Ex-post evaluation of Interruptible Load programs with a system optimisation perspective

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Abstract

The deployment of demand response in reserve markets has been widely discussed. Interruptible Load programs contract demand capacity from consumers in exchange for fixed and variable payments. System operators contract these resources to increase system resilience and use them for economic purposes. Although common, no ex-post evaluations of the program's performance and efficiency exists in the literature. To fill this gap, the paper presents a procedure to evaluate the optimal usage of these resources from a system operator perspective. A Mixed Integer Linear Problem is set to minimise the overall cost of the system using the participant demand resources in the tertiary reserve market, while ensuring that all technical and regulatory constraints are fulfilled in the evaluation. The proposed method describes a series of metrics to compare the optimal performance with the current scenario, and we draw a set of conclusions and policy recommendations from it. We apply the method to the Spanish Interruptible Load program. Our results show that during the five and a half years of the program, demand resources could have provided savings to the system of up to 23 % of the cost of tertiary reserve.

Keywords:
Interruptible Load, Ex-post evaluation, Spain, MILP optimisation

1. Introduction

Traditionally, power systems relied on fossil generators with the capability to adapt their power generation to demand fluctuations to ensure the electricity balance. The ongoing energy transition from fossil fuel power generation to renewable energy sources generation challenges this situation as they have a stochastic nature and are not freely dispatchable [1]. Thus, the system requires increasing levels of flexible resources to secure the grid operation [2, 3]. Demand Response (DR) can provide this flexibility to the system by adapting and controlling itself to fulfill system needs in a decentralised way [4], therefore, arising as a potential and prominent solution to be exploited to improve the system's operation achieving operational improvements and economic savings [5, 6].

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DR refers to modifications in consumers' consumption patterns to respond to signals provided by market agents or electricity prices [7]. DR actions can refer to load-shifting actions or load-shedding actions [8]. The first actions relate to postponing or moving part of the electricity consumption from one hour to another, while the second refers to the interruption of the energy consumption without considering a recovery. DR actions are achieved through incentive-based and economic-based programs. The programs that aim to obtain load-shedding responses through economic incentives are known as Interruptible Load (IL) programs, and they are the focus of this study.

Authors state that DR can deliver benefits by supplying services at a lower cost than traditional generation [9, 10]. In particular, IL programs are services that System Operators (SO) use to ensure the security of supply and grid reliability [11]. However, many System Operators are still reluctant to use DR as generation resources and tend to use these demand programs as a last resource reserve without optimising their participation in the overall system operation. This aversion to DR usage has a technical nature related to its constraints such as time availability and power response capacity. Besides, DR also faces social constraints associated with consumers' preferences, the inelastic nature of electricity demand, and operators' habits of using the generation side to balance the grid [12]. In this regard, there is a need to analyse the usage, performance, and efficiency of these programs in real environments to understand their real costs and potential benefits [12]. Moreover, there is a need to provide system-wide analysis and policy recommendations to improve their performance [13, 14] and understand what the benefits of IL programs from a system wide perspective are [15].

IL programs exist around the world, but to our knowledge, no *ex-post* evaluations about their specific performance and hypothetical optimal use exist in the literature. To address this gap, we aim to contribute by providing a methodical analysis and a set of comparison parameters to evaluate IL programs. We use this approach to analyse five and a half years of the Spanish IL program (SI, for its initials in Spanish) by responding to the following questions. First, how the Spanish SO used the SI program, under what conditions it use the demand capacity, and what cost it represented to the overall system. Second, what could the optimal usage of this program have been to optimise the available resources? In particular, when should the SO have used demand resources, and what the extra costs paid to consumers by the system would have been? Third, what insights the public policy evaluation presented can provide for both SOs and policymakers. Particularly, to determine if the Spanish IL program could have been cost competitive compared with the traditional resources or the price paid was above the average prices during the period.

We implement the analysis by formulating a Mixed Integer Linear Program (MILP) that considers the technical and regulatory characteristics of an IL program to optimise the hypothetical optimal usage of the demand resources by the system operator and defines a set of economic metrics. With the data provided by the Spanish SO [16], we analyse the eight periods of the Spanish SI program considering historical data and the program characteristics. Then, we optimise its performance under a system perspective, evaluating the participation of these demand resources in the tertiary reserve market and we extract a set of conclusions and policy and operational recommendations.

