Towards a Robust, Distributed and Decentralised Smart Energy Management of Microgrids

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Abstract: Modern energy systems comprise different entities that interact to allow an intelligent production, distribution, and consumption of energy. They need efficient and distributed demand-response management mechanisms to find optimised configurations of parameters of the grid components. When working with time schedules, optimisation algorithms used for this purpose usually rely on forecasts. However, forecasts bring uncertainty, which is rarely considered in optimisation. This work presents a robust and decentralised optimisation approach that deals also with such uncertainty by searching for optimal power schedule solutions, which are also reliable in unexpected circumstances. Based on message passing, our approach uses meta-heuristics for performing local optimisations. The implementation and validation of our proposal was conducted by means of a distributed multi-agent system, where the obtained results have shown the efficiency of our approach.

1 INTRODUCTION

Smart grids became one of the solutions to deal with climate change and the continually increasing demand for energy (Tuballa and Abundo, 2016). It is an intelligent electrical grid with a distributed energy generation, storage, integrating of customer power supply and renewable energy. It is intended to enhance the effectiveness and efficiency of power delivery by using intelligent algorithms to manage the production, distribution, and consumption of electricity. The successful implementations of smart grids have increased the research interest in this field.

This article focuses on a part of smart grids, called microgrids. Microgrids are networked groups of distributed energy resources, such as solar panels or wind turbines, located at the distribution network side, and able to provide energy to small geographical areas (Saad et al., 2012). It connects consumers (a.k.a prosumers), which are small-scale co-providers of energy, and allows local electricity interchange among them. Such interchange reduces their dependence on the public grid, placing the generation of electricity near the end-users. Efficient demand-response management mechanisms allows users to be energy-efficient in the long term (Mesaric et al., 2017).

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Efficient demand-response management mechanisms are essential for microgrids since they pursue to find the best configuration parameters of the components for an optimised grid performance (Colak et al., 2016). Such mechanisms manage the grid and try to achieve an optimised performance for a given objective(s) such as reducing the bill, avoid power peaks and/or energy losses, without violating the constraints imposed by the grid definition. These decisions are considered as optimisation problems, and are the focus of many recent studies (Gomez-Sanz et al., 2014). In practice, the grid configuration parameters vary from the time schedules (for a given time horizon), to the real-time parameters (Gamarra and Guerrero, 2015). Unfortunately, the complexity arises with the number of variables to be optimised such as the time setups for self-controlled resources of the grid (Mohamed and Koivo, 2007).

To work with scheduled configurations, optimisers usually rely on forecasts instead of real-time setups. Forecasts provide an estimation on what may occur in the near future, allowing to plan the strategy in advance. Currently, many types of forecasts can be considered in a microgrid optimisation problem: some of them are related to power consumption/generation such as consumption schedules, battery levels, production curve; others are related to weather prediction, such as solar radiation and wind speed. However, since forecasts are not 100% ac-

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curate (Mahat et al., 2013), the observed parameters may vary from the forecasted ones, which leads to unexpected situations. In this case, the optimised solutions (based on the non-accurate forecasts) are more likely to lie far from the optimal ones (García et al., 2012), which may provoke looses in money, resources, and/or time (Liang and Zhuang, 2014). Therefore, forecasting reliability is a key factor in optimisation solutions (Moreno et al., 2017).

In this paper, we present a robust and decentralised optimisation algorithm implemented in a distributed manner for finding the best setup configuration for the devices in a microgrid. We refer to robustness as the capacity of the approach to provide stable solutions with a performance that does not drop when unexpected scenarios are faced. Our proposal is based on the adaptation of the message passing algorithm proposed by Kraning et al. (Kraning et al., 2014), where optimisation is split in less complex problems that are locally solved in different nodes of the grid. The global optimisation is achieved by means of a negotiation protocol amongst all of the grid nodes. Local optimisations are performed using evolutionary computation (Zhang et al., 2011), which is considered an adequate approach for this kind of problems (Moghaddam et al., 2011; Ramaswamy and Deconinck, 2012). For instance, metaheuristics as “Particle Swarm Optimisation” (Chen and Yu, 2005) and SPEA2 (Zitzler et al., 2001) are adapted to our problem. Furthermore, in order to deal with the reliability of forecasts, we consider the *robustness* concept by extending the decentralised optimisation algorithm with a robust approach, which allows handling the uncertainty in forecasts within the optimisation process.

Our proposal was implemented by means of a distributed multi-agent system (Al-Hinai and Alhelou, 2021), a technology that has been proven to be very suitable for microgrid solutions (Farhangi, 2010; Amin and Wollenberg, 2005). A sliding window over different year-observations (extracted from real data sets) was used to carry out our validation tests. According to the results, our algorithm provides effective solutions by considering uncertainty in its parameters. Comparing the optimised schedules obtained from forecasted parameters to the equivalent real-time ones, we can see that costs are reduced up to 60% in some of the tested scenarios.

