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Explainergy: Towards Explainability of Metaheuristic Performance in the Energy Field

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***Abstract*—We propose the concept of "explainergy", a new way of including explainability in the metaheuristic performance of algorithms solving problems in the energy domain. To this end, we open the discussion around eXplainable Computational Intelligence (XCI), focusing on using metaheuristic optimization for complex energy-related problems. It is well known that computational intelligence applied to optimization cannot guarantee optimality theoretically and also faces issues related to premature convergence, tuning parameters, and variability of the results. These aspects slow the adoption of such methods by energy industry practitioners. Our proposal considers incorporating ideas already applied to the artificial intelligence paradigm, namely those related to eXplainable AI, to motivate current research in this field and provide solutions from metaheuristics with explainability characteristics. Through a case study solving a bidding problem in local electricity markets, we shed light on some ideas that might be advantageous to understanding the metaheuristic performance for energy experts unfamiliar with approximate algorithms. If an XCI framework is successfully developed, it can increase metaheuristic adoption, reliability, and broader success.**

***Index Terms*—artificial intelligence, explainergy, explainable decision support systems, explainable computational intelligence, metaheuristics.**

I. Introduction

Power energy systems are rapidly incorporating new resources for consumption and production, such as electric vehicles (EVs) and renewable sources. Moreover, new entities, such as aggregators, prosumers (consumers with generation capabilities), and distributed generation and demand response, are emerging, evolving the current traditional grid and changing its characteristics in new ways [1], [2]. Considering that integrating these resources brings higher dimensionality and uncertainty to energy-related problems, conventional optimization methods might lose their efficiency, reaching their limit for this new paradigm.

As a result, energy experts are exploring innovative ways to manage and operate power distribution systems properly. In this context, Computational intelligence (CI), including metaheuristic optimization, is gaining more visibility currently. Metaheuristics are high-level methods used to explore solution search spaces. These methods should have a dynamic balance between the utilization of collected search knowledge (often known as intensification) and the exploration of the search space (which is commonly called diversification) [3]. Metaheuristics can find good solutions to complex problems and are effective problem-solvers even when non-linearities and uncertainty are considered, finding a good result in a reasonable time without requiring the computational effort more traditional mathematical models need [4].

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Although several studies have demonstrated the efficiency of metaheuristics in real-world applications [5], [6], energy experts are hesitant to use these approaches to deal with the sector's growing complexity. This reluctance comes in part from the lack of a theoretical background guaranteeing the optimality of solutions. Due to this, we hypothesize that novel methods to explain metaheuristic performance and how those attain acceptable results in situations where other strategies fail might be the key to a broader acceptance of the methods. As the "No Free Lunch Theorem" states, it is impossible to design an algorithm that can effectively deal with all different problems out there [7]. However, CI practitioners can borrow methods similar to the ones used in eXplainable AI (XAI) [8] and use them in the field of CI, given rise to the idea of eXplainable CI (XCI) to achieve successful metaheuristic applications.

The concept of XCI can be a nice step towards the explainability of metaheuristic performance and improve the acceptance of metaheuristic optimization applied to energy-related problems. We propose incorporating a new framework with a layer that explains the solution obtained in a given problem in a more user-conventional way. As such, this paper provides; first, i) insight into energy-related problems incorporating XCI techniques for an explainable decision support system (DSS); and second, ii) a case study based on a bidding optimization problem to show some features that can be added into the description and analysis of metaheuristic solutions.

The article is organized as follows: after this introductory section, Section II briefly describes what is intended with XCI applied to the energy domain. In Sections III to V, we use a problem already solved with metaheuristics in [9] to show how, through the use of figures and tables, we can provide a better understanding of solutions in an energy-related problem. Final remarks and conclusions taken from this article are described in Section VI.

II. From metaheuristics to eXplainergy

In a nutshell, "eXplainergy" is a concept that arises from the combination of some well-developed lines of research in computer science applied to a specific application domain. Figure 1 positioned the concept idea of "eXplainergy". As can be seen, XCI comes from the combination of explainability (i.e., using the same concepts applied in artificial intelligence (AI) [10]) and CI. While the term XCI can be referred to any application of explainability into any of the CI areas (e.g., artificial neural networks (ANN), evolutionary computation (EC), Fuzzy Systems (FZ), probabilistic methods, etc.), in this article, we focus on the optimization component of CI. More specifically, we do not only restrict the optimization component of CI to the EC, but we give it a more general character through the use of metaheuristics. This narrows the scope of the proposed concept and allows us to center our ideas on the topics that are interesting in our application domain, namely energy-related problems and the use of metaheuristics.

