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Maximizing the Profit for Industrial Customers of Providing Operation Services in Electric Power Systems via a Parallel Particle Swarm Optimization Algorithm

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ABSTRACT Integration of renewable energy sources require an increase in the flexibility of power systems. Demand response is a valuable flexible resource that is not currently being fully exploited. Small and medium industrial consumers can deliver a wide range of underused flexibility resources associated with the electricity consumption in their production processes. Flexible resources should compete in liberalized operation markets to ensure the reliability of the system at a minimum cost. This paper presents a new tool to assist industrial demand response to participate in operation markets and optimize its value. The tool uses a combined physical-mathematical modelling of the industrial demand response and a Parallel Particle Swarm Optimization algorithm specifically tuned for the proposed problem to maximize the profit. The main advantages of the proposed tool are demonstrated in the paper through its application to the participation of a meat factory in the Spanish tertiary reserve market during a whole year using a quarter-hourly time resolution. The enhanced performance of the proposed tool with respect to previous methodologies is shown with these four flexible processes examples, where the maximum available profit obtained in the simultaneous consideration of all different flexible processes is computed. The flexible processes are technical and economically characterized in a way that makes the tool valid for most of the processes in the industry.

INDEX TERMS Demand response, energy resource management, industrial production, end-user tool, parallel particle swarm optimization.

INDICES

t	Time period
g	Flexible process
d	Day of the month
m	Month
r	DR event

SETS

T	Set of time periods on a day in a month m
G	Set of flexible processes
D_m	Set of days in a month
M	Set of months in a year
R_{dm}	Set of DR events on a day d in a month m

PARAMETERS

t_{PTU}	Program Time Unit (h)
ΔP^1_{gdm}	Power reduced during any DR event (kW)
ΔP^2_{rgdm}	Power increased before DR event (kW)
ΔP^3_{rgdm}	Power increased after DR event (kW)
T^{Max}_{gdm}	Maximum time duration of a DR event (h)

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T^2_{rgdm}	Preparation time of a DR event (h)
T^3_{rgdm}	Recovery time of a DR event (h)
T^{Min}_{gdm}	Minimum time between DR events (h)
T^E_{gdm}	Recovery time from previous day event (h)
T^{ava}_{tgdm}	Availability of a DR event
T^{IA}	Notification time in advance (h)
π^{CB}_{tdm}	Price of the capacity band (€/kW)
π^{ED}_{tdm}	Price of the energy delivery (€/kWh)
π^{e}_{tdm}	Price of the consumed electricity (€/kWh)
CF_g	Investment cost of a DR process (€)
CV_{gdm}	Variable cost of a DR process (€/h)
E^{Max}_{gdm}	Maximum number of DR events
D^{Max}_{gdm}	Maximum duration of all DR events (h)

AUXILIARY VARIABLES

S_{tgdm}	Binary to express the start of a DR event

DECISION VARIABLES

A_{rgdm}	Starting time of a DR event
D_{rgdm}	Duration of a DR event

I. INTRODUCTION

Integration of Renewable Energy Sources (RES) to generate electricity has become a global priority. Renewable Energy Sources (RES) represent a key measure to reduce CO_2 emissions by replacing fossil fuel combustion with renewable electricity production. Nevertheless, RES are unpredictable, not dispatchable and present large variabilities in their generation profile due to their reliance on natural resources. This variability creates a major issue for traditional power systems and the security of supply. To overcome generation and consumption mismatches with massive integrations of RES, power systems will require three major changes: network reinforcement, deployment of storage and untapping demand response resources [1]. These actions will allow power systems to increase their flexibility and integrate a larger share of RES without jeopardizing their security [2].

Demand Response (DR) can be defined as changes in the use of electricity of end consumers from normal patterns to respond with economic incentives or price changes [3]. The scientific literature agrees that unlocking DR benefits both consumers and the power system due to its faster and more reliable response [4]–[7]. DR can also provide ancillary services in a fast and reliable way in comparison with conventional generation. In this sense, the European Clean Energy Package launched in 2016 established the foundations to unlock the potential of DR in Europe. The European Commission (EC) estimates a demand flexibility potential of 100 GW increasing up to 160 GW in 2030.

The industrial sector represents around of a third of the World's electricity consumption and it is the fastest growing energy demanding sector [8]. However, most of industrial consumers do not use their flexibility to obtain an additional income in order to reduce their energy cost, especially in the case of small and medium-sized enterprises (SMEs). Despite the existence of some DR programs in several countries, this resource is currently used below its potential [5]. This is related to the complexity and uniqueness of the underlying specific production processes of industry [6], [9]. Nevertheless, previous studies keep stating how industrial DR can provide significant benefits not only to the power system as a whole, but also to DR providers [10]. Moreover, different studies show how SMEs can deliver a large variety of flexible resources to the power system [11], especially through aggregators [2]. However, to facilitate the participation of SMEs, it remains essential to develop and make available analysis tools to industrial consumers and other agents such as aggregators or Virtual Power Plants (VPP). Clear analysis and data can optimize the potential profit associated with the use of their flexible resources and can help the industrial sector to participate in DR programs.

In [12], the authors present a tool for simulating the participation of industrial consumers in operation markets. This tool presents an adequate flexibility characterization of industrial processes. It considers all the technical and economic parameters associated with flexible processes, including their impact on the electricity supply cost [13]. The tool deals with flexible processes that must return to their normal conditions just after a DR event occurs to avoid any problem in the production process. The characterization considers the production experts' recommendations to avoid any impact on the final product or on the production performance. Other methods and tools coordinate both production schedule and DR actions in the daily energy planning of specific types of factories [14], [15]. However, these methods need essential data for companies associated with their productive know-how. This knowledge sharing makes companies extremely reluctant to cooperate and hence blocks the use of their flexibility.

In contrast, the inputs of the abovementioned tool were defined to avoid the provision of critical information of companies, trying to ease companies' collaboration. The weak point of the presented tool is the incapability to guarantee the maximum possible profit of using flexible processes [12]. The absence of any optimization algorithm does not allow the tool to capture all the benefits associated with load shifting and market participation. Therefore, it is necessary to choose on a daily basis, for each flexible process, the most profitable time periods to offer flexibility in reserve markets.

As presented in [12], [13], the flexibility of industrial processes has a complex response with several links between decision variables and intermediate dynamic information. This condition makes it difficult to achieve the formulation of the required optimization algorithm as a linear problem without altering its original features. To overcome this issue, we have selected a metaheuristic approach to maintain all the characteristics of a parametrized industrial process. Metaheuristic approaches are a valid alternative and a promising method to solve this type of optimization problem [16], [17], since they allow us to include all the links between variables without compromising computability.

Among the different metaheuristic methods, we selected the Particle Swarm Optimization (PSO) algorithm due to several positive features. Authors use it to solve electrical engineering problems, it can solve nonlinear problems, it has a high computation efficiency, it is robust and it can be easily adapted to solve any optimization problem [18].

