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A novel method for eliminating the exponential growth of computing optimal demand response events for large-scale appliances re-scheduling

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ABSTRACT

The electric grid is undertaking a change of paradigm. New requirements such as the high power loads of Electric Vehicles' charging are putting pressure on grids, and the popularisation of the figure of the prosumers, are creating new needs on the management of the system. Although the investment on infrastructure is one of the ways of alleviating the arrival of this new loads, the existence of smart controls, actuators and smart appliances opens also the door for demand modification. The so called Demand Response Events are strategies to reallocate the loads of the consumers, so the power demand is shifted towards times less critical for the grid. Some smart appliances can be considered as *shiftable*. The operation of them can be rescheduled to other times and still provide their services. On this paper we suggest an optimisation methodology consisting on a parallelisation method together with a generic algorithm that would allow an overlooking controller (such as aggregator or DSO) reduce the power peaks even with a large number of devices to control. The research here presented has looked for the smallest group size at which the optimisation is more effectible done in parallel groups rather than on a single large set. With this, we eliminated the exponential growth of the computational effort that the optimisation algorithm would need to do organising all devices in one go. The method achieves a computational time reduction of 80%, and it is only worsening the reduction of peak by 2.8% compared to an optimisation with a complete set.

1. Introduction

The actual energy system is facing the challenge of the continuous growth of electricity consumption. This comes with higher energy needs and a rise in power peaks, that could make the current grids non-adequate to maintain grid stability [1]. Hence, it is crucial to find a solution to maintain the supply quality and the security of the power system. Although investment on electrical grid improvements will continue, the reduction of peaks could be a way to alleviate grid stress. An option to do so, is to involve the final consumer, making them modify their demands, so the synchronous use of appliances is avoid, resulting on a reduction of peaks.

In this context, Demand Response (DR) programs are strategies to achieve peak shaving. To avoid power peaks, end-users are asked to shift loads to off-peak time periods or to reduce consumption on a given time. In exchange, the consumers receive either better tariffs or other incentives [2]. One of the most common classifications of the DR programs are: price-based DR programs, which are based on using a variable price of electricity to change the demand; and incentive-based programs, which are more focused on promoting specific direct actions. On incentive-based programs, a third party, namely the electric utility or the load-serving entity, can call an *event*, i.e. take control of the customer's appliances, and change its operation (including heating, ventilation, and air conditioning (HVAC) systems) on what is called a Demand Response Event (DRE). For what appliances is concerned with respect to DREs, they are classified in the literature into: deferrable, flexible deferrable, curtailable, and critical, but this can be reduced from the point of view of operation into *shiftable*, *non-shiftable* and *controllable* [3]. The flexibility of the appliances is evaluated and, depending on that, a DR event

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can imply the reduction of the consumption if the load was controllable (as on HVAC) or the reallocation of the time of use to another period if it was shiftable. This one is studied on this paper, as it is the most common shiftable loads in dwellings.

Several DR programs have already been designed and applied in the world, but up to now they could not overcome two main issues. The first one lies in the fact that if all the users shift their consumptions together, a new peak will shape [4–6], which is usually called as *rebound-peak problem*. This is crucial, and an important problem that is solved with the methodology here presented. An overarching entity will need to design the shifting of the loads to make sure that the peaks do not appear again somewhere else. Precisely because the re-scheduling has to be done at a rather large scale (dozens of end-user) the decision space of an optimisation would become unfeasibly large, even with the use of heuristics the optimisation would become prohibitive, as the number of variables to be optimised make the decision space grow on an exponential manner. This paper shows a way of eliminating that exponential growth of the decision space.

The other issue goes with people's acceptance: users' comfort is often affected by demand response events. Classical DR programs are mainly based on direct load control programs and interruptible/curtailable load programs [7]. With regard to such interruptible events, some studies demonstrated that users were more willing to subscribe to a DR program if the events were interruptible [8,9]. Data about participants' overriding behaviour is investigated in the literature and the rate of interrupted events reached 39% [10–12] on direct load control of controllable devices. Hence, the design of DR strategies needs to be improved and optimised, to find a balance between energy saving and people's comfort. It is thus necessary to evaluate the impact that the shifting of loads may have on the consumer comfort. Indeed, the authors found a few contributions focused on optimising the shifting of the loads while the impact over the consumer comfort was minimised, mainly because it was not found an optimisation that includes potential consumer comfort degradation under DR strategies. On this paper, real behaviours are used to measure this comfort degradation realistically.

This work is a comprehensive study from a multi-agent perspective on how the optimisation of shiftable loads can be performed, and what the implications are on different objectives that are relevant for the user and for the aggregator/utility. Also, the implications of scalability of the optimisation have been studied and a new way of performing the design of the events, which is scalable is proposed. This paper is in line with recent contributions, focused on developing bi-directional energy trading models to minimise electricity costs and estimate optimal day-ahead bids under certain customer inconveniences, such as thermal discomfort due to interruptible/curtailable load programs [13]. The paper is structured as follow: in Section 2 the state of the art is presented. Section 3 shows the methodology and the algorithm tested, in Section 4 main results are presented. The paper closes with Conclusion, and References. State of the art

When talking about the design of DR programs, the approaches presented in the literature are distinct depending on the work as the topic is faced from various points of view. Also, the approach changes depending on the kind of DR program considered. About DR programs-potential and technologies, an extensive survey is presented in Siano [2]. To contextualise the DR programs' design, in Patnam and Pindoriya [14] an overview of modelling and optimisation of DR algorithms is presented. Besides, differences in the approach to the problem, depending on the context are highlighted (home level, network level, market level) on the work of Patnam and Pindoriya. With respect to the economic implications, Martinez and Rudnick [15] analysed how DR programs' design developed according to territorial market needs. Through lessons learnt from US and European experiences, they highlighted the potentialities that such programs would have in emerging countries. But the design of overarching algorithms that could mandate when to operate certain shiftable loads remains underdeveloped.

Analysing the algorithms used in the literature to design the DR programs, it is possible to distinguish two main objective functions: one cost-based and one power/energy-based. The cost-based are related to the search of minimum cost and/or maximum profit normally on the side of the end user. As an example, Murakami et al. [16] proposed an incentive design method tested with reinforced learning. The optimisation problem is an inverse optimisation, and it is based on the optimised incentive payments to engage consumers, but the users is the one supposed to do the action at the right time considering those incentives. On the other hand, the power/energy-based algorithms are commonly expressed in the form of minimum energy or minimum peak, and often also the objective function related to the maximum comfort. For instance, Islam et al. [17] designed a model to mitigate over electricity generation, a side effect of the diffusion of renewable sources in the electricity grid. The model optimised an electricity demand response program in order to balance demand and supply, but again it assumes that the incentives will take the users to make the actions. Babar et al. [18] proposed an algorithm for load curtailment based on dynamic programming in aggregated demand response program, but the optimisation was done considering the whole cohort to be optimised, what can lead to long computational times when extended to a large number of households. Herath and Venayagamoorthy [19] proposed a scalable framework for DR optimisation, that can be used by the utility to consider how many participants is convenient to include in a same DR program.