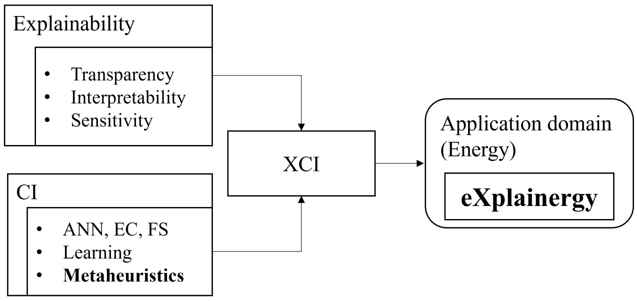

Fig. 1. The eXplainergy idea.

The development of our proposed idea will certainly benefit from a formal mathematical definition of the type of problems we are dealing with and how metaheuristics can be used as an alternative solution method. Thus, a deterministic combinatorial optimization problem (DCOP) can be defined as [11]: Given a finite set S of feasible solutions x, and a real-valued cost function $G(x)$, find min $G(x)$. Notice that the set S is the solution space, and its structure may be complex by constraints on solutions or by uncertain, stochastic, and dynamic information in the formulation. The global optimal solution x^* is the one with minimal objective function value (i.e., $G(x^*) \leq G(x) \forall x \in S$).

Many of the problems faced not only in energy but in real-world applications belong to the class NP-hard, and thus, algorithms that guarantee to find the optimal solution (i.e., exact algorithms) in bounded time might require too much or prohibitive time to return a solution for practical applications. In this situation, designing algorithms that find approximate solutions in reasonable times becomes relevant. Metaheuristics belong to this class of "approximate algorithms".

The optimality of metaheuristic optimization cannot be theoretically guaranteed so far. This aspect can give place to worries about the stability and robustness of such approaches. For instance, practitioners unfamiliar with metaheuristics and their "approximate" search procedures might find it odd that new solutions are generated every time the algorithms are run. In fact, one of the primary drawbacks of applying CI in optimization is the difficulty in understanding metaheuristic performance using sound mathematical foundations.

To overcome this issue, we propose the exploration of topics that are being studied in the field of AI, for example, post-hoc explainability techniques [8] such as text, visual, local, and simplification explanations could be applied to give a better understanding of how the metaheuristic solves a specific problem. Transparent Machine learning (ML) methods could be integrated into the metaheuristic frameworks providing the needed explainability without needing post-hoc analysis. In [12], multiple surrogate models using ML: linear regression, decision tree, and random forest were used to provide a variable ranking index representing their importance for numerous binary benchmark problems. These ML techniques were integrated with a genetic algorithm, and the variable ranking suggested which variables were not needed and could be discarded for the given problems. Authors in [13] present a methodology toward understanding the metaheuristic decision process through which a combination of variables greatly influences solution quality, similar to what we offer in this work. Solutions are extracted from a surrogate fitness model (Markov network fitness model), and the authors analyze the local sensitivity of solutions regarding the minimal cost and mean coefficient energy values for a building's facade.

Thus, XCI emerges as the combination of CI and explainability in an attempt to provide transparency to metaheuristics by including a rigorous analysis, such as fitness, drift, and exploration/exploitation analysis, into the metaheuristic design. Classical metaheuristics such as the particle swarm optimization (PSO) [14], genetic algorithm (GA) [15], differential evolution (DE) [16], to name a few, can be enhanced by different means (for instance using parameter tuning, adaptive operators, combination with other heuristic-mathematical techniques, etc.), achieving better flexibility of implementation for different problems. These improvements, however, might not increase the trust and acceptance of these methods compared to mathematical techniques.