Particle Swarm Optimization (PSO) is a nature-inspired technique developed by Eberhart and Kennedy [19]. In contrast with other genetic algorithms, each particle establishes its new position based on its own previous experience and those of its neighbors. The particle i at iteration d has a position defined by an n-dimension vector $x_{id} = (x_{id1}, x_{id2}, \ldots, x_{idn})^T$ and particles' velocity is another n-dimension vector $v_{id} = (v_{id1}, v_{id2}, \ldots, v_{idn})^T$. The parameter p_{id} shows the best visited position $(p_{id1}, p_{id2}, \ldots, p_{idn})^T$ and p_{gd} represents the particle that had the best result of the swarm at iteration d. After a proposal to improve exploitation made by Shi and Erbehart [20], the velocity and position of the resulting particles commonly applied is:

$$v_{i(d+1)} = w * v_{id} + c_1 r_1 (p_{id} - x_{id}) + c_2 r_2 \left(p_{gd} - x_{id}\right) \quad (1)$$

$$x_{i(d+1)} = x_{id} + v_{i(d+1)} \quad (2)$$

where the characteristic parameters are inertia weight (w), the cognitive and social scaling parameters (C_1 and C_2) and random numbers from a normal distribution (r_1 and r_2), these parameters must be specifically tuned for solving the targeted optimization problem.

Based on a real meat processing factory, the tool optimizes and evaluates the participation of four flexible processes (drying, maturing, freeze storing and slicing) in the Spanish tertiary reserve market. The operation results and the cost-benefit analysis involved largely improve the solution obtained with the previous tool [13], which used a margin of profit to decide whether or not to perform a DR event.

The optimization method included in the tool for the participation of industrial consumers in operation markets presented in this paper provides two main contributions to the existing literature:

- A new tool for evaluating the participation of flexible consumers in operation markets. The proposed solution respects the mathematical complexity of the original problem and optimizes the consumer profit through a tailored Parallel Particle Swarm Optimization (PPSO) algorithm. Furthermore, we applied it to a real case, and the results obtained validate the profitable participation of flexible processes of SMEs in reserve markets and the efficiency of a PPSO algorithm to model electrical engineering problems.
- A new mathematical codification of decision variables related to physical parameters of DR events in matrix format. This codification replaces the classical binary representation. The selected parameters are the starting time and the duration of each DR event, which allow movement from a non-linear binary problem to a non-linear integer problem.

The rest of the paper presents the following organization: Section 2 describes the problem description and mathematical approach of the problem. Section 3 describes the PSO algorithm and presents how it is tuned for this problem. Section 4 shows a real case application. Finally, Section 5 summarizes the main conclusions.

II. PROBLEM DESCRIPTION AND MATHEMATICAL APPROACH

This section presents the problem and mathematical descriptions. Subsection A briefly describes the discussed problem. Subsection B deals with the decision variables and other parameters involved in the proposed optimization problem. Subsection C presents the objective function to be maximized and subsection D enumerates the constraints that apply in the calculation process.

A. PROBLEM DESCRIPTION

Flexibility is going to be essential in future power systems and demand side management will be a key part of it. These resources will participate under competition in operation markets. SMEs can offer their demand flexibility to the system in a cost-effective way, but they tend to lack the technical and human resources to effectively offer it. There is a need to assess how consumers could maximize the benefits associated with the participation of this flexibility based on technical and economic parameters. These parameters include power demand profiles, technical restrictions of flexible processes (maximum duration of reduction and minimum time between them), power available for flexibility (capacity band), reserve market price and electricity supply price. It is also important to prepare these analyses for future changes such as future quarter-hourly markets and contractual restrictions. In this sense, the tool aims to solve this problem and optimize the potential profits of providing the flexibility of SME's processes in reserve markets and at the same time shifting electricity usage to periods when electricity is cheaper.

B. DESCRIPTION OF THE VARIABLES

To optimize the participation of DR processes in reserve markets the decision makers need different parameters. First, the energy delivery ($\boldsymbol{\pi^{ED}_{tdm}}$) and capacity ($\boldsymbol{\pi^{CB}_{tdm}}$) prices of the involved reserve market for the evaluation period. Second, the power reduction that a DR event may imply during, before and after the events. Third, the electricity prices ($\boldsymbol{\pi^{e}_{tdm}}$) associated with the flexible consumer's electricity supply contract. Fourth, the initial investment ($\boldsymbol{CF_g}$) to adapt an industrial flexible process to participate actively in reserve markets. Fifth, the variable cost ($\boldsymbol{CV_{gdm}}$) associated with the implementation of flexibility.

The main features to characterize a flexible process are illustrated in Figure 1. Based on the tool and technical

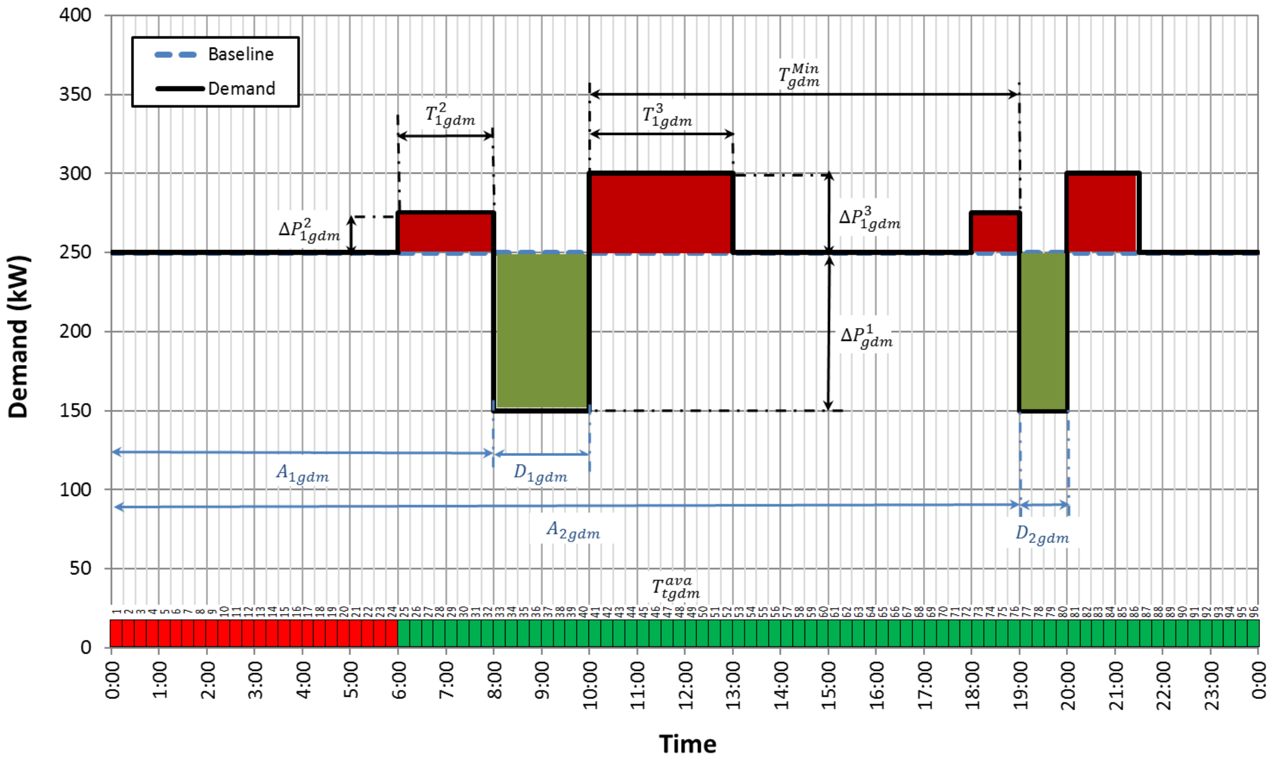

FIGURE 1. Parameters' description of a DR event.