With respect to optimisation methods for energy management, the versatility of Genetic Algorithms (GA) made them a good solution for the optimisation of building-related design [20]. An example of application on energy management in buildings is given by Hansen et al. [21] who used GA with Markov chain process to design a sequential decision technique that optimises energy usage. They analysed the response of users to dynamic pricing of electricity, modelling flexible and non-interruptible smart appliances that users are ready to use. They concluded that the energy management system that they designed allowed them to save 30 US dollar on a one month's bill. Pombeiro et al. [22] used GA to search for the best balance between the user comfort and the cost of electricity, demonstrating that GA are capable of optimisating the use of the HVAC also in presence of PV panels and battery systems. Veras et al. [23], applied the GA to the Demand Response optimisation process. They aimed to reduce the energy consumption costs considering as variables the price of the electric energy, the home appliances preferred and the location. In this way they obtained an optimisation model of how to shift the consumptions, avoiding to overload the grid during peak periods. About load shifting in a demand response context, also Pavithra and Priya [24] used GA to optimise savings in cost and peak load reduction. The simulation involved the hourly power demand for different area types (rural, urban and villas area) and the input data was taken from the devices used by the occupants. Regarding self-scheduling in demand response programs, optimisation problems were formulated by Javadi et al. [25,26] in the form of a Mixed-Integer Linear Problem (MILP). They managed to obtain an efficient shifting of consumption that took into account both different energy tariffs and the occupants' comfort, by introducing the discomfort index as a variable of the model. The same authors also considered the cases of the presence of inverter-based HVAC systems [25], the presence of electric vehicles parking lot management systems [27] and the presence of a self-generation asset [25], reformulating the problem for homes that are equipped with photovoltaic panel and battery. This configuration allows to make the most of the shifting potential, and the proposed model calculated the optimal schedules for several case studies. About energy management in microgrids, Mansouri et al. [28] implemented a model to reduce operation cost and emissions in an 83-bus distribution system with 11 microgrids. Several methods were compared, and the best outcomes were obtained with a tri-objective optimisation framework.

Recently, Home Energy Management Systems (HEMS) emerged as a consequence of the demand side smart energy usage. HEMS aims to provide a mutual satisfaction between the utility and customers, considering their comfort preferences as well [29]. However, Tostado-Véliz et al. [30] recently affirmed that some thermal premises (among them thermal comfort), should be relaxed by the HEMS with the aim to achieve other complementary goals. In this way, Kadavil et al. [31] concluded that customers would sacrifice on comfort to attain savings in cost or carbon emissions. To determine a trade-off between energy cost and the user comfort, Rocha et al. [32] proposed a methodology based on the k-means technique to determine a comfort matrix through data obtained from real smart homes. In addition, the term Residential Energy Management Information Systems (REMIS) can be also found in the specific literature, as a class of information system focused on monitoring, analysing or benchmarking residential consumption and energy use [33].

2. Novelty and contributions

The previous section shows the developments on the field. According to them, the authors have seen a research gap in terms of methods to coordinating optimisations at a federated level. There is a large body of literature that shows that the optimisation of operation at the home level, via Home Energy Management System has been investigated in the past. In this paper, we have investigated how to perform optimisation of devices operation at a district level, considering each home a set of decision variables on the optimisation problem. With this research, we identify the number of dwellings that could be optimised independently to convert the exponential growth of the optimisation problem, into a geometrical growth, avoiding with this the curse of dimensionality.

With this work, we contribute to the body of knowledge providing a methodology to optimise the load shifting actions on a district with the aim of reducing the PAR, and with that alleviating the workload of the grid.

On this work, we take into consideration the distorsion that the occupants may suffer due to the modification of the operation of their devices. Although this has been done in the past, the work here presented used validated behavioural models to mimic the stochastic behaviour of a real population. With this, not only we represent real power profiles, we also are capable of quantifying for the first time the impact that the change on operation of certain devices may have over a realistic population with stochastic behaviour (as it happens in the real world).

3. Methodology

There is evidence that Demand Response events will need to be more common in the near future, mainly due to the integration of renewable energy sources into the power grid [34]. The transformation of the energy system towards a fully electric one, and the absorption of part of the transport system are requiring a rethinking on how the grid is used.

With respect to DR programs, one must separate the programs in which pricing is used to produce modifications on the demand, and has a non-trivial market response intermediate step [35], and those in which direct load control is used to modify the operation of certain devices, that are called "shiftable-loads" [3]. This direct control can be carried out thanks to the new devices that exist on buildings and act as gateways [2]. As in [36], our work considered the shiftable loads to be the wet appliances namely dishwasher and washing machine, and Plug in Hybrid Electric Vehicles (PHEVs) as these are the most common to be in dwellings in the following decade. For this work, full knowledge about their consumption has been considered. There are three factors that may affect the decision of re-scheduling of shiftable loads in dwellings. These three factors are:

– Change on cost of electricity after the re-scheduling (to be minimised)

– Distortion on operation, as the amount of time that the appliances operation is delayed or anticipated. (to be minimised)

– Resulting power peak of the district or community (to be minimised)

On this work we try to evaluate the distortion of operation with realistic methods of occupant's behaviour based giving it a more realistic approach for the generation of the loads in terms of power, but also in terms of evaluating the impact to occupants. Fig. 2 shows the framework including the modelling of occupants and their energy use. One may think that it is likely that some of these objectives are conflicting, resulting to the necessity of a trade-off from one another. The optimisations found on the literature to re-schedule the operation of the shiftable devices have in many cases taken the side of the consumer, and the optimisation has been done within the dwelling to minimise cost normally defining it as a knapsack problem. When all consumers receive the same tariffs, this could lead to a movement of the same peak to a different location, resulting on a pernicious effect for the grid, yet losing the revenues due to all consumptions moving to cheaper time slots as said by Dusparic et al. [37]. Dusparic takes into consideration this issue, but no analysis of the conflictivity of the objectives have been found in their or other works of the literature.

Optimising the operation for the grid functioning and for the households to benefit from the re-scheduling would be ideal, but researchers have already identified that these optimisations require large computational times [38,39]. This has been evaluated on our framework and the result of the computational time growth can be seen on Fig. 1. It was seen that the problem really exists. Also, as the decision space increase three dimensions each time we add a new home (corresponding to the three appliances), the number of points that one may need to explore the decision space if we took for example four points for dimension, will have the following formula:

$$S(n) = 4^{3n} \tag{1}$$

With $S(n)$ the number of points to explore the decision space with at least 4 points per dimension, and n the number of homes. The time that will require the algorithm to explore the decision space will grow on the same others as the decision space, as it has been shown on Fig. 1.

With respect to the other objectives of the optimisation of demand response events, Barbar et al. (2013) made an approach to minimise the computational cost of the optimisation of operation, and introduced the concept of consumer inconvenience. The work we present here also considers the consumer inconvenience, and also suggest a way of reducing the computational time of a full optimisation with all agents of the energy community. However, the method described here used a realistic scenario based on agent based modelling with real probability distributions of operation of the shiftable loads what allows to have a detailed measurement of the users distorsion due to the DRE taken from the scientific literature.

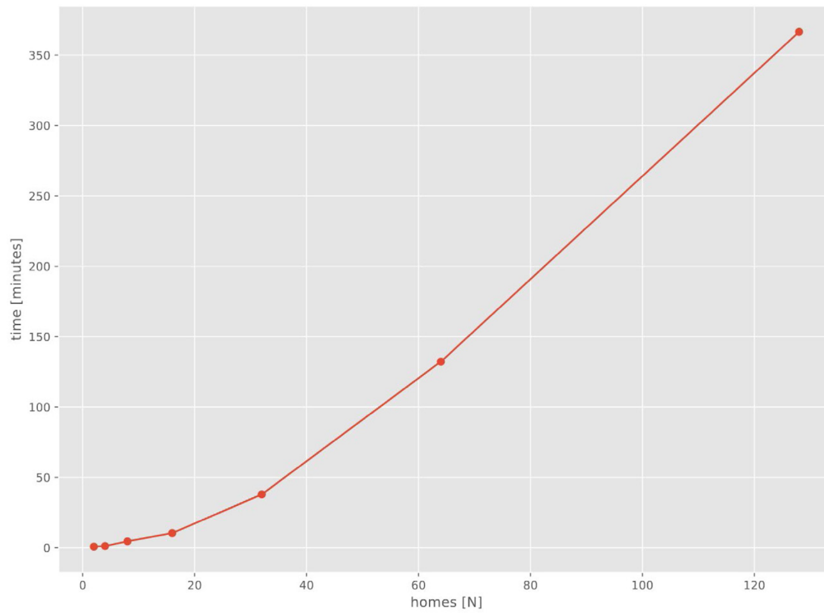

Fig. 1. Fast growing computational times of the optimisation of large scale DRE planning as the number of dwellings increase.