The rest of the paper is organised as follows, Section 2 discusses the current literature around DR, especially IL programs, section 3 presents the case study and the mathematical formulation to optimise and assess the program. Section 4 shows the results from the different simulations and discusses them and their implications. Finally, section 5 concludes summarising the main findings of the paper.

Nomenclature

Indices

t	Time index [hours]
p	Period index
s	Index of small capacity products
l	Index of large capacity products
m	Index of months

Sets

S_p	Set of all small capacity products in a period p
L_p	Set of all large capacity products in a period p
T_m	Set of all time periods in a month m
T_p	Set of all time periods in a period p
T	Set of all time periods
P	Set of all periods

Parameters

Q_t^T	Tertiary reserve originally used in t [MWh]
Q_t^{SI}	SI originally used in t [MWh]
Q_t^{Tmax}	Tertiary reserve and SI used in t [MWh]
π_t^T	Price of tertiary reserve in t [€ /MWh]
π_p^{ref}	Reference price for SI usage in p [€ /MWh]
k_p^{ref}	Tertiary usage factor for SI price in p
π_t^{SI}	Price of SI in t [€ /MWh]
π_t^{SPOT}	Spot price in t [€ /MWh]
K^T	Maximum consecutive usage of a SI product [h]
K^{MS}	Maximum usage of a small capacity products in a month [h]
K^{ML}	Maximum usage of a large capacity products in a month [h]
K^{YS}	Maximum usage of a small capacity products in a year [h]
K^{YL}	Maximum usage of a large capacity products in a year [h]
SI^{max}	Maximum SI capacity usage in t [MW]

SI^{min}	Minimum SI capacity usage in t [MW]
N_p^S	Number of small capacity products in p
N_p^L	Number of large capacity products in p
P_p^S	Power of the small capacity products in p [MW]
P_p^L	Power of the large capacity products in p [MW]
Δt	Time range used in the program [h]
FC_p^S	Price of the small capacity products in p [€ /MW/year]
FC_p^L	Price of the large capacity products in p [€ /MW/year]
M_p	Months of p
B^M	Sensibility usage coefficient of monthly resources [%]
B^Y	Sensibility usage coefficient of yearly resources [%]
Variables	
q_t^T	Tertiary reserve used from the system after optimising SI [MW]
$\alpha_{t,s}^S$	Binary variable that is equal to 1 if the small capacity product is used in the time period t
$\beta_{t,l}$	Binary variable that is equal to 1 if the large capacity product is used in the time period t
γ_t	Auxiliary binary variable that is equal to 1 if any SI product is used in the time period t
Metrics	
TC_p^{SI}	Total cost of the SI program in p [M€]
CF_p	Fixed cost of the SI program in p [M€]
CV_p^{SI}	Variable cost of the optimised SI program in p [M€]
CV_p^T	Variable cost of the optimised tertiary reserve in p [M€]
CV_t^{SI}	Variable cost of the optimised SI program in t [€]
CV_t^T	Variable cost of the optimised tertiary reserve in t [€]
$C\bar{V}_p^{SI}$	Average variable cost of the optimised SI program in p [€ /MWh]
$\bar{C}_p$	Average cost of the optimised products in p [€ /MWh]
$\bar{C}_p^S$	Average cost of the optimised small capacity products in p [€ /MWh]
$\bar{C}_p^L$	Average cost of the optimised large capacity products in p [€ /MWh]
S_p	Savings with the optimised SI program in p [M€]
$\bar{\pi}_p^T$	Mean price of the tertiary reserve in p [€ /MWh]
π_p^U	Tertiary triggering price [€ /MWh]

2. Related work

2.1. Demand response benefits and potential

The literature related to DR states that wider inclusions of DR in the system provide benefits to the system as a whole. These range from economic benefits related to investment deferral [17], cost reductions [10, 18], impact on spot prices [14] and increasing market competition [19]. Environmental benefits associated with reductions in fuel generation and improvements in grid operation and reliability [20], and positive impacts for the different stakeholders of the system such as cost reductions due to consumer engagement [15]. However, the full implementation of DR also suffers a wide range of barriers and handicaps associated with regulatory, economic, and social aspects [21, 22].