requirements previously developed by authors in [12], the figure shows the power variations during, before and after a DR event, as well as their timings. Following the methodology illustrated in [14], the parameters of each process are characteristic for each month of a year considering the particularities of each process, the type of day and the potential seasonality linked to the effect of external weather conditions or the variations in production. This allows us to obtain the maximum power capacity to offer ($\boldsymbol{\Delta P_{gdm}^{1}}$), the maximum duration of a DR event ($\boldsymbol{T_{gdm}^{Max}}$) and the minimum time between two consecutive DR events ($\boldsymbol{T_{gdm}^{Min}}$).

The power required during the preparation ($\boldsymbol{\Delta P_{rgdm}^{2}}$) and recovery ($\boldsymbol{\Delta P_{rgdm}^{3}}$) periods of a DR event depends on the duration of the event, type of day and flexible process, as well as the month. Consequently, a set of formulas describe how these parameters vary according to the mentioned variables, but all of them depend on the duration of each specific DR event. This feature provides the mathematical formulation enough flexibility to optimize different types of nonlinear responses. In the same way, similar restrictions apply to the duration of the preparation ($\boldsymbol{T_{rgdm}^{2}}$) and recovery ($\boldsymbol{T_{rgdm}^{3}}$) periods, as shown below:

$$\boldsymbol{\Delta P_{rgdm}^{2}} = f\left(\boldsymbol{D_{rgdm}}\right) \tag{3}$$

$$\boldsymbol{T_{rgdm}^{2}} = f\left(\boldsymbol{D_{rgdm}}\right) \tag{4}$$

$$\boldsymbol{\Delta P_{rgdm}^{3}} = f\left(\boldsymbol{D_{rgdm}}\right) \tag{5}$$

$$\boldsymbol{T_{rgdm}^{3}} = f\left(\boldsymbol{D_{rgdm}}\right) \tag{6}$$

Therefore, the dependency among all these variables causes a nonlinearity in the optimization process which makes it impossible to use linear programming algorithms without modifying the proposed formulation.

The optimization of a flexible process occurs daily considering the results from the previous day. Regarding decision variables represented in Figure 1, two types of variables define a DR event, $\boldsymbol{A_{rgdm}}$ and $\boldsymbol{D_{rgdm}}$. $\boldsymbol{A_{rgdm}}$ holds the number of the period when the event starts, while $\boldsymbol{D_{rgdm}}$ represents the duration of the event expressed as the number of time intervals. Moreover, $\boldsymbol{S_{tgdm}}$ is an auxiliary binary variable that indicates the start of a DR process.

C. OBJECTIVE FUNCTION

The objective function considers the consequences of the participation in the reserve markets to maximize the industrial consumer's performance. The first term of the objective function relates to all income obtained for the participation in the market. This participation can provide revenues associated with both capacity and energy delivery. The second term represents the variable costs which the customer incurs for participating in the market. The final three elements characterize the shifts in electricity consumption. While the reduction during the event generates a net profit, the increase of electricity consumed for preparing and recovering of the event has a net cost.

$$\begin{aligned} Max & \left[\sum_{r}^{R_{dm}} \left(\sum_{t=A_{rgdm}}^{t=A_{rgdm}+D_{rgdm}-1} \left(\left(\pi_{tdm}^{CB} + \pi_{tdm}^{ED} * t_{PTU} \right) \right. \right. \right. \\ & \left. * \Delta P_{gdm}^{1} - CV_{gdm} * t_{PTU} + \pi_{tdm}^{e} * \Delta P_{gdm}^{1} * t_{PTU} \right) \\ & - \sum_{t=A_{rgdm}-T_{rgdm}^{2}-1}^{t=A_{rgdm}-1} \pi_{tdm}^{e} * \Delta P_{rgdm}^{2} * t_{PTU} \\ & \left. \left. - \sum_{t=A_{rgdm}+D_{rgdm}}^{t=A_{rgdm}+D_{rgdm}+T_{rgdm}^{3}} \pi_{tdm}^{e} * \Delta P_{rgdm}^{3} * t_{PTU} \right) \right] \end{aligned} \tag{7}$$

The objective function applies to each flexible process ($\forall g \epsilon G$) every day during a whole year ($\forall d \epsilon D_m, \forall m \epsilon M$) in chronological order, considering the result of the previous day, the availability of the reducible power and the market prices one day ahead.

D. CONSTRAINTS

The participation of the industrial consumer in the reserve market needs to fulfill the physical constraints of the processes, expert's recommendations and some economic constraints decided by the consumer. First, the duration of any event must be shorter than its technical time restriction.

$$D_{rgdm} \leq T_{gdm}^{Max}, \quad \forall r \in R_{dm}, \quad g \in G, \ d \in D_m, \ m \in M \tag{8}$$

Consecutive events must occur respecting the minimum time between events. Therefore, the first event of the day will have to consider the last event of the previous day, the rest of them will consider the minimum duration between events, while the last one will have to occur inside the day d.

$$A_{1gdm} - T_{1gdm}^{2} \geq T_{gdm}^{E}, \quad \forall g \in G, \ d \in D_m, \ m \in M \tag{9}$$

$$A_{(r+1)gdm} \geq A_{rgdm} + D_{rgdm} + T_{gdm}^{Min}, \quad \forall r \in R_{dm}, \ g \in G, d \in D_m, \ m \in M \tag{10}$$

$$A_{(r+1)gdm} \geq A_{rgdm} + D_{rgdm} + T_{(r+1)gdm}^{2} + T_{rgdm}^{3}, \quad \forall r \in R_{dm}, \ g \in G, d \in D_m, \ m \in M \tag{11}$$

$$1 \leq A_{rgdm} \leq T_d - D_{rgdm}, \quad \forall r \in R_{dm}, \ g \in G, d \in D_m, m \in M \tag{12}$$

On each day, a maximum number of DR events per process (E_{gdm}^{Max}) and their total duration D_{gdm}^{Max} is set before starting the calculation process, considering consumers' preferences and market rules.

$$\sum_{t}^{T} S_{tgdm} \leq E_{gdm}^{Max}, \quad \forall g \in G, d \in D_m, \ m \in M \tag{13}$$

$$\sum_{r}^{R_{dm}} D_{rgdm} \leq D_{gdm}^{Max}, \quad \forall g \in G, d \in D_m, \ m \in M \tag{14}$$

The reducible power of each flexible process is available during a specific period on a day d in a month m, and hence the process is not able to deliver the reducible power outside of this period.

$$1 \leq T_{tgdm}^{ava}, \quad \forall t \in \{A_{rgdm}, \ A_{rgdm} + D_{rgdm} - 1\}, \quad \forall r \in R_{dm}, g \in G, d \in D_m, m \in M \tag{15}$$

It is important to highlight that metaheuristic algorithms do not work directly with constraints, and hence it is necessary to include a penalty in the objective function if the solution is not a feasible solution of the problem.