3.1. Realistic synthetic environment

Testing new algorithms to design demand response events on the real world is rather complicated and no option was found to do so by the authors. For our work, and to test a potential method to optimise demand response events, a comprehensive simulator was created that used agent based modelling. To create a realistic demand, each household was modelled with state of the art behavioural models, and with real data from electric equipment. This made the simulating framework as close as a real community as possible. The simulator includes a series of geographic points located in realistic positions to simulate the grid of a neighbourhood. This was considered relevant as it could be necessary for the study of over loading of electric lines on parts of the grid. The arrangements of the nodes of the consumers are mimicking a real neighbourhood. Each one of the consumers have been equipped with a parameter that represents the number of occupants living in the building. With this, and using the algorithms of [40], the simulator can have a realistic profile of occupation. Considering the time series of occupation, the operation of the rest of the appliances was modelled using real probability distributions. A key element of the synthetic testing framework to be valid was to have household electric appliances and giving them realistic consumption profiles. For that, the framework includes realistic profiles of appliances as a time series that depends on the given device. This was taken from real-world data published in the work of Issi and Kaplan 2018. These data provided the power profiles of the appliances included on the simulator.

For the detailed modelling of realistic behavioural profiles, we have created the framework what is represented in Fig. 2. To have realistic profiles the matrices representing the Markov Chains created by Richardson et al. [40] have been implemented as the first section of the framework. After considering a realistic occupation, the probability distributions of wet appliances used by Vellei et al. [41] were used, and a profile of electrical vehicle charging has been added to the framework. The probability distributions of the appliances can be found on Fig. 3.

3.2. Load modelling

For this problem, a simulated load that contains consumption of electrical appliances in several households (depending on the test) has been created in the simulator. In the work at hand, the operation of the washing machine, the dish washer and the EV charger have been considered as the shiftable loads that the optimisation engine could move to modify the demand. These three appliances are located in each one of the homes considered, and therefore, the decision space will have a dimension of n x 3 with n the number of homes.

The problem has been simplified to three "movable" devices, as they have been the appliances considered in most of the literature of this field, but the methodology could work with more appliances in the same way. Each of these appliances has a power profile which represents the power consumed by each of them in the operating time, that is, there is a time series of the power consumed by the appliance over a period of time. In this work, for the first time according to the authors' knowledge those profiles are from real devices and have a sampling period of 5 min [42].

Once this is considered, the objective is to obtain the total sum of all the power profiles of all the users of the system, in other words, when all the power profiles of all the electrical appliances of all the users are added, a time series of the power is calculated. This time series will have a granularity of 15 min and will have a duration of one day. This interval has been chosen as it relates to the ISP slots of the USEF flexibility framework, that is likely to be adopted as a standard of communication for demand response events in Europe [43]. This implies that it will be a time series that has a length of 96 periods of 15 min.

3.3. Problem definition

On the context of the problem at hand, the objective is to minimise the maximum peak, changing the times that users have chosen but without disturbing their comfort too much or offering improvements in the prices of the electricity tariff. In other words, there is a multi-objective optimisation problem: on the one hand, reducing the maximum peaks of the system, and on the other, disturbing the user as little as possible and, finally, minimising the cost of each user.

In order to finish defining the problem, it is only necessary to define the objective functions:

- Peak: the maximum aggregated of the instant power demand for a given solution.

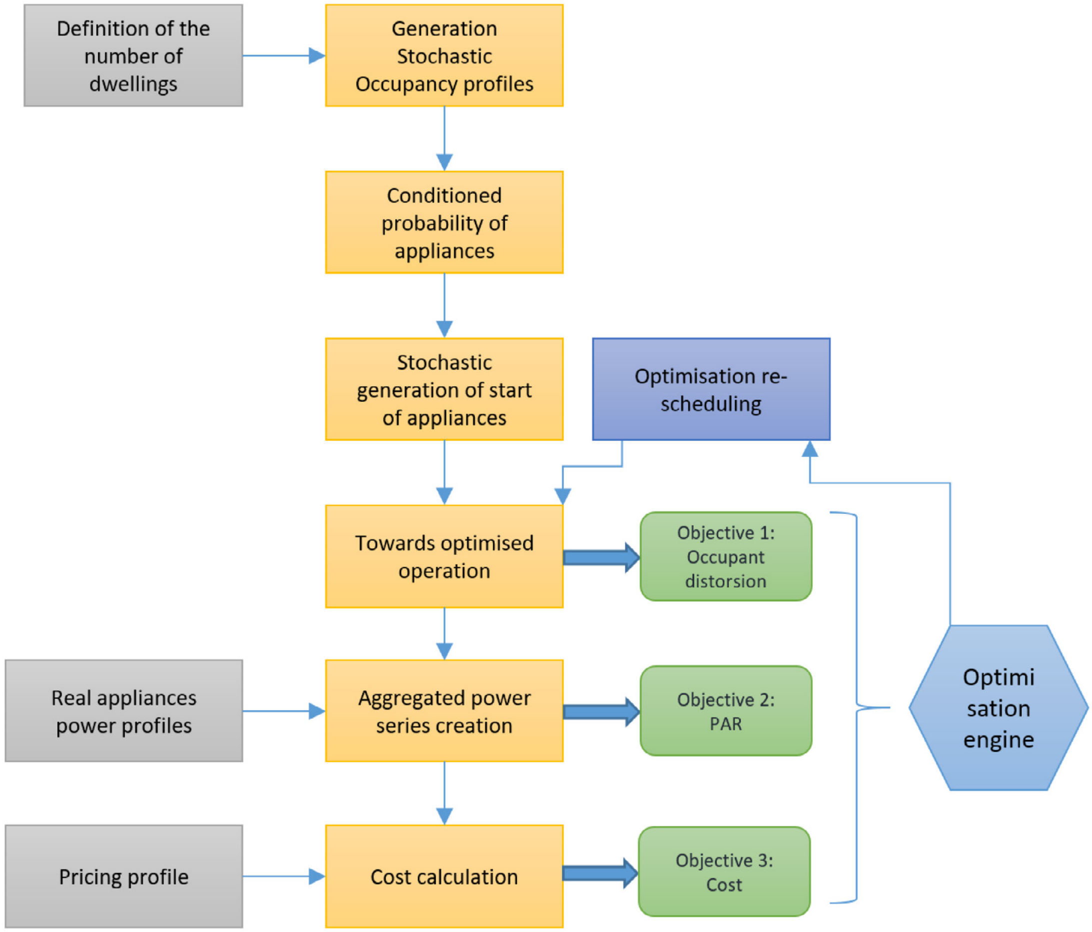

Fig. 2. Flow diagram of the behavioural generation and its connection with the optimisation algorithm.

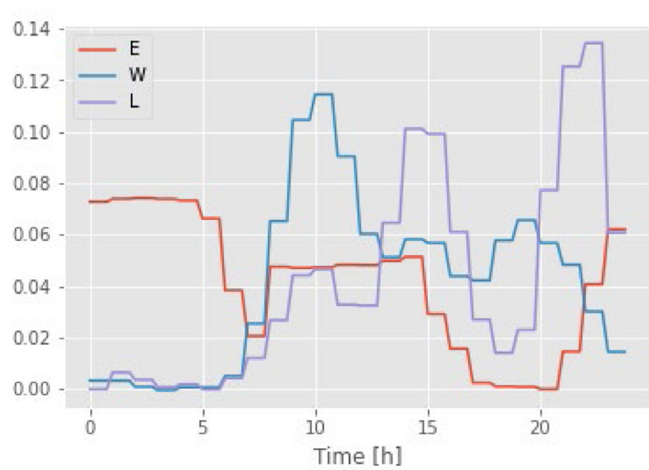

Fig. 3. Probability distribution of the Electric vehicle charging (E), washing machine (W) and dishwasher (L) for a given day.