This paper is organized as follows: Section 2 reviews the state of the art about distributed optimisation algorithms for microgrids; Section 3 presents the algorithm in which the proposed solution is based; Section 4 details our contribution, whereas Section 5 reports on the validation results. Finally Section 6 concludes our work and discusses the future lines.

2 RELATED WORK

Demand response algorithms emerged in the 1970’s, but have experienced a renaissance by the appearance of microgrids (Mihaylov et al., 2019). These algorithms try to optimise the schedules of the controllable loads to satisfy the grid objectives, such as valley filling and peak shaving to mention a few.

The literature reports on many optimisation algorithms for microgrids, which aim at reducing the energy imbalance and at covering the demand and supply gap. Some of these approaches are based on predictions only, whereas others consider the unreliability of predictions, aka uncertainty. One of the main sources of uncertainty in smart grids is the integration of stochastic renewable energy sources and the introduction of new energy intensive appliances, which make it increasingly difficult to find an optimised planning of resources in the smart grid (Deconinck et al., 2008; Veldman et al., 2013).

The authors in (Haring et al., 2016) developed and compared three different schemas for optimising the energy market, involving the customers and focusing on the trade-off among privacy, resource exploitation and the reward earned. The first schema provided a centralised optimisation in which the user information is shared with the system operator; the second applied a centralised optimisation, based on an aggregator, with whom the user partially shares cost information; and the third schema proposed a decentralised schema, in which the prosumers exchanged energy among each other without revealing their cost information. Prediction is used in the second schema, but without considering uncertainty.

Alternating Direction Method of Multipliers (ADMM (Boyd et al., 2011)) was used in (Rivera et al., 2017) and (Diekerhof et al., 2014). (Rivera et al., 2017) proposed a scalable distributed convex optimisation framework for electrical vehicle aggregators, and covered local and global objectives and constraints. It is intended to resolve valley filling and minimising charging costs by providing optimised charging plans. It focused on demonstrating the possibility of integrating electrical vehicles in the grid and on the scalability of the framework, but it does no tackle the uncertainty. (Diekerhof et al., 2014) proposed a distributed optimisation system for intelligently controlling electrical heat pumps at district level, based on an ADMM, where the local objectives of each participant are considered achieving the global objectives. The authors in (Diekerhof et al., 2016) showed the advantages and disadvantages of distributed optimisations and proposed a particular usage of ADMM for scheduling electro-thermal heating units. Dantzig-Wolfe decomposition (Dantzig and Wolfe, 1960) was used by (McNamara and McLoone, 2015), who proposed a hierarchical demand-response algorithm. The objective of this approach was to peak minimisation and achieve both: the device and the customer objectives. Furthermore, it tried to minimise the communication overheads and to improve the quality of service by improving the response time for the devices that need their energy as soon as possible. This work does not consider considering uncertainty either.

The following proposals focused on decentralised frameworks without including uncertainty (de Cerio Mendaza et al., 2016; Meyn et al., 2015): (i) (de Cerio Mendaza et al., 2016) proposed a hierarchical and decentralised framework that is intended for controlling the demand-response in low voltage networks, where the system operator plays the aggregator role for trading energy demand flexibility and for ensuring reliability and security. Since the framework only focused on the demand side, just loads were considered. The authors modelled the heat pumps systems to respond to demand aggregations, which is used in their hierarchical structure; (ii) (Meyn et al., 2015) proposed a decentralised decision making architecture for automated demand response that can be used for maintaining demand-supply balance. The authors provided a solution based on a randomised control strategy (using a Markovian Decision Process) to obtain an aggregate model for a large number of loads. Then, a so-called linear time-invariant system approximation of the aggregate nonlinear model is used for control design at grid level.

However, there are some proposals in the literature which do consider different kinds of uncertainty in their optimisation algorithms (Moreno et al., 2017). The authors in (Diekerhof et al., 2014) applied ADMM in a hierarchical architecture, and combined it with robust optimisation and model predictive control to handle uncertainty in heat pump scheduling (Diekerhof et al., 2017). (Tajalli et al., 2021) presented an approach for uncertainty aware management of smart grids by using cloud based LSTM interval prediction. (Chakraborty and Okabe, 2016) used probabilistic programming approach that utilises a Bayesian Markov Chain Monte Carlo (MCMC) sampling method to create energy based balanced groups. This allows grouping similar customers whose aggregated demand has higher predictability. To face energy imbalance problem and cost reduction, the authors proposed a multi-objective optimisation based on ADMM for scheduling electrical storage units, considering the demand uncertainty. (Zhang and Giannakis, 2016) formulates a stochastic optimisation problem based on ADMM also considering uncertainty for market clearance. (Zhang et al., 2017) contributes with a distributed robust optimiser, considering uncertainty, which uses the aggregation of loads for service provision. Finally, (Dehghanpour et al., 2017) also showed a hierarchical multi-agent system framework for modelling demand response of air conditioning loads with a day-ahead planning. Such framework uses machine learning to model the behaviours of agents at different levels of the framework. The authors compared linear modelling and ANN-based modelling to check the learning model that provides more cut in the consumption cost and maximise the benefits of the retailer.