III. PSO'S PARAMETER ADJUSTMENTS

Metaheuristic algorithms greatly depend on the adjustment of certain parameters to ensure efficient optimizations. It is necessary to carry some tests to tune the algorithm. Damping factor, inertia coefficient, cognitive and social scaling parameters (C1 and C2 respectively) are the main adjustment parameters in the PSO algorithm. Additionally, two other parameters have been studied to solve the problem described above:

- Percentage of particles without movement (stop criterion). This parameter expresses the number of particles with a zero-velocity vector in an iteration. Meaning that this swarm has reached the maximum in the iteration and allowing us to avoid unnecessary iterations. Tuning this parameter aims to reduce calculation time.
- Percentage of initialized particles inside the feasible solution space. Due to the nature of the presented problem, particle initialization highly correlates with the probability of finding a global maximum as a problem solution. To improve it, a loop ensures a certain number of initialized particles inside the feasible solution space.

Different tests with real data of energy and market prices have determined the adjustment of these parameters in four flexible adjustment processes. Each process has a different correlation between event duration and duration of recovery period. In this sense, process 1 has no recovery period, but it has a cost of impact on the productivity of the process. Processes 2, 3 and 4 have respectively a recovery period of three, two and one times the duration of the event.

The next subsections present and discuss the obtained results for each different test. At each comparable configuration, 100 tests determined the optimal value depending on its success rate, defined as the finding of a global maximum of each process and the total (previously calculated using deterministic methods). This analysis also considers other parameters such as the total daily profit, the successful first iteration and calculation time.

All the tests performed in this section considered the following default values: each swarm has 100 particles, the cognitive and social scaling parameters are equal to 2, social

TABLE 1. Cognitive scaling parameter sensitivity analysis.

C1	2	1,75	1,5	1	0,5
Process 1	55%	51%	39%	39%	37%
Process 2	69%	64%	50%	40%	25%
Process 3	54%	59%	41%	25%	11%
Process 4	53%	63%	59%	35%	22%
Total	11.0%	11.0%	8.0%	2.0%	0.0%

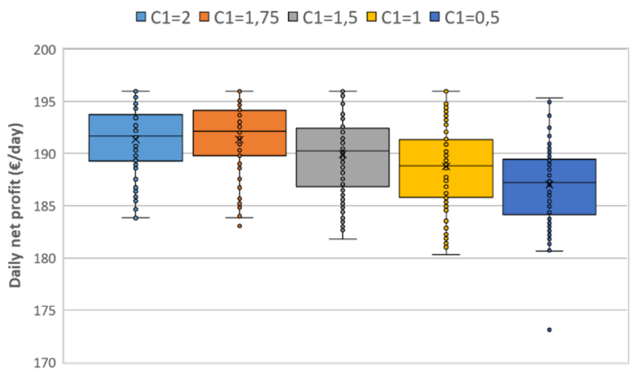

FIGURE 2. Daily net profit with respect to C1.

TABLE 2. Social scaling parameter sensitivity analysis.

C2	2	1,75	1,5	1	0,5
Process 1	55%	50%	47%	17%	2%
Process 2	65%	54%	31%	27%	1%
Process 3	55%	40%	22%	18%	1%
Process 4	66%	59%	33%	19%	1%
Total	11.0%	6.0%	1.0%	1.0%	0.0%

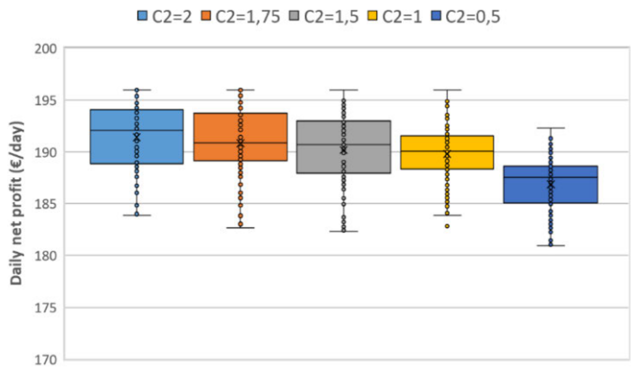

FIGURE 3. Daily net profit with respect to C2.

TABLE 3. Cognitive & social scaling parameter sensitivity analysis.

C1 & C2	2	1,75	1,5	1	0,5
Process 1	50%	50%	28%	3%	1%
Process 2	57%	58%	17%	8%	1%
Process 3	61%	37%	20%	5%	1%
Process 4	70%	46%	21%	4%	1%
Total	9.0%	3.0%	1.0%	0.0%	0.0%

inertia coefficient value is 1 with a damping factor of 0.99, the number of initialized particles in the feasible region and the percentage to stop the algorithm are both 100% and the maximum iterations are 500.

A. COGNITIVE AND SOCIAL SCALING PARAMETERS

Kennedy *et al.*, state that the sum of both cognitive and social scaling parameters should be a value close to four [21]. Nevertheless, in a previous work [19], the same author did some testing and concluded that the social scaling parameter tends to increase the probability to get caught in a local maximum. Therefore, he proposed a solution based on the asymmetry of the components, giving more weight to the cognitive component.

Regarding these premises, it is necessary to adjust both parameters considering that the feasibility space of the solutions is unknown. A sensitivity analysis varying these coefficients from 0.5 to 2 showed the success rate and the dispersion of the total net profit. The results presented in TABLE 1 validate how better results arise from setting the cognitive scaling parameter to 2 and 1.75, obtaining for both a total success rate of 11%.

In FIGURE 2, a box and whisker plot represents the daily net profit for each calculation. This representation shows how with larger values of the cognitive scale parameter (2 and 1.75), the simulations present higher medians and smaller dispersion. In conclusion, these values provide better simulating results. The maximum daily net profit is 195.96 €/day. For the case of C1 equal to 2, the median value is 191.7 €/day with a standard deviation of 3.27 €/day, while the median value for C1 equal to 1.75 is 191.2 €/day with a standard deviation of 3.42 €/day.

TABLE 2 shows how the social scaling parameter (C2) is more influential in the success rate than C1. Smaller values of C2 considerably reduce this rate. Therefore, the best value for C2 will be 2, which provides an average success rate of 11%.

FIGURE 3 represents the same box and whisker plot for C2. As well as for C1, higher values (2 and 1.75) present higher medians and smaller dispersion. These values provide better simulating results. For the case of C2 equal to 2, the median value is 191.9 €/day with a standard deviation of 3.42 €/day, while the median value for C2 equal to 1.75 is 191 €/day with a standard deviation of 3.32 €/day.

The last analysis of this subsection considers a matched variation of both C1 and C2 parameters to see the effect of their reduction. The obtained results are clearer, and the algorithm obtains the best adjustment if both scaling parameters are set in 2. Table 10 shows an average success rate of 9%, while setting both at 1.75 will diminish it to 3%.