A. Incorporating XCI algorithms in the energy domain

Problems in the energy field, for example, the energy resource management or the optimal bidding in local markets, need to consider multiple sources of uncertainty, including renewable generation (wind and photovoltaic (PV) generation), EVs (standard and autonomous), various forms of load consumption, and local electricity transactions. Moreover, those problems generally have many variables to optimize (high dimensionality) and a small window time for making decisions (from day-ahead to real-time), requiring effective and efficient solution methods. In this context, metaheuristics can be used and integrated into the optimization process. However, due to the stochastic nature of those techniques, algorithms incorporating an explainable framework for solution transparency would be key to understanding algorithm performance.

Another aspect that needs to be explained is how the choice of parameters and the problem's structure to be addressed significantly impact metaheuristic performance [4]. For instance, metaheuristics can incorporate starting solutions from deterministic techniques and combine operators from multiple algorithms. However, how to do it in a simple manner, to give confidence to the user applying such techniques, has been barely discussed in the specialized literature.

But not all are bad news regarding using metaheuristics in the energy domain. In fact, novel CI optimization algorithms have already been developed and implemented to solve mathematical models formulated for various energy problems involving uncertainty. Algorithms such as Cellular Univariate Marginal Distribution Algorithm with Normal-Cauchy distribution (CUMDANCauhy) [17], Hybrid-Adaptive Differential Evolution (HyDE) [18], and Vortex Search (VS) [19], to name a few, already showed good performance for problems in the energy field. Therefore, through XCI, integrating a new framework that provides explainability techniques would further enhance the applicability and acceptance of such methods, enabling a better understanding of why these algorithms work well in such problems.

III. eXplainergy Use Case

We now present an energy application where eXplainergy can be used. The problem, in turn, published in [9], considers a local electricity market with consumers, prosumers (consumers with PV generation), and local producers (combined heat and power (CHP) generators) trading energy to minimize costs and maximize incomes. In addition, the problem considers a distribution system operator that validates the transactions in the network and detects voltage and line violations.

The problem is modeled as a bi-level optimization problem, considering a set of consumers $I = \{1, 2, \ldots, N_c\}$, and producers $J = \{1, 2, \ldots, N_p\}$. The details of the mathematical formulation can be found in [9]; what is essential for us here is to consider that, at the upper-level, consumers search for the optimization of the bids of quantity and price into the local market $(s_{i,t}, d_{i,t})$, to minimize costs as:

$$\underset{s_{i,t},d_{i,t}}{\text{minimize}} \quad C_i = \sum_{t=1}^{T} \left(\sum_{j} cp_t \cdot x_{j,i,t} + c_t^{\text{agg}} \cdot E_{i,t}^{\text{buy}} \right) \tag{1}$$

where $s_{i,t}$ represents the price bid, and $d_{i,t}$ represents the quantity of energy in that bid, for consumer i at time t. $x_{j,i,t}$ is the energy bought by agent i from j (kWh); $E_{i,t}^{\text{buy}}$ is the energy bought by agent i from the grid (kWh); cp_t is the clearing price in the local market resulting from the bidding process (EUR/kWh); and c_t^{agg} is the aggregator tariff (EUR/kWh).

Similarly, still in the upper-level, producers search for the optimization of incomes resulting from their bids $(s_{j,t}, g_{j,t})$:

$$\underset{s_{j,t},g_{j,t}}{\text{maximize}} \quad P_j = \sum_{t=1}^{T} \left(\sum_{i} cp_t \cdot x_{j,i,t} + c_t^{\text{F}} \cdot E_{j,t}^{\text{sell}} - c_t^{\text{m}} \cdot G_{j,t} \right) \tag{2}$$

where $s_{j,t}$ is a variable representing a price bid again, and $g_{j,t}$ represents the quantity of energy to offer in the LEM for producer j at time t. $x_{j,i,t}$ is the energy sold by agent j to agent i (kWh); $E_{j,t}^{\text{sell}}$ is the energy sold by agent j to the grid (kWh); cp_t is the same clearing price obtained by the market mechanism and used for consumers (EUR/kWh); c_t^{F} is the feed-in tariff (EUR/kWh); and $c_t^{\text{m}} \cdot G_{j,t}$ is the marginal cost associated to the production of agent j (EUR).