As for the technologies used in the implementation of the algorithms that control microgrids, multi-agent systems (MAS) technologies are considered as potential solutions to the power industry providing flexible, extensible, and fault-tolerant solutions (McArthur et al., 2007a; McArthur et al., 2007b). They enable the implementation of large and complex distributed applications by allowing the development of autonomous control agents that are able to coordinate in a cooperative and fault-tolerant environment (Al-Hinai and Alhelou, 2021). The distribution and communication characteristics of MASs are attracting the attention in smart grids due to their ability to unlock their potentials (Farhangi, 2010); i.e, the autonomy of agents are adequate for the smart devices, whereas the grid energy consumption and production optimisation, usually performed by negotiations, can be easily implemented using the agents communication mechanisms and protocols.

Our system allows scheduling electrical units by using the decentralised and distributed optimisation algorithm (Kraning et al., 2014) that relies in local optimisations. Furthermore, it considers uncertainty in the optimisation so that solutions become more stable against not accurate predictions. Unlike the papers mentioned in this section, our robust mechanism can be adapted to any optimisation algorithm since it deals with robustness within the cost function. Moreover we introduce an uncertainty estimation which is only calculated from forecasts and can be applied to any device whose forecast values are considered for the optimisation. This means that we do not need to create a new robustness measure for each device model since uncertainty is specifically computed for each device according to its historical observations and forecasts.

3 BACKGROUND

Our proposal is based on a fully decentralised method for dynamic network energy management that uses message passing between entities (Kraning et al., 2014).This work models a cooperation network composed by two types of nodes, namely: the *devices* and the *nets*. The devices (i.e. generators, fixed loads, deferrable loads, alternate direct current transmission lines, storage units, etc.) have their own constraints and objectives. Devices are connected through terminals to each other by means of a net (i.e. bus), which also has its own objectives and constraints. In the same way, nets are connected through double terminal devices, such as transmission lines. A *terminal* is a connection point or a link between the net and the device.

The goal is to minimise the total network objective subject to device and net constraints over a time horizon. For this, (Kraning et al., 2014) method relies on the *alternating direction method of multipliers* (ADMM), which is an algorithm that solves convex optimisation problems by breaking them into smaller pieces so that they will be then easier to handle (Boyd et al., 2011).

By relaxing the equations (see (Kraning et al., 2014) for details), the result is an iterative algorithm that runs until the convergence criteria is satisfied. Therefore at each iteration k the following operations are performed in parallel:

- Every **device** d computes, for each terminal, a new proximal power schedule $p_d = [p_d(1), ..., p_d(H)] \in \mathbb{R}^H$ that minimises a local objective function.

  The problem is formulated as shown in Equation 1:

$$\begin{array}{ll} \underset{p_d}{\text{minimize}} & f_d(p_d) + \frac{\rho}{2}||p_d - (p_d^k - \overline{p}_d^k + u_d^k)||_2^2 \\ \text{subject to} & constraints_d \end{array} \tag{1}$$

  Formally, H is the number of time periods to schedule (time horizon) and ρ is a scaling parameter. p_d^k is the current power schedule of device d computed in previous iteration, and $\overline{p}_d^k$ the average of p_d^k of each terminal (in case of just one terminal devices $\overline{p}_d^k = p_d^k$).

  In the same way, $u_d = [u_d(1), ..., u_d(H)] \in \mathbb{R}^H$ is the scale price received from the net in the previous iteration. $f_d(p_d) = c_d(p_d)$ represents the cost function $c_d(p_d)$ of applying p_d to d. Note that each kind of device has a specific $c_d(p_d)$ formula.

  However, solving the equation 1 also requires to satisfy the constraints imposed by the device model. Some of them are already considered within the cost function $c_d(p_d)$ of the device, whereas local optimisers deal with the rest (see section 5.1 for more details).

  Finally, the device sends a message with p_d to its corresponding neighbour net(s). In case of two terminal devices, the previous operations are repeated to compute p_d for each net terminal.

- Every **net** n updates its scale price as $u_n = u_n^k + \overline{p}_n$, where $\overline{p}_n$ is the average of all p_d received from their devices. Finally, u_n is sent to all its linked devices.