However, the variation between 2 and 1.75 does not affect the total profits. As can be seen in FIGURE 4 for the case of C2 equal to 2, the median value is 191.3 €/day with a standard

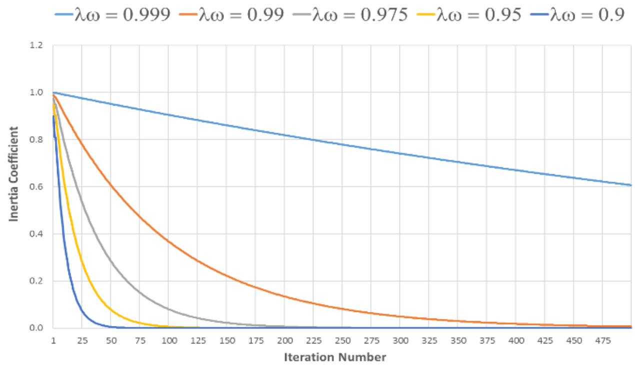

FIGURE 4. Inertia coefficient evolution.

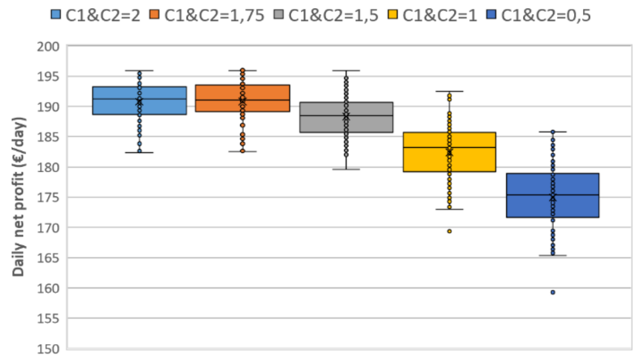

FIGURE 5. Daily net profit with respect to C1&C2.

TABLE 4. Computational time sensitivity analysis.

Time (s)	2	1,75	1,5	1	0,5
C1	2.23	2.24	2.25	2.26	2.33
C2	2.23	2.24	2.25	2.25	2.14
C1&C2	2.22	2.25	2.24	2.26	2.07

TABLE 5. Dumping factor parameter sensitivity analysis.

λ_ω	0,999	0,99	0,975	0,95	0,9
Process 1	55%	65%	50%	58%	51%
Process 2	72%	59%	64%	69%	61%
Process 3	58%	65%	55%	56%	49%
Process 4	61%	66%	50%	59%	60%
Total	14.0%	19.0%	4.0%	14.0%	6.0%

deviation of 3.41 €/day, while the median value for C2 equal to 1.75 is 191 €/day with a standard deviation of 3.41 €/day. Showing that not much difference in the result is observed for this problem.

Finally, TABLE 4 shows the different time values for each simulation. It can be concluded that varying these paraments does not affect the computational time.

Regarding the different values obtained and following the recommendations of Kennedy *et al.* [21], both cognitive and social scaling parameters were set at 2 for the simulations in the case study.

B. DAMPING FACTOR

The first version of the PSO algorithm did not include this coefficient [19], which was included afterwards by its authors [20]. The damping factor tries to balance the exploration of possible optimums and the capacity of the particles to converge into a solution. Shi and Eberhart [22] stated that large inertia coefficients enhance the global search of solutions, while a smaller ones improves local search. Many authors have tried to find the best dynamic adjustment of this coefficient.

A comparison of different strategies to dynamically obtain this coefficient occurs in [18]. The results of this study show that the better strategies to obtain the minimum error are "Constant Inertia Weight" and "Linear decreasing Inertia Weight", while the least average error can be obtained with "Chaotic Inertia Weight". Nevertheless, the presented algorithm uses a different controlled inertia weight. In this case, a constant damping factor multiplies the inertia coefficient in each iteration as shown in Eq (16).

$$\omega_{i+1} = \lambda_\omega \omega_i \tag{16}$$

This method provides different ways to dynamically modify the inertia coefficient depending on the selected damping factor. Some authors propose a damping factor of λ_ω equal to 1, but Kalivarapu *et al.* [23] propose a damping of 0.95 as the optimal. The use of different damping factors explores the best strategies to obtain the inertia coefficient in the presented problem. FIGURE 4 shows the evolution of the inertia coefficient at each iteration applying different damping factors.

TABLE 5 shows the best damping factor with a value of 0.99, which provides a success rate of 19%. However, process 2 has long recovery periods and the best damping factor for it resulted in 0.999. This shows an interesting research point to determine why some processes are better suited for different damping factors.

In FIGURE 6 a box and whisker plot represent the daily net profit for each damping factor. For all cases the median and the standard deviation values are very similar. Therefore, we select a value of λ_ω equal to 0.99 with a median value of 192 €/day and a standard deviation of 3.58 €/day. As in the case of cognitive and social scaling factors, no meaningful computational time differences exist between damping factors.

C. INITIALIZED PARTICLES WITHIN THE FEASIBLE ZONE

Aiming to reduce the computational time of each simulation, we performed an analysis of each of the described tests dividing the algorithm in two parts. First, the algorithm initializes the particles. Then, the algorithm performs an iterative process to find a global maximum that ends after reaching the maximum number of iterations or other stop criteria.

This process of analysis showed that simulation consumed 60% of the time in the loop for initializing the particles in the

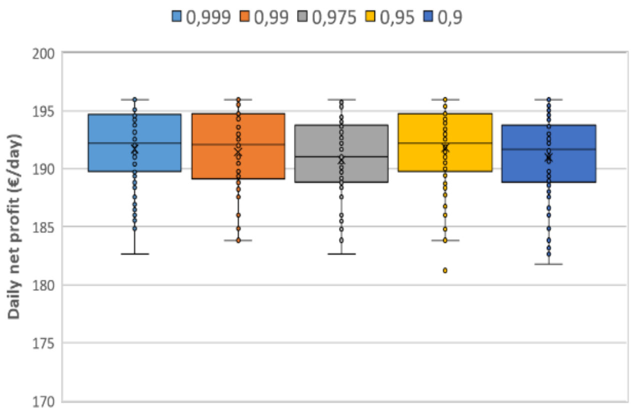

FIGURE 6. Daily net profit by damping factors.

TABLE 6. Particle initialization sensitivity analysis.

Initialization	100%	75%	50%	25%	10%
Process 1	51%	62%	54%	49%	55%
Process 2	68%	68%	59%	53%	58%
Process 3	55%	60%	49%	45%	47%
Process 4	68%	58%	60%	54%	58%
Total	14.0%	14.0%	4.0%	5.0%	7.0%

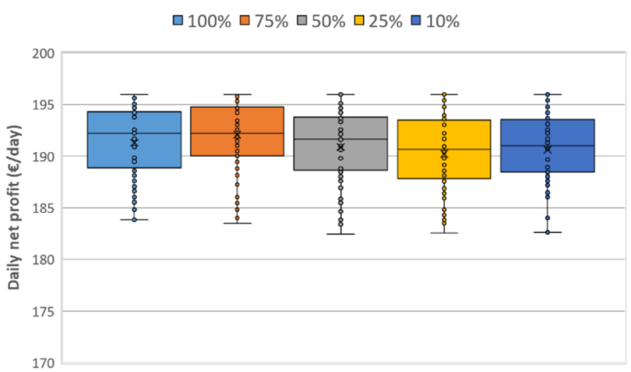

FIGURE 7. Daily net profit respect initializations.

feasible zone. TABLE 6 shows how less initialized particles reduce successful cases. This might seem obvious. However, a closer analysis shows how passing from larger rates of initialized particles to lower rates does not always imply a reduction in the total number of successful cases. This might occur because the proposed value of the initialized particles fixes the lower limit but more particles than the proposed number can be inside the feasible solution space.

