was conducted using HyDE as the base algorithm for comparison, as Table 4 shows. The table shows four results: R+, R-, p-value, and L-sign. The R+ and R- to the total of positive and negative ranks that show the base algorithm's performance compared to the other algorithms. As expected, HyDE consistently outperformed the compared algorithms. The p-value demonstrates how significant the difference is, as the obtained p-values are more than the 5%. Finally, the L-sign is the sign (+, -,=) representing the statistical performance attained, where HyDE for the proposed problem obtained the best statistical performance.

HyDE, provides exceptional outcomes because of the self-adaptive processes like jDE [14]. It also makes use of perturbations inspired by EPSO [15], which have been shown to increase the algorithms' convergence while tackling optimization problems in the energy domain.

## 4 CONCLUSIONS

In this paper, we verified the application of multiple EAs to the proposed risk-based ERM competition. The risk associated with extreme events was evaluated through the CVaR mechanism for a 100% risk-averse formulation.

**Table 2: Average costs, expected costs, worst scenario, penalties, and computational time obtained by each EA (random).**

| EA | Cost/fitness (m.u.) | $z^{\text{ExCost}}$ (m.u.) | Worst scenario (m.u.) | penalties (m.u.) | time (min) |
|---|---|---|---|---|---|
| **PSO** | 173,369 | 20,526 | 208,462 | 6,875 | 5.23 |
| **DE** | 116,007 | 17,779 | 138,517 | 4,565 | 5.27 |
| **HyDE** | 43,881 | 12,966 | 49,654 | 1,850 | 6.10 |
| **HyDE-DF** | 61,571 | 15,564 | 71,235 | 3,272 | 6.14 |
| **VS** | 64,959 | 16,776 | 75,004 | 4,260 | 6.11 |
| **SHADE** | 175,956 | 18,482 | 212,184 | 7,087 | 5.29 |
| **L-SHADE** | 173,071 | 18,711 | 208,582 | 6,955 | 5.31 |

**Table 3: Average and standard deviation scenario costs for each EA.**

| EA | Avg. Scenario Costs (m.u.) | Std. Scenario Costs (m.u.) |
|---|---|---|
| **PSO** | 28,006 | 50,252 |
| **DE** | 22,708 | 32,348 |
| **HyDE** | 15,256 | 11,002 |
| **HyDE-DF** | 18,803 | 16,205 |
| **VS** | 20,170 | 17,009 |
| **SHADE** | 25,786 | 51,570 |
| **L-SHADE** | 25,856 | 50,667 |

**Table 4: Wilcoxon signed rank test.**

| HyDE vs. | R+ | R- | p-value | L-sign |
|---|---|---|---|---|
| **PSO** | 210 | 0 | 1.91E-06 | + |
| **DE** | 210 | 0 | 1.91E-06 | + |
| **HyDE-DF** | 207 | 3 | 9.54E-06 | + |
| **VS** | 208 | 2 | 5.72E-06 | + |
| **SHADE** | 210 | 0 | 1.91E-06 | + |
| **L-SHADE** | 210 | 0 | 1.91E-06 | + |

The preliminary results for the 2022 competition show that the HyDE algorithm achieved both the lowest CVaR and total day-ahead costs compared to the other algorithms, even an improved version such as HyDE-DF. Because HyDE could reduce the worst scenario costs majorly. This was further proved by the implemented Wilcoxon signed rank test. Different DE algorithms SHADE and L-SHADE together with PSO showed similar, but poor performances for this problem, achieving the highest aggregated day-ahead costs.

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