The authors showed that their approach converges to a solution when the objectives and constraints of the devices are convex. Such solution is decentralised solution and needs no global coordination other than synchronizing iterations; the problems to be solved by each device can be locally solved efficiently and in parallel according to the authors (Kraning et al., 2014).

4 ROBUST DECENTRALISED POWER SCHEDULING OPTIMISER

This paper proposes a novel robust and decentralised approach algorithm for solving power scheduling problems in microgrids. Relying in the decentralised method for dynamic network energy management presented in section 3, we developed a robust adaptation to deal with uncertainty of parameters during the optimisation process. Our approach is implemented within a distributed multi-agent system which allows solving it in parallel.

In order to calculate the best power schedules p_d for each time period, the optimization algorithm needs to know, in advance for these periods, the power load curve for those devices whose regimes cannot be controlled and the power curves estimations (as maximum power generation, expected consumption...) in case of self-controlled devices. Unfortunately, those forecasts are estimations about the future which cannot be certain. Big deviations from real conditions may lead to inefficient power schedules that can provoke several losses as money, energy, etc. A main contribution of this paper is the consideration of such forecasts uncertainty to guide the optimisation process. We developed a robust mechanism which, adapted within the cost function of those devices subject to uncertainty, increases the reliability of solutions by remaining more stable when unexpected situations are faced.

The following Section 4.1 shows the implementation of the proposed approach whereas section 4.2 describes its robust mechanism.

4.1 Implementation

Our algorithm is implemented within a distributed Multi-Agent System, which is based on the re-usable architecture already introduced in (Garcia-Rodriguez et al., 2016). Each device/net composing the microgrid is managed by an agent in our system which is in charge of running a local optimisation and exchanging messages with its neighbour agents. Since decentralization allows distributed implementation, problem complexity is reduced by splitting computation load in different nodes. Moreover, unlike centralised systems which depend on a central node, our approach achieves smartness by the negotiation of all of them. This way the probability of facing bottle neck situations is significantly reduced.

Evolutionary computation (Zhang et al., 2011) is selected for solving the local optimisation function of equation 1. The use of this kind of algorithms is recurrent in the literature since they are proved to be good approaches to solve microgrid problems (Sanseverino et al., 2011). For instance, their flexibility allows to handle most of the hard constraints in the optimisation process (as the ones of transmission lines presented in section 5.1). Moreover, their operators can be easily modified to improve the algorithm performance in the specific problem to solve. Our approach counts with the following meta-heuristics:

- Mono-objective optimisers (problems with just one objective function): naturally inspired algorithms as particle swarm optimisation PSO (Chen and Yu, 2005), differential evolution (Storn and Price, 1997) or CMAES (Auger et al., 2004).
- Multi-objective optimisers (two or more objective functions): evolutionary algorithms such as NSGA-II (Deb et al., 2002) or SPEA2 (Zitzler et al., 2001).

Thanks to the architecture of our framework (Garcia-Rodriguez et al., 2016), algorithms can be easily added/replaced. This allowed us choosing the best one for each local cost function.

4.2 Dealing with Uncertainty

The robust method presented here is applicable when device forecasts (that are subject to uncertainty) are used to optimise the microgrid power schedules. Based on historical forecasts and observations, our approach guides the optimisation process towards solutions that shall remain stable even when forecasts result to be very inaccurate. The main strength of this approach lies in the use of a penalty factor, $w_d(p_d)$, used to penalise the device cost function $f_d(p_d)$ of Equation 1. The fact of placing such penalty within the device cost function makes it easily adaptable to any other optimisation algorithm. The penalty factor is computed for each device d according to its proposed power schedule p_d and its historical set of observations-forecasts.

Therefore, for any device d whose forecasts are used for optimising its power schedule over a time horizon H, we can apply the robust improvement that works as a two-phase algorithm.

4.2.1 First Phase

It is run *offline* and before the optimisation process starts. Relying in the set of historical pairs forecasted-observed parameters of the device, it computes three values that will be used in the second phase:

- Of_d: proportion of all observed values of d that were greater than their forecasts in the historical observations-forecasts set. $Of_d \in [0,1]$.
- Fo_d: proportion of all observed values of d that were smaller than their forecasts in the historical observations-forecasts set. $Fo_d \in [0,1]$.
- UF_d: performance of the forecast algorithm used for computing the forecast parameters of the device. Its value is calculated in Equation 2 by measuring the absolute proportional deviation between the historical real observations and their corresponding forecasts over the time periods $[1...H]$ to be optimised:

$$UF_d = \frac{1}{max_d * H} \sum_{t=1}^{H} |fp_d(t) - op_d(t)| \qquad (2)$$

where H is the time horizon; $fp_d(t)$ is the forecasted parameter and $op_d(t)$ the observed parameter, both for time periods $t \in [1...H]$; and max_d the maximum observed value registered in device d.