The bids and offers in the upper level are constrained by the lower-level optimization problem defining the clearing price cp_t. The lower-level problem (single leader) represents a symmetric pool-based market. First, supply and demand curves are obtained by the sets GE (including offers of energy $(g_{j,t})$ in ascending order by their price $s_{j,t}$) and DE (including bids for energy $(d_{i,t})$ in descending price order $s_{i,t}$) respectively. With those sets, a linear problem is defined as:

$$\underset{d_i^*,g_j^*}{\text{maximize}} \sum_{i=1}^{N_c} \lambda_i^d \cdot d_i^* - \sum_{j=1}^{N_p} \lambda_j^g \cdot g_j^* \tag{3a}$$

$st.$

$$\sum_{i=1}^{N_c} d_i^* - \sum_{j=1}^{N_p} g_j^* = 0 \qquad : cp_t \quad \text{(dual variable)} \tag{3b}$$

$$0 \leq d_i^* \leq DE_i \qquad i = 1, ..., N_c \tag{3c}$$

$$0 \leq g_j^* \leq GE_j \qquad j = 1, ..., N_p \tag{3d}$$

where d_i^* and g_j^* are the demand and supply bids ordered by price (i.e., belonging to sets DE and GE), and λ_i^d and λ_j^g are the corresponding bid/offer prices. It can be seen that Eq. (3a) maximizes the social welfare of market participants; Eq. (3b) is the balance constraint (matching supply and demand), and its dual variable is the clearing price cp_t; Eqs. (3c) and (3d) guarantee the supply and demand limits. From the solution of this optimization problem, it is possible to determine the upper-level parameter cp_t and the transacted energy $x_{i,j}$ from the accepted bids/offers d_i^*, g_j^*.

Simplifying the modeling of the problem, a solution needs to provide the best decisions for those variables considering the constraints of the problem and the bounds defined for the variables. The problem can be optimally solved under the assumption of perfect competition and complete information, an assumption that is far from reality in a LEM. Therefore, [9] proposes using ant colony optimization (ACO) to learn the best bidding strategies for the agents without sharing information. To solve the problem with ACO, the authors need to define the encoding of solutions and the fitness function of the problem. These two steps are straightforward for a metaheuristic practitioner, but they can be hard to follow for people not used to working with these techniques. While we use ACO as an example in the case study, the approach can be easily extended to other metaheuristics. In fact, in [9], the same encoding is used in other algorithms, namely, CUMDANCauhy [17], [20], HyDE [18], VS [19]. Therefore, the analysis performed here can be applied to other metaheuristics straightforwardly.

IV. Encoding of solutions using eXplainergy

As can be seen, a solution will include all the quantity and price bids/offers from agents into the LEM. It is easy to see that the dimension of the problem will be $D = N_k * 2 * T$, i.e., one variable of quantity and one of price, for each agent k, for each period t. A complete solution to the problem is encoded as a vector $\vec{x} = \{[q_{k,t}] \cup [p_{k,t}]\}$, including all bids/offers registered. The variables for the problem are also bounded, meaning that a bid/offer of price can be made only between the feed-in tariff c_t^{F} and the grid tariff c_t^{grid}. In contrast, a bid/offer of quantity depends on the type of agent (i.e., either a consumer or a producer), yet, those values are also bounded between 0 and the load or maximum generation capacity.

While the explanation of the encoding of individuals might be easy to understand for people working with meta-heuristics (please see [21] for more details on the ACO and encoding), it might be hard to follow this transformation of solutions. Thus, eXplainergy proposes the use of other resources, in this case, Tables I-III, to clearly show how the solutions are encoded and, at the same time, show some characteristics of the solutions that are not evident from the original publication.

For instance, in the case study presented in [9], the optimization of bids/offers of 61 agents (13 consumers, 42 prosumers, and 6 CHP producers) for the day-ahead 24 hours (i.e., T=24) is done. That means that the dimension of the solution will be $D = N_k * 2 * T = 61 * 2 * 24 = 2928$. Showing the whole vector solution can be hard to visualize by someone that has not worked on the problem; however, the entire vector solution $\vec{x} = \{[q_{k,t}] \cup [p_{k,t}]\}$ can be broken into different parts to understand better how a solution is encoded.

Thus, Table I shows the set of variables in the vector solution that represent the quantities to buy in the LEM by each consumer for each time t. Here, it is easy to appreciate that variables 1 to 312 of $\vec{x}$ are the concatenation of quantities searched in the LEM by consumer agents. Another characteristic that is mentioned in the article is that consumers are inelastic loads, which means that the bounds of that variables are closed to a single demand value $d_{k,t}^{\mathrm{Total}}$.