The DR potential is calculated either by defining the physical parameters and nature of the consumer flexibility capacity or by considering an economic profit of its usage related to both the SO or the consumer. The physical calculation does not evaluate the economic profits associated with DR usage and focuses on the physical energy and power parameters of DR, which has been characterised by regions [23], countries [24], or by sectors of activity such as meat industries [25], the residential sector [26–28], service sector [29], and commercial buildings [30]. In contrast, the profitability approach includes the valorisation of DR in specific markets such as day ahead [8], large-scale reserve and Ancillary Services (AS) [31–33], and local electricity markets at the distribution grid level [5].

Finally, as digitalisation advances in the utilities sector, the usage of modelling and control techniques such as Machine Learning and Artificial Intelligence represents an opportunity to enhance the participation of DR in the system [34]. These algorithms are effective to improve predictive and optimisation models for the participation of demand in the system [35]. These approaches are useful and have been studied at the household level [36], commercial level [37], electric vehicle level [38], and at the industrial level [39]. Presenting at all subsectors great potential due to the increasing importance and benefits of Energy Management Systems.

2.2. Demand response in Ancillary Services

SOs are the responsible agent to ensure the security and reliability of the transmission grid and have to ensure power stability to avoid quality deterioration and ultimately system blackouts [40]. To do so, SOs use a combination of operation markets, auctions, and contracts to ensure sufficient reserves to provide AS. The SEDC report presents the situation of European countries relating DR and the inclusion of them in AS markets [41] and a classification of these programs based on their main economic and physical parameters is performed in [11]. Although DR can now participate in several countries, in most of them, this participation remains low or faces different barriers such as minimum capacity constraints, generation structured programs, or the impossibility to provide DR from aggregated resources.

These difficulties to participate contrast with the potential and benefits the authors estimate in the participation of DR in AS markets and contracts. Koliou et al. study the participation of DR in the German balancing mechanisms and conclude that these resources may be of most value for the system [40]. Mathieu et al. show the benefits of the participation of residential consumers according to their DR potential in the CAISO AS market [42]. Rodríguez-García et al. present the benefits associated with the optimum usage of the flexibility of a meat factory in the Spanish tertiary reserve market [43]. Finally, the economic evaluation of reserve provision from a chlor-alkali industrial process is analysed in [13].

2.3. *Evaluation of IL programs*

IL programs use interruptible parts of consumer load during high peak or emergency periods to obtain reserve capacity to rapid responses to solve these situations and increase system reliability. The most common way to use IL is by signing contracts between SOs and particular consumers [44]. These contracts agree in the conditions to interrupt the electricity usage of the consumer under specific contexts established by the operator willing to obtain operation reserves. In return, the consumer receives a payment from the operator related to the offered capacity, the energy delivered, or both [45]. Traditionally, these contracts only involved large industrial consumers that could be easily monitored and had a large response in critical moments [11]. In contrast, advances in monitoring and control technologies allow the opening up of these contracts to small and medium consumers, either via direct contract or through intermediaries that aggregate resources.

Strategies on how to operate and the benefits of IL programs and actions have been studied. Different authors present studies such as a Markov decision process to assess the use of the IL resources [12], the usage for the operation of power transformers [46], its operation in microgrids [47], and in primary frequency response [48]. However, these analyses do not consider the system as a whole, do not have real case studies, nor intend to provide any operational recommendations to the SOs. In this sense, auditing and optimising the usage of IL programs remain essential to continue improving system operation and including DR resources in power systems.

In this regard, there is a need to assess and use metrics to analyse and quantify the real impact and efficiency that IL programs could have had in real situations. Following a system perspective approach, we aim to understand the potential benefits of an IL program for the whole system and fill the analysis gap found in the literature related to *ex-post* IL program evaluation and operation. We provide a MILP method to evaluate a real IL program and set a series of efficiency metrics to compare the IL program under both real and optimised scenarios with traditional generation resources.

3. Case study, formulation and metrics

This section presents the methodology followed to perform the *ex-post* evaluation of the Spanish IL program. The procedure is suitable to analyse other programs. Nevertheless, the lack of standardisation among DR programs requires a case by case analysis of their technical and regulatory constraints, when the resource participates and payments types [11]. Therefore, first, we describe the Spanish IL and the tertiary reserve where the IL is used. Then the section focuses on the mathematical formulation of the problem that we use to optimise the IL usage, the considered scenarios, and the metrics used for the analysis.