4.2.2 Second Phase

It is called each time the optimisation algorithm evaluates the cost function of Equation 1. The steps followed in this phase (see Algorithm 1) give an evaluation of the risk and negative impact of applying the power schedule p_d to device d. Such evaluation (penalty factor) is used to guide the optimisation towards robust solutions.

For each time period (line 2), algorithm 1 first estimates the possible deviations of the proposed power schedule p_d (line 9). Then, considering the import/export prices and constraints, it computes the corresponding cost of those deviations from applying the proposed power schedule p_d to a full power control device (lines 10-17) or to a ON/OFF control device (lines 18-26). The algorithm returns such cost as a penalty factor $w_d(p_d)$ which is then used within the device cost function $f_d(p_d)$ so that $f_d(p_d) = w_d(p_d) + c_d(p_d)$.

Algorithm 1: Robustness. Phase 2.

1: INPUTS: p_d; fp_d; op_d; UF_d; $[Of_d; Fo_d]$; H as the time horizon;
$[imp, exp]$ as imported/exported energy cost established by the utility:
$imp/exp > 0$ microgrid pays,
$imp/exp < 0$ microgrid is paid,
exporting energy not allowed: $exp(t) == \infty$,
importing energy not allowed: $imp(t) == \infty$.
2: **for all** $t \in H$ **do**
3:   **if** $imp(t) < 0$ **then**
4:     $imp(t) = 0$
5:   **end if**
6:   **if** $exp(t) < 0$ **then**
7:     $exp(t) = 0$
8:   **end if**
9:   $dev(t) = |p_d(t) * UF_d + p_d(t)|$
10:   **if** device d allows full control **then**
11:     **if** $dev(t) > fp_d(t)$ **then**
12:       **if** $imp(t) = \infty$ **then**
13:         $acum+ = Of_d * exp(t) * (dev(t) - fp_d(t))$
14:       **else**
15:         $acum+ = Of_d * imp(t) * (dev(t) - fp_d(t))$
16:       **end if**
17:     **end if**
18:   **else**
19:     **if** $exp(t) = \infty$ **then**
20:       $acum+ = (Fo_d * imp(t) + Of_d * imp(t)) * (dev(t) - fp_d(t))$
21:     **else if** $imp(t) = \infty$ **then**
22:       $acum+ = (Fo_d * exp(t) + Of_d * exp(t)) * (dev(t) - fp_d(t))$
23:     **else**
24:       $acum+ = (Fo_d * exp(t) + Of_d * imp(t)) * (dev(t) - fp_d(t))$
25:     **end if**
26:   **end if**
27: **end for**
28: $w_d(p_d) = |acum|$
29: OUTPUT: $w_d(p_d)$

Note that the value of $w_d(p_d)$ varies since its depends on the power schedule p_d, the performance of the forecaster in such device, and the exporting/importing energy costs and constraints.

5 SYSTEM VALIDATION

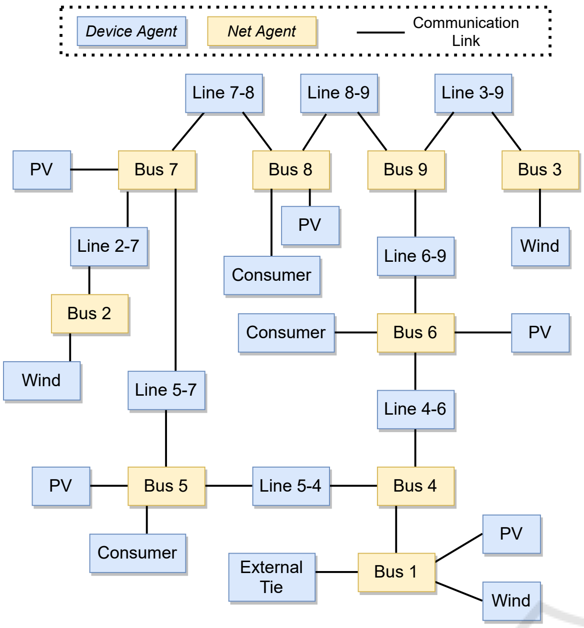
5.1 Experimental Set-up

The algorithm proposed in this paper is developed within the framework presented by (Garcia-Rodriguez et al., 2016), which was extended in order to implement our solution. Developed in Java, such framework allocates all the optimisation algorithms and implements the message passing strategy. Two main entities that exchange messages in the system are created, namely: devices and nets, which are represented as agents. Each kind of agent has its own behaviours, which define the identity of the agent. Therefore, two sets of behaviours can be assigned to an agent: the first one is to use the agent as a device, whereas the second one is for net agents.