- Cost: the cost is the overall cost of the electricity for each user.
- Distortion: gives information on how much the use of the electrical appliances of each user is disturbed.

Going further into the price metric, it is necessary to clarify the price per hour. In our case, a real time series that shows the price throughout a day was used. These data have been extracted from omie.es, which provides information about the energy market in Spain. The objective functions are calculated using the solution vectors in the following way:

$$Peak(T', t) = max(Power(T', t))/n \tag{2}$$

$$Cost(T', t) = sum(Power(T', t).C(t) \tag{3}$$

$$Distortion(T') = sum(|T - T'|)/n \tag{4}$$

where T and T' are the appliance power-on timestamps before and after optimisation. Power is the power time series, n is the number of households to optimise and c is the price of power throughout a day.

With respect to the decision variables, they have been defined in the following way. Considering the natural operation of devices given by the realistic models (see Fig. 3), one decision variable is created as the movement in time of the instant of that operation. These variables, will move the start of the appliance to an earlier time or to a later time during the optimisation process.

Once the multi-objective optimisation problem has been defined, there are several ways to solve the problem. Due to the fact that our functions need to be tested for conflictivity, it is necessary to use a resolution method that finds the solutions for all objectives at the same time. A solution to this problem is to use the multi-objective optimisation given by the NSGA II [44]. Although the NSGA-III has already been developed, we decided to use the NSGA- II algorithm is more includes the crowding distance to have a dispersed set of solutions.

Table 1
Description of the algorithm used for the multi-objective optimisation.

Library of the algorithm	pymoo.algorithms.moo.nsga2
Crossover mechanism	Integer simulated binary crossover
Mutation mechanism	Integer probability mutation
Crossover parameter	0.9
Mutation parameter	0.01
Population size	300
Termination criteria	Tolerance
Termination criteria parameter	0.05

A genetic algorithm is a search algorithm based on the mechanics of natural selection. These algorithms make a population of individuals evolve through random actions similar to those that act according to the theory of biological evolution such as genetic mutations and recombination. In addition, they make a selection according to some fitness function that decides which are the fittest individuals who survive and which are the least fit who are discarded.

The objective of this algorithm is to obtain the so-called Pareto front, which is a collection of points obtained by calculating the objective functions for the input vectors in such a way that one of the objective functions is minimised without being disturbed the others. For example, because distortion and peak value are likely to be negatively correlated, reaching the minimum peaks as possible will only be possible by greatly modifying the timestamps of appliances which will result in a distortion metric. The same will happen with the price.

The algorithm works as it follows:

- Appliance data is loaded and the appliance time stamp vector is constructed based on realistic user profiles (agents).
- The decision space is created as the variation of the starting point of operation time of the loads, being multiplied by the number of households with a range that goes within the interval [from - 96 to 96].
- Finally, the parameters of the algorithm are established.

For the implementation of the optimisation a well proven library implemented for Python has been used. The library was implemented with the parameters shown in Table 1.

Once this is established, the algorithm begins to randomly test modifications to the timestamps chosen by the users and calculates, with this new vector, the value of the three functions and makes small modifications that improve the results, in such a way that those that approach the minimum value of the functions will be chosen. At the end of the execution, the Pareto front of the possible solutions that households can take is obtained to either obtain the minimum distortion or the minimum cost, making the electricity company obtain a manageable power profile. Pareto is therefore a set of 3-dimensional vectors (one for each objective function) and its values are values of the objective functions for the vectors that optimise these functions.

On the one hand, the user will be able to choose values of a curve in which their will obtain lower prices in their bill at the cost of increasing the distortion of the timestamps of their electrical appliances, while the electric company will be able to decide how much they want to reduce the power peaks of the electrical network depending on the distortion that this will suppose to the user.

4. Results and discussion

4.1. Relationships between objectives for Demand Response Events design

After a great deal of investigation to find the optimal way of running the NSGA-II so it would work well for the problem at hand, we were able to see that an integer encoding of the algorithm with discretisation of the decision space on intervals of 15 min gave a good convergence on a Pareto front solution for 128 households on a time of 6 h using a i7-10870H with 8 cores and 5.0 GHz and 16Gb of RAM. It was seen that the high redundancy of the decision space, given by the definition of the objective function of the maximal power, gave many of the solutions the same value on this objective function with very different solution vector that gave a very different value on the other objective (the users distortion). This gives a certain proof to the authors on the algorithm selection which is purely heuristic, a gradient-based or other solution-proximity analysis algorithms would have not been able to add value to the search due to the irregularity and non-smoothness of the objective function of the power. The progression of the three objective functions as the algorithms evolves can be seen on Fig. 4 for the multi-objective optimisation of one household using NSGA-II developed by Deb in [44]. It can be seen how the algorithms has a highly exploratory nature, and it ensures that a good dispersion of the solutions is found.

As mentioned before, DREs may lead to peaks occurring on a different time leading to the non-elimination of the peak yet losing the revenue for the utility. It is important to know what happens when the behaviour of the users is realistic and the distorsion effect of the DREs on the shiftable loads is evaluated. The framework used for this work has realistic stochastic behaviours, so it allowed us to have a realistic metric of this user distorsion (named "consumer inconvenience" by Barbar). To evaluate this relationship, the multi-objective optimisation algorithm was used that looks for the Pareto optimal points of the optimisation taking into consideration the three objective functions. This is one of the novelties of this paper, is the consideration of the challenge as a multi-objectives optimisation. In the one hand the peak of the network can be reduced via re-scheduling of certain devices, but on the other hand, it is important that the distortion to the occupants is minimal. It is for this reason that the problem on this research was considered and tackled as a multi-objective optimisation. In multi-objective optimisation, the two objectives are optimised (minimised in this case) simultaneously, giving as the results a set of solutions in which none of them is worst on both objectives to any of the rest. Once the algorithm has selected the optimal compromise, higher level information can be used to decide which solution of the Pareto should be chosen, with the certainty that the solution chosen is going to be optimal for that specific weight between objective one and objective two.

In the case at hand, we run the optimisation of the three objective functions namely the cost, maximum power peak and the average distortion of the user's devices use schedules. This provided a Pareto Front that can be seen on Fig. 5 and that shows how the power peak can be reduced considerable modifying only by an average of around an hour the schedules of the users when the new schedules are defined as the algorithm is suggesting.

The fact that the solution comes on a Pareto Front gives a clear advantage to aggregators and utilities. The Pareto front can be used as the line of action of these stakeholders, and move along the front depending on the users at hand and the program needed. For communities wanting less distortion, the aggregator can send demand response events that are more on the minimisation of the distortion to users yet making substantial reduction on the power peak, whereas for other users that are more keen on reducing their peaks (maybe because they give priority to incentives from utility) the utility/aggregator can move towards solution that reduce the peak more, yet knowing that the distortion for users will be minimal.