FIGURE 7 shows the different studied parameters. Initializing 100% or 75% of the particles in the feasible solution space achieves a median daily profit of 192.2 €/day and standard deviation of 3.41 €/day and 3.21 €/day respectively. The rest of the options had values below these numbers. Therefore, the rest of the options are only recommended to be used when computational cost is a priority.

TABLE 7. Average particle initialization calculation time.

Initialization	100%	75%	50%	25%	10%
Process 1	4.01	3.55	3.18	2.73	2.45
Process 2	9.15	7.37	5.56	3.92	3.00
Process 3	8.72	6.99	5.36	3.90	2.94
Process 4	4.05	3.61	3.20	2.77	2.51
Total	25.92	21.53	17.31	13.32	10.90

TABLE 8. Inactive particles sensitivity analysis.

Inactive P.	25%	50%	75%	90%	100%
Process 1	49%	55%	52%	60%	48%
Process 2	46%	68%	72%	67%	68%
Process 3	38%	54%	51%	52%	55%
Process 4	60%	53%	54%	64%	65%
Total	6.0%	8.0%	3.0%	13.0%	9.0%

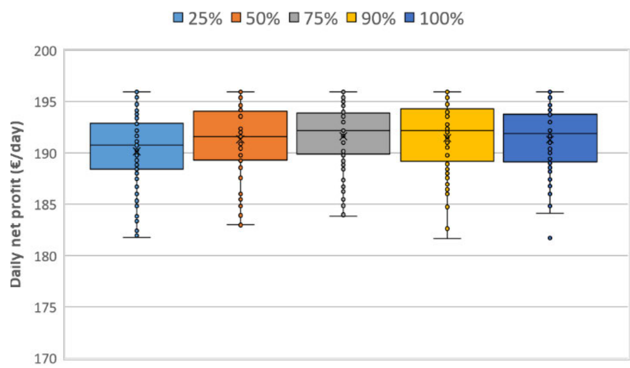

FIGURE 8. Daily net profit with respect to Inactive particles.

TABLE 7 shows the different computing average times for the different processes, as well as the sum of all of them. In this respect, minor reductions in accuracy reduce the computational time. This can help and speed up complex models. In this case, 100% of initialized particles ensure the reliability of the results.

D. INACTIVE PARTICLES

As previously discussed, we included an additional criterion that revises the particle velocity in each iteration. If the percentage of particles without movement is higher than a set number, the algorithm considers that the search for a global maximum has already finished. TABLE 8 represents the success rate regarding the number of particles that must stop in order to finish the algorithm. If fewer particles need to have a zero velocity to stop it, success rate tends to diminish. However, this does not seem to occur with the percentage of 90%, which has a higher success rate than considering 100% of inactive particles.

The results are completely different when the analysis considers the daily net profit. FIGURE 8 shows how in this case, 75% and 90% of inactive particles present the same median,

TABLE 9. **Inactive particles calculation time.**

Inactive P.	25%	50%	75%	90%	100%
Process 1	1.87s	3.52s	4.25s	4.28s	4.30s
Process 2	6.85s	8.56s	8.67s	8.80s	8.78s
Process 3	6.90s	8.19s	8.15s	8.72s	8.88s
Process 4	1.94s	4.08s	4.22s	4.21s	4.25s
Total	17.57s	24.35s	25.29s	26.01s	26.20s

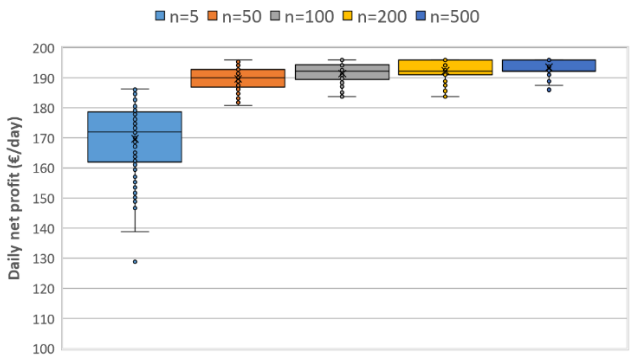

FIGURE 9. **Daily net profit with respect to number of particles.**

higher than the rest of the percentages chosen. Therefore, both values are valid according to these results.

Finally, the analysis of the calculation time for each percentage of inactive particles in TABLE 9 shows that only a significant reduction occurs if the rate is set to 25%. Nevertheless, this value considerably reduces the success rate. After this analysis, it can be determined that a value between 75% and 90% could be selected. Therefore, a value of 90% was chosen according to the presented results.

E. NUMBER OF PARTICLES

The size of the swarm depends on the specific problem solved [9]. Large numbers of particles are not necessary to obtain good quality results. The same study states that 10 particles could be enough to solve almost any problem. However, more complex problems need between 100 and 200 particles to obtain reliable results. Following these considerations, we tested swarms between 5 and 500 particles to show that swarms with more than 200 particles do not improve the results. However, less than 10 particles do not provide optimal results.

TABLE 10 shows success rates regarding the number of particles. In this case, there is a positive correlation between number of particles and success rates. In process 1 not even 500 particles are enough to provide reliable results. Moreover, 500 particles do not guarantee a total success rate but only 64%.

FIGURE 9 shows a similar pattern, the dispersion for larger number of particles does not vary in excess. This data reinforces the idea that populations of 100, 200 and 500 provide similar results. The three samples have the same

TABLE 10. **Number of particles sensitivity analysis.**

n Particles	5	50	100	200	500
Process 1	2%	49%	50%	66%	79%
Process 2	1%	37%	69%	83%	95%
Process 3	1%	40%	55%	70%	92%
Process 4	4%	51%	69%	77%	90%
Total	0.0%	2.0%	14.0%	27.0%	64.0%

TABLE 11. **Number of particles calculation time.**

n Particles	5	50	100	200	500
Process 1	0.18s	2.06s	4.26s	8.48s	21.00s
Process 2	0.39s	4.24s	8.44s	16.89s	41.58s
Process 3	0.37s	4.08s	8.18s	17.05s	41.87s
Process 4	0.19s	2.11s	4.26s	8.61s	21.21s
Total	1.12s	12.49s	25.14s	51.02s	125.65s

TABLE 12. **Parallel computing calculation time.**

PC	200	500	4x200	200	500	4x200
Process 1	66%	79%	99%	8.5 s	21.0 s	10.4 s
Process 2	83%	95%	100%	16.9 s	41.6 s	21.5 s
Process 3	70%	92%	99%	17.0 s	41.9 s	20.8 s
Process 4	77%	90%	100%	8.6 s	21.2 s	10.0 s
Total	27.0%	64.0%	98.0%	51.0 s	125.7 s	62.7 s

median 192.2 €/day, and the standard deviation ranges from 3.44 €/day for 100 particles to 2.40 €/day for 500 particles.