Among the different integrated metaheuristics to solve the local optimisations, three mono-objective algorithms (CMAES(Auger et al., 2004), DE(Storn and Price, 1997) and PSO(Chen and Yu, 2005)) were chosen for the experimental part. Their setup is as follows: DE and CMAES with a $population\_size = 50$ and $maximum\_evaluations = 250000$; CMAES also adds $CR = F = 0.5$; and PSO with $archive\_size = 50$, $maximum\_iterations = 5000$ and $mutation\_probability = 0.4$.

Experimentation was performed over multiple scenarios. We call "scenario" to a specific configuration defined by microgrid topology (devices definition and constraints), buying/selling energy costs, power limits of devices, and fix power consumption/generation curves. The combination of all these values would generate a huge number of scenarios, however just some of them would represent feasible real-world situations. Our approach was tested on a nine-bus scenario that follows the "Western System Coordinating Council" (WSCC)(Paul M. Anderson, 2003) electrical grid topology. With the aim of performing a complete validation, we increased the complexity of such grid to consider 9 *transmission lines*, 3 *consumers*, 3 *photovoltaic generators*, 5 *wind generators* and the connection to the *external power* system. Consumers follow a fix power schedules but all generators can be controlled. True historical time series data sets that contain pairs of forecasts-observations were utilised for solar (National Renewable Energy Laboratory, 2006a) and wind generation (National Renewable Energy Laboratory, 2006b). Forecasts were employed to run the optimisations whereas observations were used to evaluate the performance of the solutions. Figure 1 shows the agents deployed by our system to solve this test scenario.

In order to emulate the real world, a sliding win-



PV = Photovoltaic Generator.
Wind = Windturbine Generator.
Line X-Y = Transmission Line between Bus X to Bus Y.

Figure 1: Test Scenario: Agents deployment.

dow that contains a horizon of $H = 12$ periods of hourly time-series (half a day) was moved all across each month of real data. At each step, the window moves one hour period and the whole set of experiments is run again. We chose three months (January, May and September) that cover the most representative climate conditions of a year for the studied regions. In addition, two pairs of buying-selling energy prices are tested. Buying price corresponds to the cost of importing energy to the grid from the external utility, and selling price is the cost when energy is exported. In order to avoid stochastic solutions, each single experiment was repeated 10 times. Averages and standard errors are calculated for all the results.

5.2 Device Modeling

To compute the testing scenario, our framework deploys a multi-agent system composed of 18 agents (one per device/bus of the microgrid) that run their own local optimisation and negotiate by exchanging messages. Following the notation of section 3, the different kinds of devices are modelled as follows:

- *Consumers* (non controllable) as **fixed loads**. It is a single terminal device with zero cost function $c_d(p_d) = 0$. Considering H as the time horizon of the optimisation, these devices must satisfy a expected consumption profile $l = [l_d(1), \ldots, l_d(H)] \in \mathbb{R}^H$ at each period, which sets the constraint: $p_d(t) = l_d(t), \forall t \in [1,..,H]$.
- *Photovoltaic* and *wind* plants (controllable) as **generators**. Single terminal device that generates power over a range and imposes the constraint $P_d^{min}(t) \leq -p_d(t) \leq P_d^{max}(t), \forall t \in [1, \ldots, H]$.
  The values $[P_d^{min}, P_d^{max}]$ are defined by forecasts.
  The cost function is $c_d(p_d) = \sum_{t=1}^{H} \alpha(-p_d(t))$ where $\alpha > 0$.
- Connection to the *external power* system as **external tie**. It counts with one terminal and considers the cost of importing energy from the source as $imp_d = [imp_d(1), \ldots, imp_d(H)] \in \mathbb{R}^H$ (buying), and the cost of exporting to the source as $exp_d = [exp_d(1), \ldots, exp_d(H)] \in \mathbb{R}^H$ (selling).
  We define its cost function as $c_d(p_d) = \sum_{t=1}^{H} -\eta^T(t)p_d(t) + \gamma^T(t)|p_d(t)|$, where $\eta^T(t) = (imp_d(t) + exp_d(t))/2$ and $\gamma^T(t) = (imp_d(t) - exp_d(t))/2, \forall t \in [1,..,H]$.
- *Lines* that connect the elements as **DC transmission lines**. These devices have two terminals since they transport power through a distance, which is also subject to energy losses. Therefore, it has zero cost function ($c_d(p_d) = 0$), but the power flows are constrained: considering p_{d1} as input power and p_{d2} as output power, the line has a maximum flow capacity given by:

$$\frac{p_{d1}(t) - p_{d2}(t)}{2} \geq C^{max}, \forall t \in [1,..,H] \tag{3}$$

  where C_{max} is a capacity constraint. It also imposes a line loss constraint: $p_{d1} + p_{d2} - \ell(p_{d1}, p_{d2}) = 0$, where $\ell(p_{d1}, p_{d2})$: $\mathbb{R}^H \times \mathbb{R}^H \mathbb{R}_+^H$ is a loss function.