The result on Fig. 5 shows the Pareto front as obtained by the optimisation algorithm, but with 2D views to facilitate the

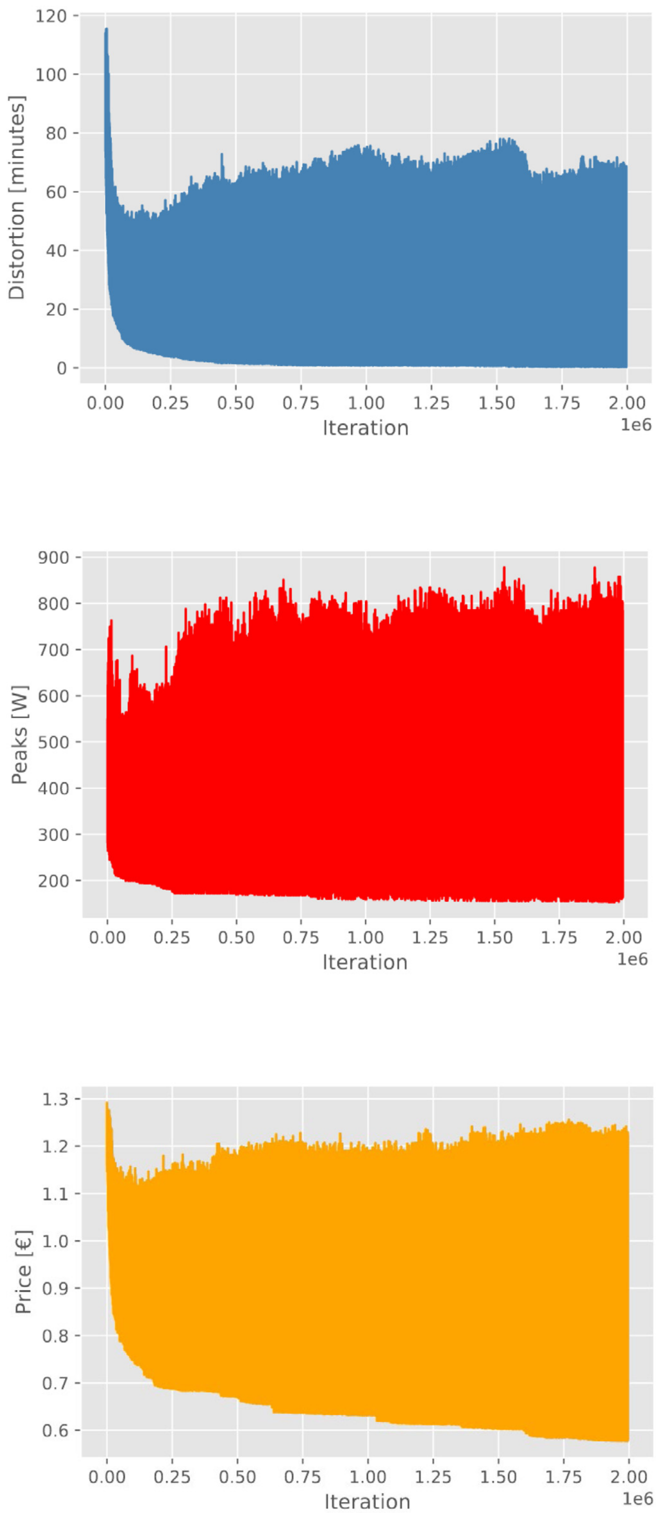

Fig. 4. Evaluations of the objective functions along the optimisation.

understanding. The representation has been chosen as is because it generates graphs that are relevant on their own as well as seen all together. Starting by graph (g), one can see on the Pareto relating the price seen by the household and the distorsion (time that the operation has been displaced from the natural one). This sub-plot is therefore the more relevant for the customer. As one may expect, it was seen that the objective of reducing price and the objective of suffering less disruption are conflicting objectives. It is seen that the more the user wants to reduce their bill via moving the appliances, larger the distorsion is going to be. This graph is interesting on its own, as it may help utilities to identify the relationship that should be established between windows of operation for the devices and monetary incentives. This has value because it has been carried out with real load profiles and with real behavioural patterns.

On the (h) sub-plot one can find the Price-Peak graph. This sub-plot is highly relevant for the aggregator or utility. The graph shows that Peak Reduction and Price Reduction are not purely conflicting objectives. This means that there are solutions of operation for the community in that reducing the price reduce the peak. This graph serves as a check that the tariffs are designed correctly. If a graph as this one, results on conflicting objectives, it would indicate that the tariffs for reducing peak loads are not properly designed. This is not the case with the peak when the distorsion is minimised. As one may expect, if no distorsion, or little distorsion occurring, the peak could never be at its lowest (as seen on the (d) sub-plot).

4.2. Parallelising the design of optimal DREs to make feasible large scale campaigns

As mentioned before, the design of demand response events needs to take into consideration the benefits of the users (or at least minimum distorsion) and the reduction of the peaks for the utility/aggregator. The previous section shows that with the adequate tariffs one should expect that the peak is reduced when the cost of the users is reduced. However, the relationship between the reduction of peak/cost and the distorsion originated to the users is more complex and a program that reduces one has to worsen the other.

Although this comes with no surprise, it is still necessary to investigate ways to make possible this optimisation, as it is not ideal to design solutions that minimising one of the objectives, are not the best-allowed solution for the other one (i.e. is not part of the Pareto Front). For this to occur, the optimisation needs to be feasible, and for large energy communities, the large number of loads that have to be coordinated may render the optimisation not possible. Our work suggested the breaking of the problem into several similar projects that make the computational time of the problem divert from the exponential tendency growth as the number of houses under consideration grows.

This is the reason why, it is necessary to divide the problem into smaller problems and then join all the results into one, following the map-reduce methodology, that is, parallelising the problem. For this, the genetic algorithm is programmed in such a way that it performs the optimisation in small groups at the same time and gathers all the solutions below, for example, instead of optimising 200 households (that is, 600 variables) it is possible to optimise 10 groups to the time of 20 households (60 variables), causing the calculation time to be drastically reduced.

Before doing so, it needs to be checked if the problem is completely separable into smaller problems, since the optimisation will be much more efficient when the algorithm has all the freedom to make changes in the time series, which is not possible when the problem is fragmented. Therefore, it will be necessary to find the appropriate division of the problem and valuate how much effectiveness one is willing to give up after a shorter calculation time.

To achieve this, we have considered that the optimisation of a given case modifies the location of the appliances until the difference between the maximum peak and the average power is small (this has been shown as epsilon on Fig. 6). To then design the strategy that helps reducing computational times, we