TABLE I
Variables in the solution $\vec{x}$ representing energy quantities for consumers.

Agent ID	Variable number from	up to	Variables	Bounds	Agent type
1	1	24	$[q_{1,1}, \ldots, q_{1,24}]$	closed	Consumer
2	25	48	$[q_{2,1}, \ldots, q_{2,24}]$	closed	Consumer
⋮	⋮	⋮	⋮	⋮	⋮
12	265	288	$[q_{12,1}, \ldots, q_{12,24}]$	closed	Consumer
13	289	312	$[q_{13,1}, \ldots, q_{13,24}]$	closed	Consumer

The next part of the solution corresponds to the quantities of energy to be bid in the LEM by prosumers. The resulting table will be similar to the previous one, showing the variables corresponding to an agent bidding in the 24 periods with bounds as a single value $d_{k,t}^{\mathrm{Total}} - g_{(k,t)}^{\mathrm{PV}}$, taking a negative value (representing production) when there is an excess of PV generation for the agent k.

The next group of variables corresponds to the quantities CHP producers can offer in the LEM. Table II shows the variables corresponding to the quantity offer of each CHP producer at each time t. For these agents, the bounds of variables change since those are not fixed as with consumers (inelastic loads) and prosumers (forced to self-consumption and to inject into the LEM the excess of PV generation). Thus, the variables in this group can take values in the range $[-g_{(k,t)}, 0]$, where $g_{(k,t)}$ represents the maximum generation capacity of the kth CHP producer.

TABLE II
Variables in the solution $\vec{x}$ representing energy quantities for CHP producers.

Agent ID	Variable number from	up to	Variables	Bounds	Agent type
56	1321	1344	$[q_{56,1}, \ldots, q_{56,24}]$	$[-g_{(k,t)}, 0]$	CHP
57	1345	1368	$[q_{57,1}, \ldots, q_{57,24}]$	$[-g_{(k,t)}, 0]$	CHP
⋮	⋮	⋮	⋮	⋮	⋮
60	1417	1440	$[q_{60,1}, \ldots, q_{60,24}]$	$[-g_{(k,t)}, 0]$	CHP
61	1441	1464	$[q_{61,1}, \ldots, q_{61,24}]$	$[-g_{(k,t)}, 0]$	CHP

Tables I-II include the information of half of the variables in the solution $\vec{x}$, corresponding to the quantities bid/offered in the LEM $[q_{k,t}]$. The second half of the solution is similar but includes the variables representing prices sent to the LEM $[p_{k,t}]$. In the formulation of the problem, it is set that agents can bid/offer in the LEM with price bounded by the feed-in tariff c_t^{F} and the grid tariff c_t^{grid}. However, consumers are assumed to be price takers, so they are forced to always bid to the grid tariff c_t^{grid}. Prosumers are price takers when acting as consumers and can bid to any price when acting as producers. Finally, CHPs can bid to any price between the established bounds.

TABLE III
Prices for CHPs

Agent ID	Variable number from	up to	Variables	Bounds	Agent type
1	1465	1488	$[p_{1,1}, \ldots, p_{1,24}]$	closed	Consumer
⋮	⋮	⋮	⋮	⋮	⋮
13	1753	1776	$[p_{13,1}, \ldots, p_{13,24}]$	closed	Consumer
14	1777	1800	$[p_{14,1}, \ldots, p_{14,24}]$	depends	Prosumer
⋮	⋮	⋮	⋮	⋮	⋮
55	2761	2784	$[p_{55,1}, \ldots, p_{55,24}]$	depends	Prosumer
56	2785	2808	$[p_{56,1}, \ldots, p_{56,24}]$	$[c_t^{\mathrm{F}}, c_t^{\mathrm{grid}}]$	CHP
⋮	⋮	⋮	⋮	⋮	⋮
61	2905	2928	$[p_{61,1}, \ldots, p_{61,24}]$	$[c_t^{\mathrm{F}}, c_t^{\mathrm{grid}}]$	CHP

With this information, it is easier to approach a user and explain how a solution is encoded. Also, by showing the tables, it is easy to understand that the variables related to CHPs are the most interesting ones when inelastic loads and price takers are considered (an assumption made in the original publication).