These results show how the probability of obtaining the global maximum of four processes only reached 65% with 500 particles. Moreover, the computational times invested in each simulation showed that this time was proportional to the swarm population in an average (0.25 s/particle) as TABLE 11 presents.

To overcome the computational burden, parallel computing is used by sending an individual problem to each core. Therefore, the premature convergence problem is solved by distributing local maximums in the solution space with different initial positions using Parallel Particle Swarm Optimization [24]. TABLE 12 presents the results obtained with the application of parallel computing with four independent cores. Four independent swarms of 200 particles present much better results than one swarm of 500 particles in half of the total computational time.

To sum up, TABLE 13 shows the final values for the PSO parameters, which will be used in the simulation of the case study.

IV. APPLICATION AND CASE STUDY

We apply the PPSO optimization to the participation of a meat factory in the Spanish tertiary reserve market during a whole year. Selecting this period and factory allows us to compare the novel solution with a profit margin decision making methodology presented in [12].

TABLE 13. PSO optimization values.

Coefficient	Value
C1	2
C2	2
λ_ω	0.99
Initialized P.	100%
Inactive P.	90%
n Particles	200x4

Currently, no market participation is allowed to DR resources in the Spanish operation market apart from the interruptible service for electro intensive consumers, which have to provide at least 5 MW. However, with the European integration directive [25], the Spanish regulator will have to allow demand resources to participate in operation markets in the same conditions as generators. In this regard, most small and medium consumers will rely on the figure of aggregators to participate in these markets [2]. Therefore, simulating a typical DR contract with an aggregator was established with limits for the number of events and total hours per day. In this case study, the total hours per day for which the consumer can be asked to provide flexibility was set at three hours, while the total number of events per day was four. These numbers are only the upper limits for the optimization algorithm, which will calculate the optimal values depending on the profits obtained in each case. On the one hand, four events per day determined an upper limit that the optimized solution never reached for any process in the completely modelled year. In case this appeared as a limiting factor, the tool accepts an increase in the number of events. On the other hand, a maximum value of three hours per day intends not to affect industrial production too much and to be similar to other demand response contracts available in several markets, as stated above.

The different flexible processes of the meat factory were presented in [12] and its main characteristics are summarized in TABLE 14. This factory focuses on the drying of ham and slicing different products. The two other flexible processes correspond to maturing and a controllable freezing store. Each of them provided flexibility based on its characteristics:

-**Drying**: disconnection of the end units in charge of controlling the drying process, while maintaining the temperature and relative humidity between preestablished levels. This process entails a production cost due to possible delays in the industrial process even though no delay could be observed during the different tests performed.

-**Maturing**: disconnection of the end units in charge of maturing the ham. This stage is characterized by larger drying periods.

-**Freezing store**: thermally controllable loads inside the freezing store, which has thousands of tons of frozen product inside it, providing a vast thermal inertia.

-**Slicing**: disconnection of the air handling units in the slicing area allowed by the thermal inertia of the installations.

TABLE 14. DR processes characteristics.

Parameters	ΔP^1_{gdm}	ΔP^2_{rgdm}	ΔP^3_{rgdm}	T^{Max}_{gdm}	T^2_{rgdm}
Units	kW	kW	kW	hour	hour
Drying	283	0	0	2	0
Maturing	102	0	34	3	0
Freezing	70/45$^{(1)}$	0	35/22.5$^{(1)}$	3	0
Slicing	82/36$^{(1)}$	0	82/36$^{(1)}$	1/2$^{(1)}$	0

Parameters	T^3_{rgdm}	T^{ava}_{tgdm}	T^{IA}	T^{Min}_{gdm}	Rec
Units	hour	hour	hour	hour	(2)
Drying	0	24	0.25	4	N
Maturing	9	24	0.25	4	N
Freezing	6	24	0.25	4	N
Slicing	1/2$^{(1)}$	Mo6-Sa6	0.25	4	N

$^{(1)}$ *Summer / Winter*
$^{(2)}$ *If it is possible to postpone the recovery period. Yes and No*

TABLE 15. Electricity tariff prices (€/kWh).

Tariff period	P1	P2	P3	P4	P5	P6
Electricity price	0.12	0.10	0.09	0.08	0.07	0.06

To make the different simulations and compare, we use data from 2013. A flexibility study in the factory provided all the data. The electricity tariff contracted by the factory has 6 different periods with fixed prices, corresponding to a 6.1 contract under Spanish legislation [26]. The following table shows the prices used in the simulation.

Although the studied company had an electricity supply contract based on fixed prices, the simulation tool internally works as if they were quarter-hourly prices, so there is no difference in the search for the maximum daily profit when it works with daily wholesale market prices.

Regarding the different prices in the operation, FIGURE 11 shows the monthly distribution of hourly prices of upwards tertiary energy reserve in 2013 [27], although the tool also works as if they were quarter-hourly prices. This resource was active between 33% and 59% hours during different months. The maximum price reached was 140 €/MWh in January, while the maximum median price was reached in December with 93 €/MWh.

With these parameters, the different PPSO evaluated the results arising from optimizing the daily participation of each one of the four processes throughout the 365 days of a year in the market. FIGURE 10 shows the results obtained with the methodology related to the margin of decision considering 20% profit over the flexibility implementation. This percentage allows us to adjust the minimum offer price for which each flexible process triggers its participation in the market. This rate obtained the best result in the profit margin tool. The larger net profit by energy reduced in a month ascended to 102.3 €/MWh in December, while the annual average is 76.2 €/MWh. This ratio is the difference between incomes

TABLE 16. Main economic indicators summary.

Method of decision making	Flexible process	NPV (€) r = 5%	NPV (€) r = 10%	NPV (€) r = 15%	NPV (€) r = 20%	IRR (%)	DPP (years)
Simulation tool based on margin of decision	Drying	49,707	43,960	39,009	34,712	136%	0.7
	Maturing	3,822	2,362	1,104	12	20%	2.5
	Freezing	6,250	5,056	4,028	3,136	45%	1.7
	Slicing	2,263	1,416	686	52	20%	2.5
	Total	**62,042**	**52,793**	**44,827**	**37,912**	**70%**	**1.3**
Simulation tool based on PPSO	Drying	72,142	64,447	57,819	52,066	189%	0.5
	Maturing	14,837	12,420	10,339	8,532	59%	1.4
	Freezing	11,615	9,956	8,526	7,286	77%	1.2
	Slicing	3,701	2,729	1,891	1,164	30%	2.1
	Total	**102,295**	**89,553**	**78,576**	**69,049**	**108%**	**0.9**

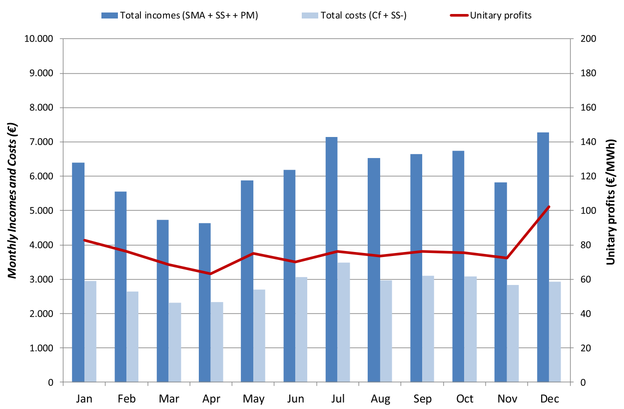

FIGURE 10. Monthly profits without PSO optimization.