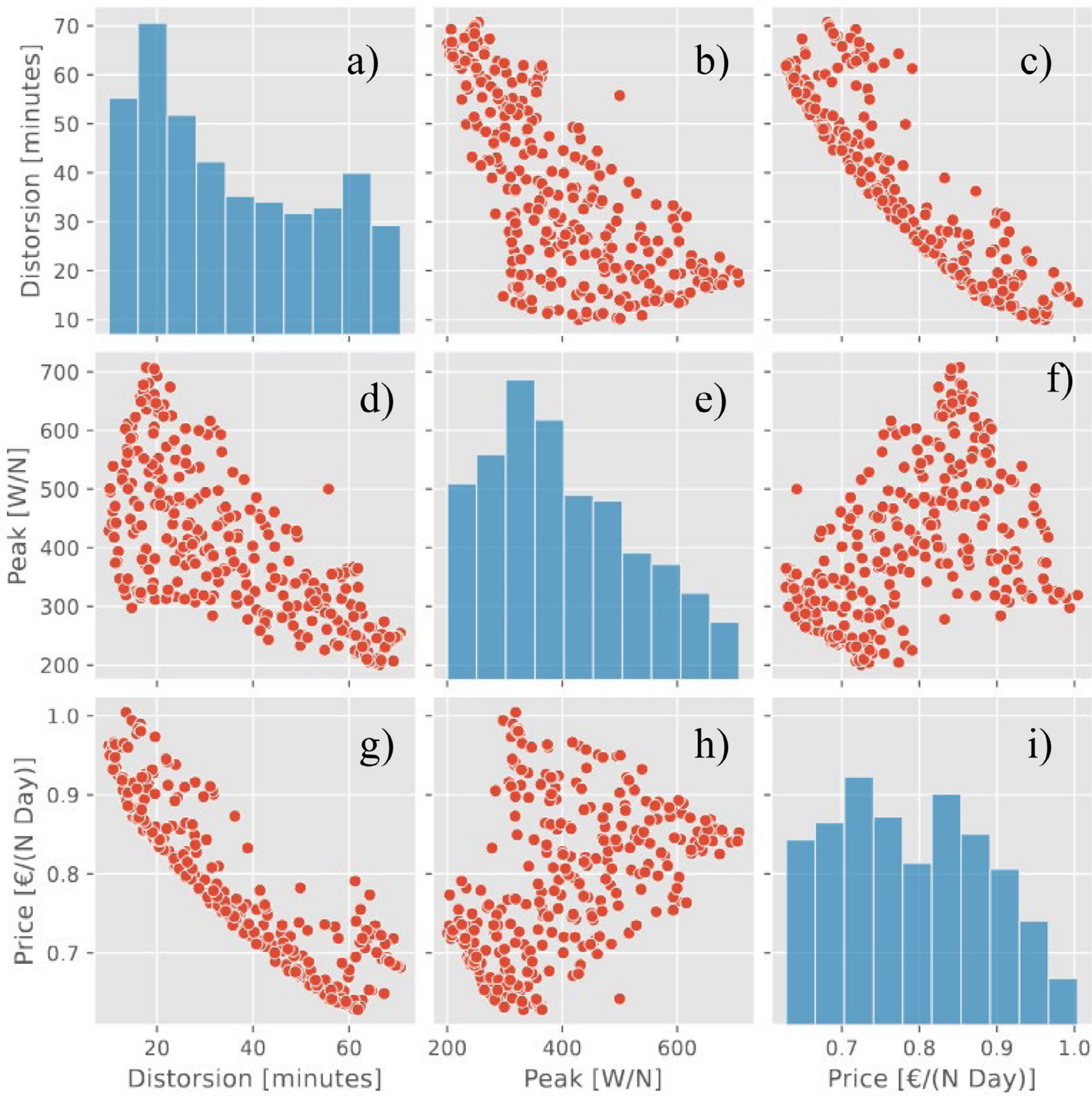

Fig. 5. Result of exploring the relationship of the three different objectives that can be relevant for a demand response event.

took advantage of the fact that the GA used to optimise the operation, has a stochastic nature. This, together with the fact that the decision space has many near optimal solutions due to the redundancy of the problem, helped envisioning the method. Optimising groups of homes and taking them to a given epsilon value, could be a good strategy, as each would have its peak at a different position. This implies that the summation of "n" optimised demands do not necessarily imply a peak of n *x* epsilon. In fact, it would be highly improbable.

$$Power\left(T_i, t_j\right) = Power\left(T_{i-1}, t_j\right) + WM\,(T_i + j) + DW\,(T_i + j) + EV\,(T_i + j) \quad (5)$$

obtaining the power is an iterative process in which the time series values of the electrical appliances (DW, WM and EV) are added for the j values, ranging from 0 to 24, where 24 are the periods of 15 min that the power-on timestamps. This iteration is carried out for all the buildings, in such a way that the profile of the series increases with each building. The maximum value of this function in the variable t_j is what will give rise to the objective function of the peaks.

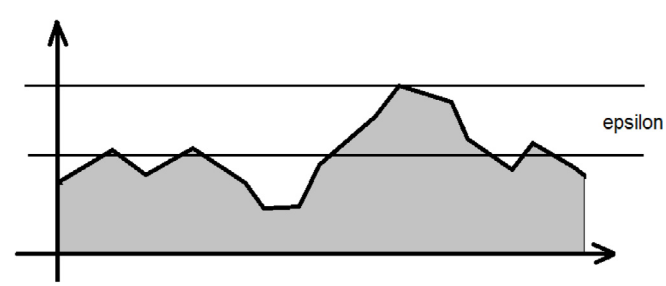

Fig. 6. Power of the demand. The variable epsilon has been considered as the difference between the maximum peak and the average power.

The first test that was done for this, was the evaluation of the minimum epsilon that one could achieve by performing the optimisation of the operation for several group sizes and this is shown in Fig. 7.

It is clear, that it is possible to perform optimisation of the scheduling of the shiftable loads, and so has been seen when

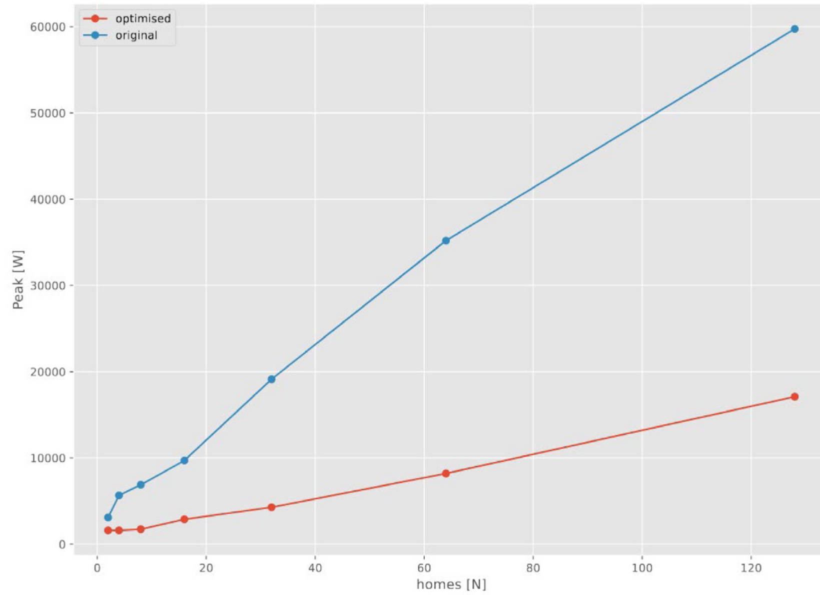

Fig. 7. The figure shows how the peak power increases when adding homes to the set (curve: original) this is because the probability distributions of the use of appliances have peaks on specific times, and therefore more appliances do not necessarily add power peaks at random times. The curve: optimised shows how the power peak can be maintained low even adding more homes if the operation of the shiftable devices is optimised.

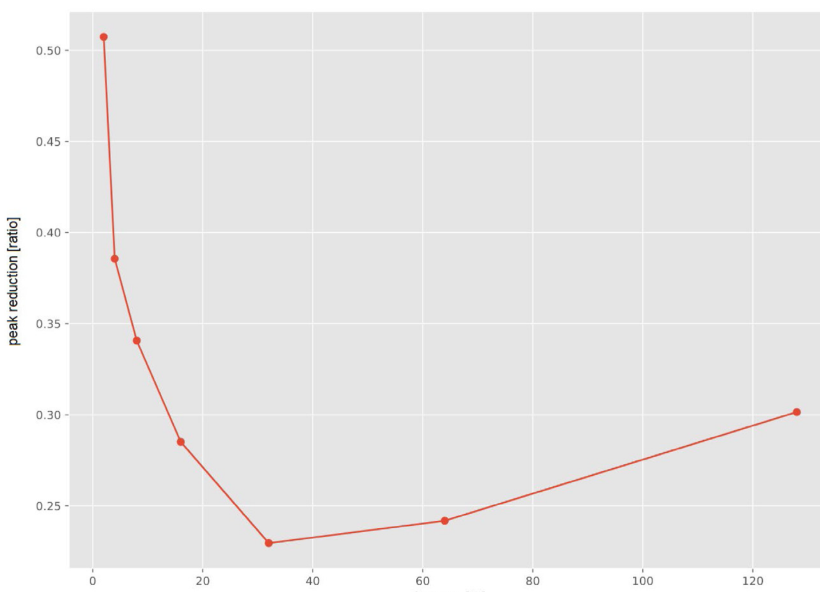

Fig. 8. Relative reduction of peak depending on the number of homes grouped. The curve shows a clear minimum for 32 households, indicating a desirable grouping size for parallelised optimisation. The cross represents this minimum.

optimising the operation with a single objective GA. The following step on the research was to evaluate if there is a natural grouping size that benefits the scheduling. The problem is highly redundant, and as said before, one can hypothesise that there can be a group size for which the optimisation is sufficient, and adding extra households can be done in parallel. This was evaluated and the result can be seen on Fig. 8. The figure shows the reduction of the power thanks to a single objective genetic algorithm, as a ratio (resulting power/ initial power), for a given number of households. The figure shows that the peak is reduced with the optimisation, on a very effective way. As the values have been normalised, the comparison between the various test is made possible. From the graph one can see that optimising groups of 32 houses makes the most effective reduction, what indicates that this is an optimal grouping size for the common shiftable loads in dwellings and for realistic behaviours.