3.1. *Spanish IL: Sistema de Interrumpibilidad*

The Spanish system presents a type of DR reserve product know as *Sistema de Interrumpibilidad* (SI), where only large industrial consumers participate. The program provides flexible and rapid responses to the operator in situations when generation and demand are not balanced. Interruptibility corresponds to reductions in demand after a notification by the Spanish SO, Red Eléctrica de Espña (REE), in charge of the transmission system. The service is also contracted by REE, who can use it as a last-resort reserve to ensure the reliability of the system under emergencies with less than 15 minutes warning in advance [49]. REE can also use this product under economic criteria as a last-resort tertiary reserve [49, 50]. In case of need, REE can call the contracted consumers, this compels consumers to respond in a contractually determined timer period, facing penalties if not delivering the service. This service is contracted by REE with a periodic auction where power packages are assigned in a decreasing price order. REE auctioned the service annually in 2015, 2016, and 2017; held two auctions per year in 2018 and 2019; and in 2020 REE called the last auction for 6 months. Since then, REE has not called any other auction and is rethinking if whether to extend the use of this program or not.

In the auctions, for each assigned bid, REE pays to the consumer according to the capacity provided with a price of € /MW per year. Two types of products exist regarding their capacity,both small and large products. Small products have a capacity of 5 MW and large products had 90 MW from 2015 to 2018 and in the second auction of 2018 they changed to 40 MW [49, 51]. When REE contracts a product, REE can use it at any time, no matter the day or hour during the period. If the program is activated, the consumer receives an extra payment according to parameters determined in each auction by REE. The payment is different if the activation is for emergencies (less than 15 minutes notice), or tertiary reserve (at least 15 minutes notice). The variable (energy) price paid for the usage of this product was set as a fixed price per period [49] but in 2017 this price became variable on an hourly basis and dependent on the spot market [52].

$$\pi_t^{SI} = \begin{cases} \pi_p^{ref} \cdot k_p^{ref} & \forall p \in [2015-2017] \\ \pi_p^{ref} \cdot k_p^{ref} - \pi_t^{SPOT} & \forall p \in [2018A-2020A] \end{cases} \tag{1}$$

The usage of the interruptible loads must fulfil a series of technical and regulatory specifications. Its application is carried out by simply reducing the demand of the contracted consumer when it is needed. Each type of product has the maximum amount of hours that can be mployed during a month, a year, and in consecutive hours. Thus, the small products (5 MW) may be employed a maximum of 40 h/month and 240 h/year, while the large products (40/90 MW) may be employed a maximum of 60 h/month and 360 h/year. The hourly constraint limits the usage of any product to a maximum of 2 consecutive hours. These constraints have been constant throughout the different periods. Finally, when REE uses the SI program as a tertiary resource, the legislation forces REE to use the hourly capacity in a range from 200 MW to a maximum of 500 MW. Table 1 presents the main parameters of each auction.

Table 1: Data summary of the different SI auction periods [51, 53–59]. * Refers to the data used in the optimisation model.

Period	**2015**	**2016**	**2017**	**2018A**	**2018B**	**2019A**	**2019B**	**2020A**
Dates	01/01/2015- 31/12/2015	01/01/2016 - 31/12/2016	01/01/2017 - 31/12/2017	01/01/2018 - 31/05/2018	01/06/2018 - 31/12/2018	01/01/2019 - 30/06/2019	01/07/2019 - 31/12/2019	01/01/2020 - 30/06/2020
M_p	12	12	12	5	7	6	6	6
k_p^{ref}	0.281	0.926	0.253	0.751	0.751	0.910	0.828	0.828
π_p^{ref}	92.95	77.13	75.12	72.20	72.20	91.24	79.14	79.14
P_p^S	5 (20)*	5 (20)*	5 (20)*	5 (20)*	5 (20)*	5 (20)*	5 (20)*	5 (20)*
FC_p^S	121,725	134,808	127,536	108,245	63,168	64,624	75,307	8,764
N_p^S	442 (110)*	434 (108)*	415 (104)*	376 (94)*	320 (80)*	352 (88)*	340 (85)*	200 (50)*
P_p^L	90	90	90	90	40	40	40	40
FC_p^L	294,875	292,013	289,125	235,167	174,174	105,429	96,925	0
N_p^L	9	8	10	8	25	21	16	0
CF_p	507.9	502.8	524.8	155.3	160.6	101.1	95.0	4.4