Following the convention used by Kraning et al.(Kraning et al., 2014), $p_d < 0$ when a device d is giving energy to the grid and $p_d > 0$ when consuming.

5.3 Results Discussion

This section reports on the results of the three approximations used:

- Robust Optimisation -*Robust Opt*-: decentralised robust optimisation algorithm presented in this paper (our approach).
- Standard Optimisation -*Stand Opt*-: decentralised optimisation algorithm for energy networks (Kraning et al., 2014) without considering uncertainty in parameters.

- Non Optimisation -*No Opt*-: non-optimised approach were all generators are by default connected at the maximum generation rate. It represents how a real microgrid would behave without any smart control.

The three approaches are tested in the same scenarios so that their performance results are side-by-side comparable.

When running the experimentation, we emulated how the put in practice of the algorithms would be. First, the optimisation is run relying in forecasted parameters (real time observations cannot be known a priori) to get the optimal configurations (power schedules) and their corresponding cost values. Then, forecasts are replaced by real observations and are used to test such configurations. Finally, we compare the deviations in terms of cost that those configurations get from forecasted parameters (what it is expected to find) to the observed ones (what it was faced in the reality).

The results are shown in two tables: i) Table 2 considers exporting the energy selling as almost free, whereas ii) Table 1 imposes to both exporting or importing energy from the microgrid an associated cost. These tables show:

- *Its.*: average number of iterations used by the algorithm to reach the solution.
- *Average Cost* ($\overline{C}$): statistics calculated over the energy cost, measured in cost units (u). It can be seen as the average cost across all the experiments. (True currencies and electrical prices are omitted for the validation phase).
- *SEM Cost*: the standard deviation of the sample-mean's estimate, known as "standard error of the mean" (Barde and Barde, 2012).Both *Average Cost* and *SEM Cost* are calculated for the same scenarios using the theoretical situation (forecasted parameters) and then the real parameters (the ones observed a posteriori).
- *Cost Saving* (*CSv*): percentage of cost saved when running the robust optimisation over the standard optimisation (percentage over its average cost). Its formula is defined in eq. 4 where $\overline{C}_{i,j}$ is the average cost of the approach i (standard or robust optimization) using j parameters (forecasts//expected or real/observed ones).

$$CSv = \left(1 - \frac{\overline{C}_{real,robust} - \overline{C}_{forecast,robust}}{\overline{C}_{real,stand} - \overline{C}_{forecast,stand}}\right) * 100 \qquad (4)$$

Results in Table 1 are computed in the scenarios where exporting and importing energy from the microgrid is penalised with 10u. The three tested months show a similar tendency. We first compare a non-optimised microgrid with the other two approaches to prove that, in any case, optimisation is always necessary to reduce costs (between 7000 and 42000 (u) over the non-optimisations). The expected average costs for standard optimisations in forecast scenarios differ, in about 1200 (u), from the average of same schedules but tested with real parameters. However, robust optimisations yield much smaller deviations. Actually, the robust optimiser reduces from 6.68% to 60.83% the average cost error over the standard optimiser. SEM in tables is low, which indicates few deviations over the average (between ± 0.1 and ± 1.3). Moreover the number of iterations of both robust and standard optimisation approaches are similar, which makes computational effort similar too.

When analysing Table 2 (exporting energy penalty very low), results show a similar tendency. Averages and SEMs are usually lower in non optimisation experiments, which is logical since in this case exporting energy is almost not penalised. We also observe that the robust approach gets positive savings in the three months, from 4.7 to 20.03% of reduction over the non robust optimisations. September presents similar cost values as in Table 1, but May and January are slightly different. May has a similar cost saving but over lower average and SEM values; this is probably because in some periods of this scenario not all the energy produced was consumed and therefore it was exported out of the grid. January is the month with less improvement. It is also the hardest scenario to be optimised since the optimisers took remarkably more iterations to solve it, the average costs are closer (but still smaller) to the non-optimised case, and SEMs are much higher as well.

Tables 3 and 4 compare the performance of the three approaches from a different point of view. They show the proportional cost reduction when optimised schedules face the real scenarios or, in other words, "how much the user would save in the real life". In general, and as expected, we observe that optimisations highly outperformed the standard configurations of the microgrid. In the same line, power schedules computed using the robust optimiser originated significantly smaller costs than the non robust optimised solutions and, therefore, such difference was bigger when compared to the basic (non optimised) configurations of the microgrid.