Following with the methodology, the group size of 32 households was used to break down the optimisation into routines with groups of 32 households. Each of the optimisations will give a resulting power series for the group, and also a recommended DRE for each household. The summation of the power series will indicate the peaks of the resulting 128 summary of groups. The reason for testing this approach was to avoid the exponential growth of the computational time seen on traditional optimisation of DREs that could make the optimisation unfeasible for communities large enough to be interesting. Our method of parallelising the optimisation with the optimal group size allows to make the growth of the computational time of the optimisation

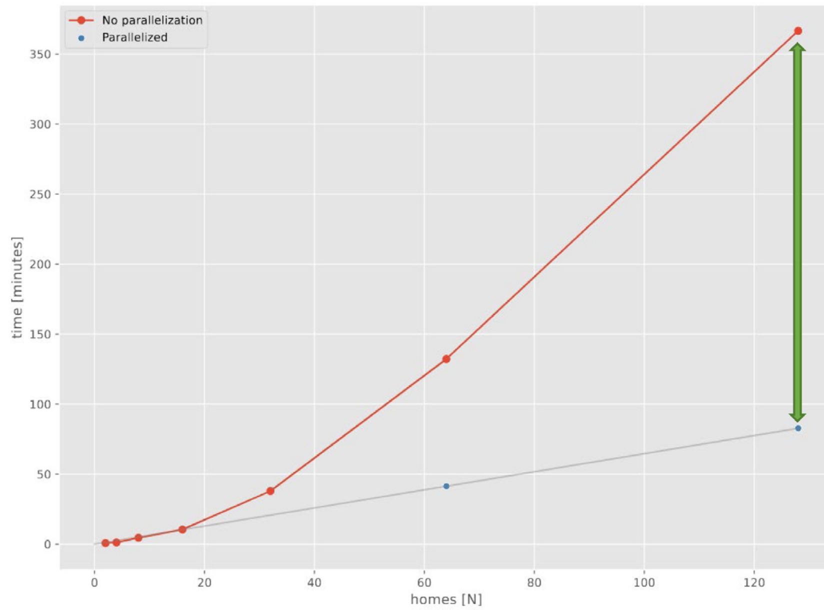

Fig. 9. Reduction of the computational time of the optimisation of the DRE with respect to the number of final users. The reduction of computational time is exponential with the number of users. On a DRE of 128 users the parallelisation has reduced the computational time by 78%.

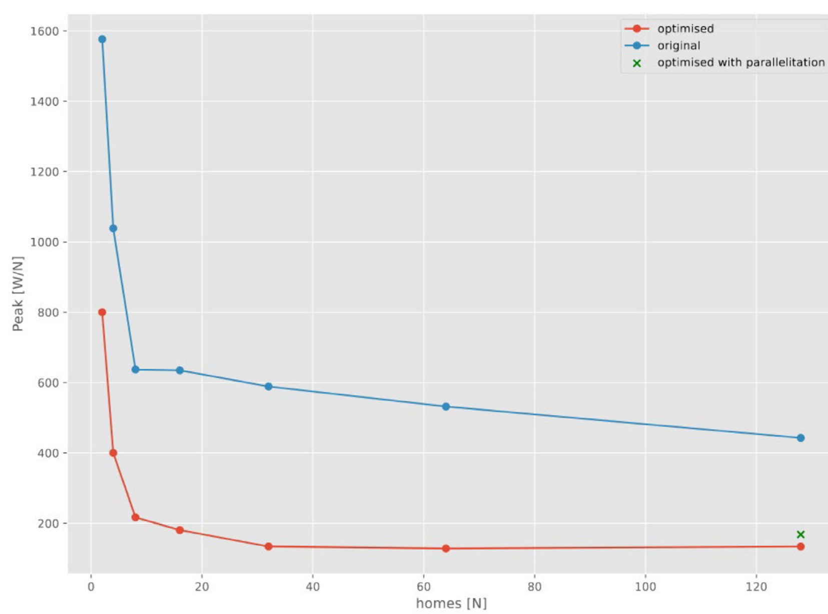

Fig. 10. Reduction of the power peak thanks to the optimisation. The green cross represents the peak after Applying a parallelised DRE optimisation with a reduction of the computational time of 80%, the worsen of the optimisation due to the parallelising was 2.8%.

linear. This more reasonable times enable the design of optimal DREs for large communities, making them possible. The transformation of the computational times with the traditional, and with our parallelised method can be seen on Fig. 9.

Having seen that the method presented here can represent a great advantage on the computational time, eventually enabling large scale DREs planning, the next step was to see if the new power series is not highly compromised with the parallelisation, and the peak reduction is similar. This test was done with 128 households as it represents the case with the highest difficulty for the algorithm yet representing a realistic neighbour size. The result has been shown on Fig. 10 as a crossing of curves of the power peak reduction. The evaluation has shown that the parallelisation, only modifies the reduction of peak by 2.8% what is almost non-perceptible and to the authors opinion, acceptable considering that the reduction on the computational times was of 80% and particularly the elimination of the exponential growth on the DREs optimisation with the number of households. (see Fig. 9).

4.3. Effectiveness of parallelising for the multi-objective optimisation

Although DREs are meant to be design for reducing the peaks that could make the distribution line either fail or need more investment, it has been shown in this work, that a multi-objective optimisation can be beneficial. We have seen that the grouping of households of the optimisation of DREs could be the enabler for large scale DRE optimal design, but the authors considered