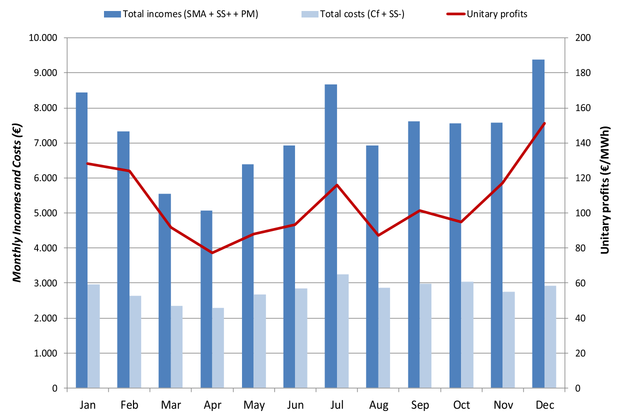

FIGURE 12. Monthly profits with PSO optimization.

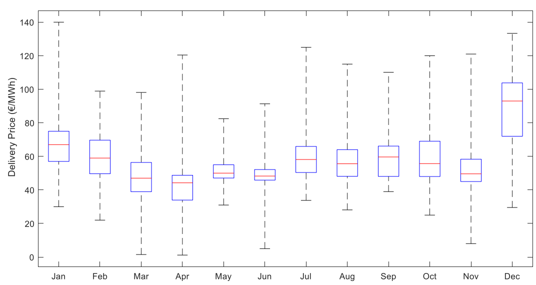

FIGURE 11. Monthly tertiary reserve prices.

and variable costs. In this case, the annual reduced energy is 513.4 MWh, which produces a total profit of 39,123 € after earning 73,525 € and has a total variable cost of 34,402 €.

FIGURE 12 presents the results obtained with the PPSO simulation tool. This figure also shows December as the most profitable month. The net profit per energy reduced rises to 151.4 €/MWh instead of the previous 102.3 €/MWh, while the annual average increases from 76.2 €/MWh to 106 €/MWh. These results present an increase of approximately 40% of the unitary profit compared with the profit of the previous tool. With the PPSO simulation tool, the annual reduced energy is 513.4 MWh, which produces a total profit of 53,905 €after earning 87,452 €and having a total variable cost of 33,547 €. The initial investment costs ($\sum_g^G CF_g$) necessary to prepare the identified processes are approximately 44,500 €. These costs include the study and the flexibility validation, the required monitoring and control equipment, including the modification of existing control systems and other costs on certification processes and documentation.

To show the profitability of industrial consumers participating in tertiary reserve markets, different economic indicators analyzed the participation. The Net Present Value (NPV), Internal Rate of Return (IRR) and the Discounted Payback Period (DPP) are analyzed for a 3-year period. TABLE 16 shows the different values obtained for each process of these indicators. For a typical 10% investment rate (r), the NPV has risen from 52,793 € to 89,553 €, meaning a 70% increase on capital profitability. The values obtained for the IRR show an improvement in all the processes. In total, the IRR has grown from 70% to above one hundred per cent (108%).

With the same discount rate, the DPP of all the processes decreases, reaching in total an improvement from 1.3 years to just 0.9 years. These results exhibit an easy commercial exploitation of these flexible resources by third agents such as Virtual Power Plants or aggregators due to the large profit margins observed.

Paying attention to each individual process, it is important to note that the process with the largest improvement is the one with the largest recovery period, maturing. For a typical 10% investment rate (r), the NPV of this process has risen from 2,362 € to 12,420 € and the DPP has reduced from 2.5 years to 1.4 years, as well as the IRR having grown from 20% to around 60%. This is one of the stronger points of the PPSO simulation tool compared with its predecessor.

The PSO algorithm was implemented in MATLAB from scratch and solved with a machine with 8 GB RAM and Intel(R) Core (TM) i7-7700 CPU clocked at 3.6 GHz with 4 main cores.

V. CONCLUSION

The massive integration of renewable energy sources in power systems requires an increase in the use of flexible resources from both the generation and demand side. These resources will participate, in a competitive context, in operation markets to guarantee the security of supply of the system. Small and medium industrial consumers can offer their demand flexibility to the system in a cost-effective way. However, it is still necessary to develop tools to evaluate and exploit the potential profit associated with the participation of industrial consumers in these markets.

This paper proposes a new simulation tool that maximizes, for a very wide range of multi process flexible industries, the profit obtained throughout the use of flexible demand of industrial processes in operation markets. This tool selects the best daily participation strategy using a metaheuristic algorithm based on PPSO, which allows us to maintain the technical and economic complexity associated with the characterization of demand response of industrial processes. Moreover, the use of a metaheuristic technique also facilitates the inclusion in the optimization algorithm of any complex function linked to flexible process behavior such as the ones related to the preparation and the recovery periods of a DR event shown in the section 2 mathematical approach.

The formulation of the proposed optimization algorithm considers a new codification of the decision variables to move from a non-linear binary problem to a non-linear integer problem, in which the decision variables are the starting time and the duration of each DR event. This codification allows the use of a PSO algorithm that would otherwise be extremely difficult to make use of and facilitates the consideration of the technical constraints in the optimization algorithm associated with flexible resources and restrictions of participating in operation markets.

The article also presents a comparison with a previous advanced tool used to solve the proposed problem in order to validate the solution, by using a multi-process application case in the industry. In this case study, both tools analyzed the participation of a meat factory in the Spanish tertiary reserve market during a whole year using a quarter-hourly time resolution. According to the results of the case study, the new tool can enhance the maximum profit per unit of reduced energy up to 40%, which considerably improves the economic results.

Regarding the results of each individual process, the simulation tool based on PPSO significantly improved the economic indicators associated with longer recovery periods. This is because the previous tool only considered the possibility to reduce the demand at time periods when additional specific payment for reserve services was offered by the system operator. In contrast, the new tool analyzes if it is profitable to reduce the power also depending on the energy prices, even if there is no payment for ancillary services.

The inclusion of the daily optimization algorithm logically results in an increment in the overall simulation time in comparison with the previous tool. Nevertheless, this increment does not represent any restrictive burden to the use of the tool according to its main goal. Moreover, the parallel computing was only applied to the optimization algorithm, and hence the parallelization of other calculation processes of the simulation tool will considerably improve this aspect.

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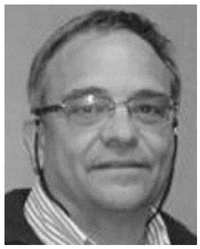

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