Figure 1 presents the usage of the service for economic purposes during the eight periods. The usage of the SI is rare, with no use in half of the periods, and only in the first period of 2018 the usage exceeded 10% of the available capacity. The tertiary price used to trigger the service ranged from 0 € /MWh to a maximum of 107 € /MWh during 2018, showing that REE did not use clear critera to trigger the service with economic purposes and posing the question about the optimal use of this resource.

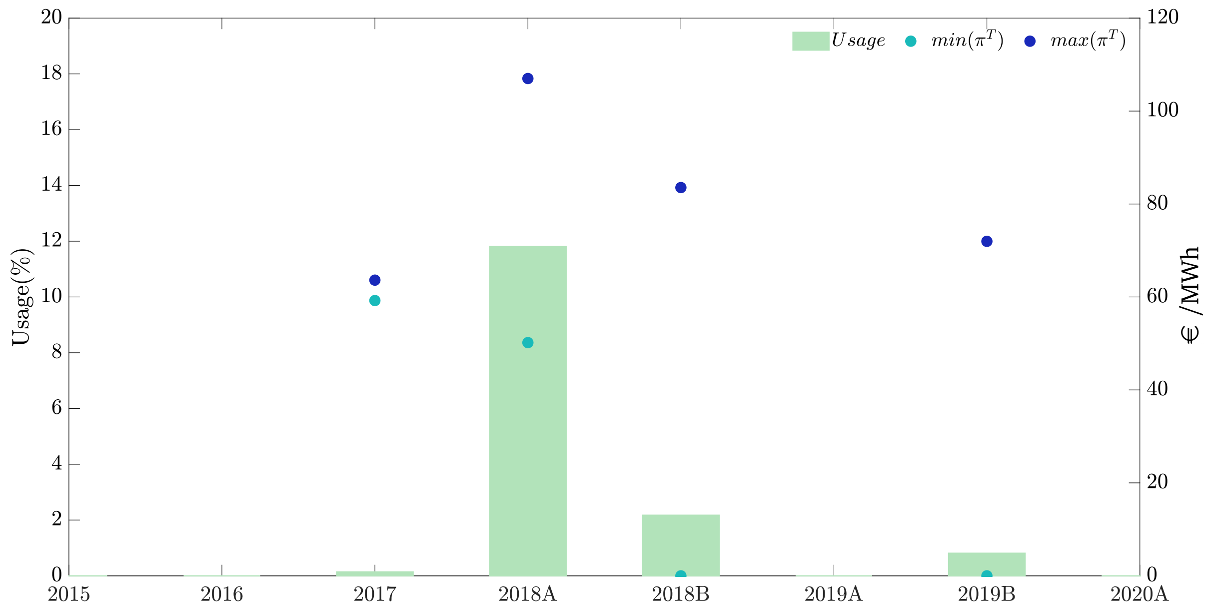

Figure 1: Summary of the historical SI usage [16].

3.2. *Tertiary reserve*

REE is in charge of ensuring the reliability of the power system with different reserve products. During the daily operation, REE uses tertiary reserve, Replacement Reserve in ENTSO-e terminology, by dispatching price-quantity bids in a real time based market. Tertiary reserve is not used every hour of the year, but only when the system requires reserve. The demand side cannot participate in this market and the price paid to the generators that procure tertiary reserve is based on an hourly marginal price. Figure 2 represents the price distribution of the tertiary reserve market during the analysed periods, the mean values vary around 60 € /MWh in each period with some periods having extreme values over 100 € /MWh.