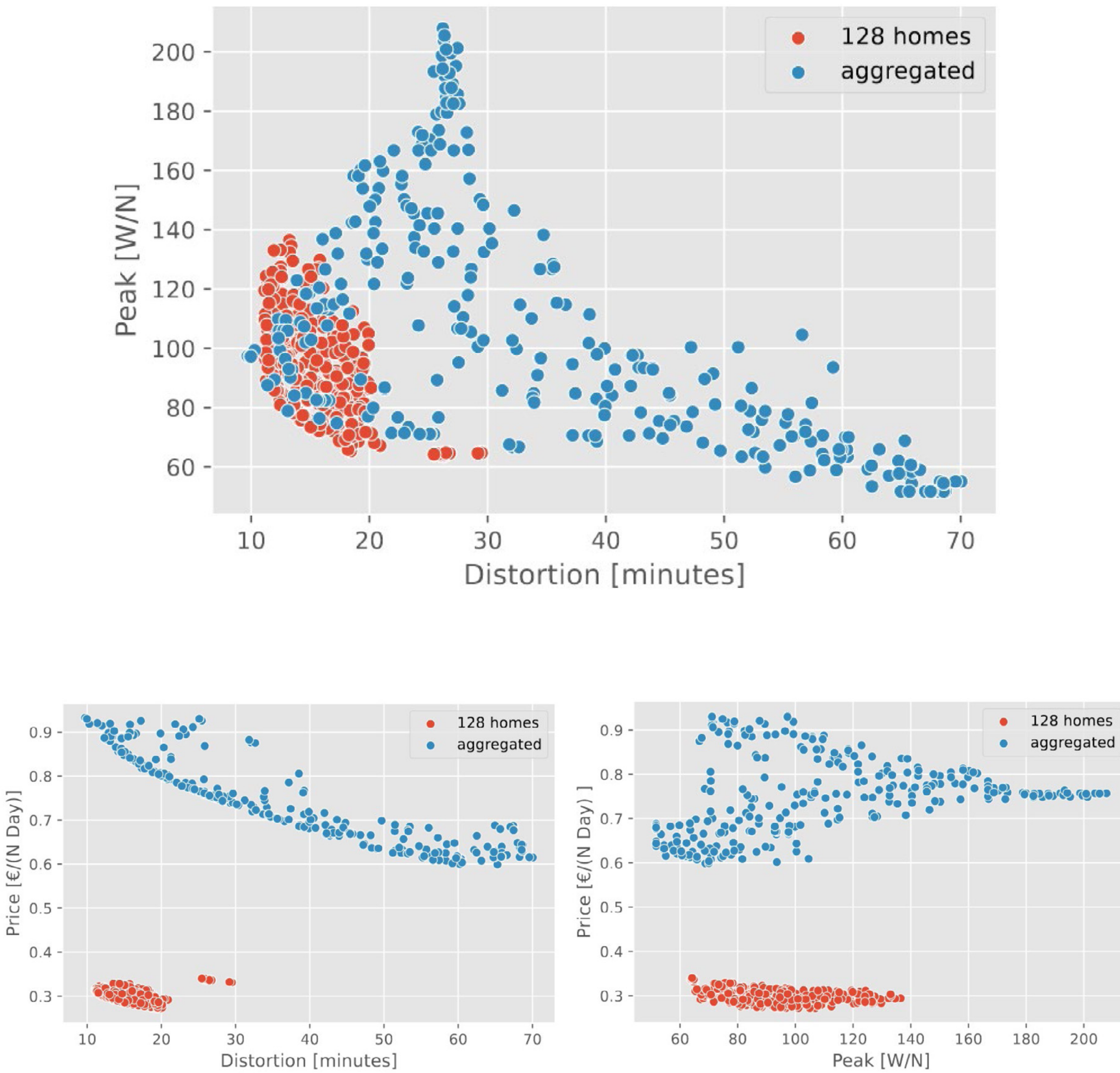

Fig. 11. Results of the multi-objective optimisation with two objectives (price and distorsion) with the 128 homes and with four groupings of 32 users.

interesting to evaluate if the grouping will also allow to perform multi-objective optimisation with a low computational price. For this, a similar exercise as the one performed on Section 4.1 was performed.

The method used to obtain a joint pareto consists of calculating the individual Paretos of each set of households, in such a way that a matrix of objectives is obtained for each set of households. One of the Paretos is chosen arbitrarily, and point by point the points of the other Paretos that minimise the Euclidean distances are obtained, thus to each vector of the arbitrarily chosen pareto, a number of vectors equal to the number of Paretos is assigned. In such a way that the joint pareto is not the union of the Pareto but more isolated points are eliminated in this pareto. The results are shown on Fig. 11.

The results of the multi-objective optimisation with the grouping of the household on their optimal size showed a clear reduction on the computational time, even higher than in the single objective optimisation. However, it was seen that the resulting Pareto fronts when calculated with the parallel groups were far apart from the resulting Pareto front of the general optimisation if the process is considered. This indicates that the method presented here may not be extrapolated for the case including the price, and its use is therefore limited. This comes with no surprise, as the method was designed taking into consideration the reduction of peak, but not price (which is a smoother objective function). It should be taken into consideration, that the grouping of homes works rather well when considering only peak and distorsion. This is an interesting finding as it can be of great use when the DREs are design on a direct load control fashion, and the price does not come into play. Considering the findings of the relationships between the objectives given by Section 4.1, one can see that the single-objective optimisation, with the parallelisation should be enough for the optimal design of DREs, allowing large scale broadcasting of shiftable appliances re-scheduling and with them changing the way in which the large scale demand operates.

5. Conclusions

The work here presented aims at studying the design and optimisation of Demand Response Events from three different points of view: the reduction of the peak power (seen as the most relevant one on most of the literature), the reduction of the price for the user (seen as the second most important) and the distorsion for the user on their existing habits (seldom investigated). The use of realistic profiles of behaviour taken from the literature, have allowed us to create a comprehensive framework for evaluating the different effects. Within the framework, a realistic simulator with a variety of consumers have been created, and agent-based modelling type behavioural models provide with the realistic profiles of each user.

The framework allowed us to have a realistic scenario to test the different strategies to optimise the DREs that until now had been seen as effective tools, but that have been seen to have a limiting factor on designing them on an optimal manner for large scale interventions. The tariffs, or the sending of unified DREs have been the strategies so far without making the large scale re-scheduling of the shiftable loads that are shown here, due to the computational effort being a limiting factor.

In the work here presented, we show how the three relevant objectives of a DRE are related to each other. To the authors knowledge, this has been done for the first time on this paper, as not using realistic profiles of appliances operation did not allow to quantify the distorsion on the user's habits on other works. The results show that a well design tariff will make the price reduction of the final consumer and the peak reduction for the grid non-conflicting objective. The results also show that multi-objective optimisation is a good tool to check the internal consistency of a tariff; and to see, if it is well defined for reducing the peak. The realistic tariff used in this paper has been seen to be well designed.

In addition, the multi-objective optimisation has shown how the distorsion on the user's habits and the reduction of peak are clearly conflicting algorithms. This comes with no surprise as the test was done with real probability distributions that show that the households tend to use certain shiftable-loads at specific hours. However, the fact that the Pareto Front of these two objectives was obtained, helps on quantifying the relationship between the two. At the same time this allows to design more effective and less disruptive DREs that minimise the peak with the minimum distorsion to the user.

The question of the long computational times for the optimal design of DREs and specially its exponential growth was of key importance for this work. We hypothesised that a group size can be found that makes ideal the grouping of the optimisation as if they were energy communities, and that the aggregation of these optimised groups can then lead to an optimal overall profile, yet keeping the computational times feasible. The results are highly positive. It was seen that the optimal group has 32 households for real shiftable loads, and for real household's behaviour. This is a finding on its own, as the design of groups to be optimised can help on several aspects of the new paradigm of electricity grids. The parallelisation for the optimisation gave also outstanding results. The reduction of time was 80%, and the worsening of the solution was of 2.8% for the case of 128, but the figure of time reduction grows exponentially with the number of households involved. This shows that the method here presented clearly eliminates the burden of the exponential growth, and therefore it allows the optimal design of large scale DREs.

The grouping of the optimisation was a tempting exercise to be extended to the multi-objective optimisation. This was done on the same way that was done for the single-objective optimisation but running the algorithms with three objectives. The results show that the method is not convenient for this case. As one may expect, the design of the method was planned considering the final power peak reduction, and the minimisation of several objectives may be slightly different as the evaluation of the objective functions have other implications. Yet, the grouping method worked well for multi-objective optimisation as soon as the price is not included Making it also valuable for the design of multi-objective demand response programs.

There are relevant devices on households that may be interesting to include on the optimisation. Specifically, refrigerators and freezers have the necessary thermal inertia to be turned off for some minutes without noticing a substantial rise in the internal temperature. The consideration of these devices on the optimisation of demand response events is suggested for further work.

Summarising, we have seen that with the current shiftable loads on real households and considering real behavioural patterns for their use, the method here presented can reduce the large computational times for large scale DREs allowing to do large scale design of these events and to reduce the peaks of the grid largely. It is recommended for further work to investigate other ways of complementing this for multi-objective optimisation, but according to what we have seen, it is likely that the large scale broadcasting of DREs with the method here presented together with overrides of some users will result on optimal operation of the shiftable devices for the monetary and the comfort of the end users and for the grid.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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