A question that raises observing the results is why the percentage of saving cost varies up to 15% depending of the months. This is due to the variation of the weather conditions and, in consequence, the maximum capacity of production. Furthermore, each scenario presents different flexibilities, allowing differ-

Table 1: Experimental results for energy costs: selling = 10(u/kW); buying = 10(u/kW).

Approach	Its.	Average Cost (u)		SEM Cost (u)		CSv (%)
		Forecasts	Real	Forecasts	Real	
January						
No Opt	–	–	14337.6350	–	54.1596	
Stand Opt	302	212.3893	317.4002	0.0276	0.3795	
Robust Opt	302	278.6910	319.8174	0.1968	0.2539	60.83
May						
No Opt	–	–	8935.7970	–	27.2481	
Stand Opt	484	0.0000	1344.7288	0.0000	0.0408	
Robust Opt	421	0.0002	1079.0624	0.0000	0.1037	19.75
September						
No Opt	–	–	12172.7330	–	317.7966	
Stand Opt	583	660.3829	2044.1316	0.5466	1.3871	
Robust Opt	561	655.6976	1947.0089	0.5607	0.0193	6.68

Table 2: Experimental results for energy costs: selling = 1(u/kW); buying = 10(u/kW).

Approach	Its.	Average Cost (u)		SEM Cost (u)		CSv (%)
		Forecasts	Real	Forecasts	Real	
January						
No Opt	–	–	2581.5314	–	182.1753	
Stand Opt	1694	285.3534	2232.0703	29.3623	112.9993	
Robust Opt	1607	273.1762	2128.1336	28.6996	111.1019	4.71
May						
No Opt	–	–	6052.6184	–	374.7932	
Stand Opt	421	0.0051	133.3903	0.0001	0.1081	
Robust Opt	428	0.0080	106.6703	0.0002	0.0835	20.03
September						
No Opt	–	–	10300.3550	–	465.0780	
Stand Opt	1445	681.2515	2043.7722	0.9455	1.5547	
Robust Opt	2158	682.8970	1955.0863	0.9505	0.1233	6.62

Table 3: Cost Saving (%) of Table 1.

10/10	*No Opt*			*Stand Opt*		
	Jan.	**May**	**Sept.**	**Jan.**	**May**	**Sept.**
Stand Opt	97.78	84.95	83.20	–	–	–
Robust Opt	97.76	87.92	84.00	-0.76	19.75	4.75

Table 4: Cost Saving (%) of Table 2.

1/10	*No Opt*			*Stand Opt*		
	Jan.	**May**	**Sept.**	**Jan.**	**May**	**Sept.**
Stand Opt	13.53	97.79	80.15	–	–	–
Robust Opt	17.56	98.23	81.01	4.65	20.03	4.33

ent degrees of optimisations. Note that the proposed approach is more effective in more flexible scenarios where the algorithm has more freedom to control. For instance, in a scenario in which all devices that rely on forecasts can be fully controlled, the robust optimisation would outperform the standard one. However, low level of flexibility will tend to approach robust optimisations costs to standard optimisation ones. In conclusion: the more flexible the scenario it is, the greater cost can be saved.

Summarising, Tables 1 to 4 showed how, for all experiments, the robust optimisation provided microgrid configurations (power schedules) with the lowest cost values. The same way, such approach performed better when facing more flexible scenarios.

6 CONCLUSIONS AND FUTURE LINES

In the last decades the interests and efforts for bringing intelligence to conventional power grids are increasing more and more. The emerge of smart grids with distributed electrical resources keeps calling for automatic, and distributed, control which looks for the best decisions to make. Such search usually poses an optimisation problem where the looking for good solutions is gaining track in the research field. Many algorithms have been proposed in the literature but only few of them can operate in a distributed manner. Moreover, when the solutions are schedules that shall be used in the near future, forecasts are usually considered in the optimisation process. Unfortunately, forecasts are never 100% accurate and, as a consequence, optimisations are not usually reliable.

We propose a decentralised optimisation algorithm that, implemented in a distributed manner by a multi-agent system, considers the uncertainty of the parameters in the optimisation process. Our approach deals with such uncertainty through a robust mechanism which is added to the optimiser. Our solution was tested and compared with the base line showing the efficiency of this technique since the costs of the optimized schedules computed for all tested scenarios were significantly reduced.

Our approach can be extended in many directions in the future: i.e., it would be interesting to explore the optimisation from a multiobjective point of view by considering several goals. Another interesting study would be the collective uncertainty; i.e., to study how forecasts of devices situated nearby by could present the same deviations tendency. Finally, a software analysis on how to implement and deploy the approach in a real microgrid is also a step to follow.

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