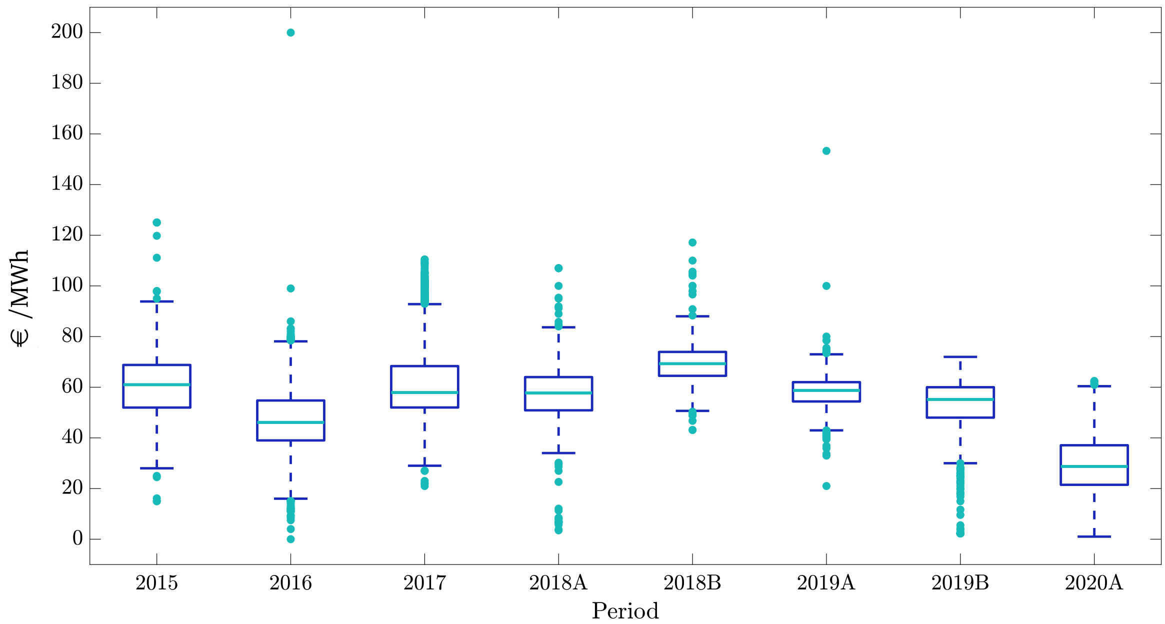

Figure 2: Price distribution of the tertiary reserve in the Spanish system by period [16].

For instance, Figure 3 represents the evolution of the tertiary reserve price during a day with high prices during 2017. This evolution shows how during certain hours there is no reserve requirements while the optimisation of the usage needs to cover several options with similar high prices.

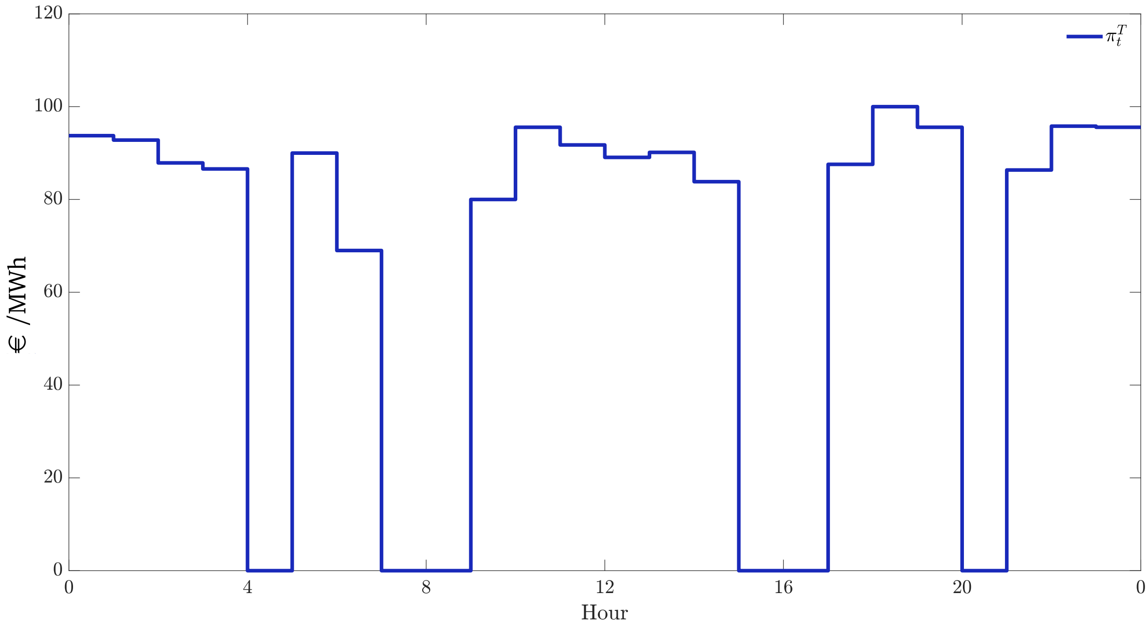

Figure 3: Evolution of the tertiary reserve price during January 21 2017[16]