V. eXplainergy post-optimization analysis

For post-optimization analysis, we take some ideas from [12], analyzing the solutions found post-optimization. To do this, first, we recover the best solution found in [9], to later apply some post-processing and determine the importance of variables in the solution.

So, in the first step, the best-found solution with the metaheuristic, $\vec{x}^{\text{best}}$, is recovered, and its fitness value (assumed to be near-optimal) is computed as:

$$S^{\text{fit}} = f(\vec{x}^{\text{best}}) \tag{4}$$

where $f()$ is the fitness function that associates a value to a given solution. After that, a simple procedure varying the value of each variable one by one is employed to evaluate new solutions in the neighborhood of $\vec{x}^{\text{best}}$. Taking into account the lower and upper bounds of the variables $\vec{x}_i^{\text{lb}}$ and $\vec{x}_i^{\text{ub}}$, we provoke two changes in each variable as:

$$c_i^{\text{lb}} = min(\vec{x}_i^{\text{lb}}, \vec{x}_i - 0.01(\vec{x}_i^{\text{ub}} - \vec{x}_i^{\text{lb}})) \tag{5}$$

$$c_i^{\text{ub}} = max(\vec{x}_i^{\text{ub}}, \vec{x}_i + 0.01(\vec{x}_i^{\text{ub}} - \vec{x}_i^{\text{lb}})) \tag{6}$$

These two values are replaced independently in the solution $\vec{x}^{\text{best}}$, generating two new solutions, $\vec{x}^{\text{move1}} = \vec{x}_i^{\text{best}} \leftarrow c_i^{\text{lb}}$, and $\vec{x}^{\text{move2}} = \vec{x}_i^{\text{best}} \leftarrow c_i^{\text{ub}}$ in the vicinity of $\vec{x}_{best}$ and variable i. In fact, the value of 0.01 is used to set a movement of 1% around a given variable i. The solutions are evaluated in the fitness function, and the modification or effect that those movements have in the fitness reference value is computed as:

$$S_i^{\text{move}} = |S^{\text{fit}} - f(\vec{x}^{\text{move1}})| + |S^{\text{fit}} - f(\vec{x}^{\text{move2}})| \tag{7}$$

The 1% movement effect on the fitness function is recorded in S^{move}, and we proceed to rank the importance of the variables in the function of these values to grasp some sense of the importance of the variables. Figure 2 shows the variables ranked in function of the values obtained by Eq. (4). Notice that, as expected, the most important variables are the ones related to the CHPs energy offers in the LEM (variables from 1321 to 1464 from Table II), and CHPs price offers (variables from 2785 to 2928 in Table III).

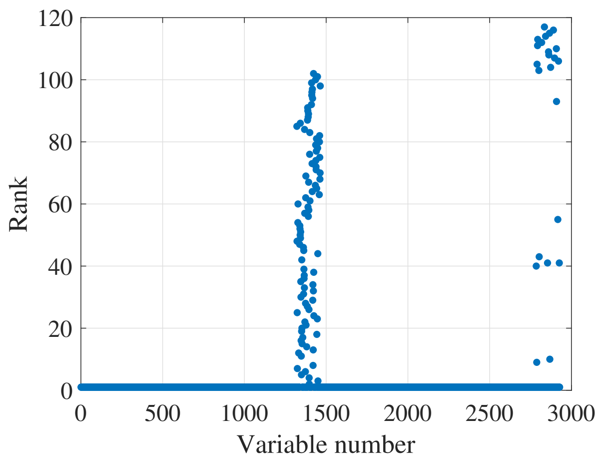

Fig. 2. Variables ranked in function of the disturbance occurred in the fitness value. A higher rank indicates that the fitness value is more affected by a change in that variable.

Since it is evident that the most important variables are the ones associated with CHPs, the concept of eXplainergy can focus deeper on analyzing these variables. To do so, Fig. 3 shows only the rank of variables corresponding to the CHPs energy offers (i.e., variables 1321 to 1464). The intuition can already indicate that a trend can be inferred, noticing that some variables with high rankings follow a group of variables with no relevance. If we recall the ordering of the variables, a group of $T = 24$ successive values correspond to one CHP (we have put the tick markers in the variables that correspond to a new CHP agent in the plot).

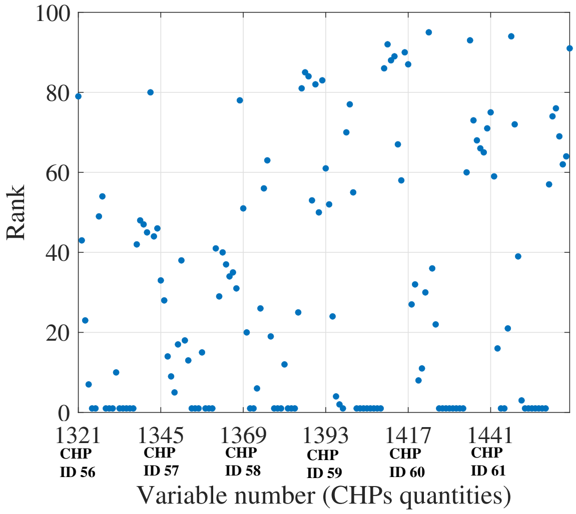

Fig. 3. Variables corresponding to the CHPs energy offers ranked by the effect a movement in the solution has in the fitness function value.

In any case, since this does not give us the information we are looking for, we plotted the effect in the fitness function by period, also showing the impact by each of the CHPs in Fig. 4. While this figure contains information on the analysis of the importance of variables, it can already be linked to the interpretation of the values to the specific case study and, therefore, can be used to explain what is happening with the proposed values to an energy practitioner. For instance, we can see that the impact in values is relatively low (the most significant change in the fitness function is around 0.04), and it is almost null between periods 10 and 16. Looking at the original publication [9], those periods, in fact, correspond to the hours where PV generation is satisfying the demand in the LEM. Hence, it makes sense that the optimization variables corresponding to CHPs have low importance in those periods.

A similar analysis can be done by considering the variables associated with the CHPs' prices. However, due to space limitations, we will provide this analysis in further research.

VI. Conclusions

We introduce "eXplainergy," a novel concept to explain metaheuristic performance for energy problems, more specifically, an optimal bidding problem in LEM. Premature convergence, tuning challenges, and stochasticity are widely recognized barriers to adopting such methods in the energy sector. We explore ideas previously applied,

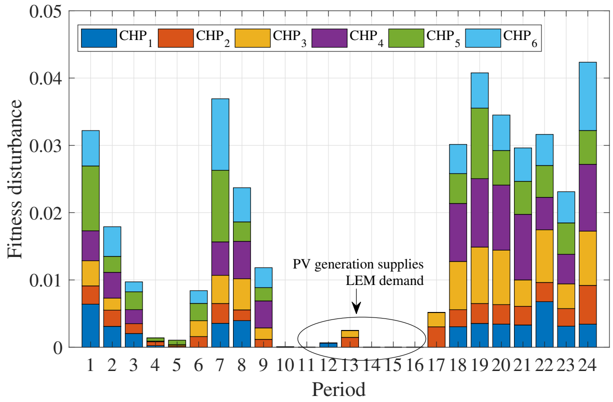

Fig. 4. Relative change (Eq. (4)) in the fitness function of variables representing energy offerings ordered by periods and CHP.

such as eXplainable AI, encouraging current research in this field to propose solutions using explainability features to comprehend CI performance and its results (XCI). We used a case study with a local environment and multiple players for this bidding problem to explain metaheuristic performance to energy specialists unfamiliar with stochastic algorithms. With XCI, it was possible to identify which variables would most affect the objective function according to their rank. It was also possible to verify the impact of CHP's bids on the final operation cost (fitness function). Even though we used this problem and case study, the proposed approach can be applied to different energy problems and case studies, consolidating the applicability of such analysis.

Other ventures such as quality diversity [22], fitness landscape analysis [23], and even algorithm configuration procedures [24] can be exciting topics and ideas for implementation in the energy domain that allow a better understanding of metaheuristic behavior in the optimization process. In future implementations, our idea for eXplainergy is to make it run in real-time rather than post-optimization, analyzing the variations of actual results over time. Such a procedure will allow users to understand better what is affecting the method's performance. Also, the discussion should be extended to other domains of CI, for instance, considering the implementation of "explainability" into application in the energy field of artificial neural networks or fuzzy systems.

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