3.3. Assumptions and scenarios

The *ex-post* evaluation hereby presented is framed under a series of assumptions and limitations. First, the participation of each SI product is assumed to operate at a constant rate during each hour that REE activates it. Thus, if employed during one hour, the product will remain active until the next hour, when REE can decide to use it or not. Second, the usage of IL products only affects the tertiary reserve, it is activated 15 minutes in advance, and it does not affect the hourly price of the tertiary reserve considered in the market. Even though the tertiary reserve has a marginal market price, the reductions in price that arise from a reduction in the quantity are not considered. Third, due to tractability and computational limitations, the small products (5 MW) are modelled as a mixture of 4 small products resulting in modelling products of 20 MW. This simplification does not have a major impact as the minimum SI hourly capacity results is 200 MW, forcing the aggregation of DR resources to activate the program. Fourth, no recovery periods with energy increases are considered. In this sense, the SI products are modelled as pure load shedding DR and not considering any load shifting or recovery in the product. Fifth, we assume that consumers will not fail to deliver the contracted capacity and no reductions in the participation would have arisen from a more active usage of the program. We derive this assumption from the particularities of the program, in which the failure to deliver the contracted capacity more than once means exclusion from participation and retribution during the whole period [49]. Moreover, the penalty arising from failing to deliver the demanded capacity would entail a payment that would overcome the extra cost in extra reserve. Finally, the historically used IL capacity in the different hours is added to the tertiary needs of the corresponding hour to consider the historical system needs. Furthermore, as the analysis considers an evaluation of a past policy, no time burdens exist regarding computational times as no short term operation is assumed.

We perform two sensitivity analysis with two scenarios. The first scenario of analysis considers all the technical and regulatory constraints existing in the program, maximum consecutive hours, maximum monthly and yearly hours, and minimum and maximum capacity used per hour. The second scenario eliminates this last requirement and does not constrain REE to have maximum and minimum usage boundaries during each hour. In this sense, the SI program can provide the total amount of tertiary required in an hour even when large quantities are demanded. We do not consider these boundaries in the second set of scenarios as they represents a regulatory constraint that could not exist as it does not have technical implications.

Regarding the sensitivity analysis, two security parameters are included in the model to safeguard SI capacity to use it for security reasons without violating the hourly limits. One parameter limits the monthly hours that IL can be used for economic reasons, while the other limits the yearly hours used. Both parameters vary in steps from 10% to 100% and aim to deliver the marginal profits that arise from a percentage usage of the IL products.

3.4. Mathematical formulation

The presented mathematical formulation results in a Mixed Integer Liner Problem, whose objective is to minimise the cost of providing tertiary reserve to the system by using the existing resources but also optimising the SI resources of a period. The SI costs only consider variable costs as the fixed costs are assumed to be a sunk cost for the system.

Therefore, the objective function is:

$$min \qquad Cost_p = \sum_{t}^{t \in T_p} \left(CV_t^{SI} + CV_t^T \right) \qquad \forall t \in T_p \tag{2}$$

where CV_t^{SI} and CV_t^T represent the hourly cost of providing the tertiary reserve needed by the system. The first one is a sum of small and large SI resources used during the time period t, while the second quantifies the needs of the tertiary reserve from traditional sources after the usage of SI resources.

$$CV_t^{SI} = \pi_t^{SI} \left(\sum_{s}^{S} \alpha_{t,s} \cdot P_p^S \cdot \Delta t + \sum_{l}^{L} \beta_{t,l} \cdot P_p^L \cdot \Delta t \right) \tag{3}$$

$$CV_t^T = \pi_t^T \cdot q_t^T \tag{4}$$

Subject to:

$$\sum_{s}^{S} \alpha_{t,s} \cdot P_p^S \cdot \Delta t + \sum_{l}^{L} \beta_{t,l} \cdot P_p^L \cdot \Delta t + q_t^T \geq Q_t^{Tmax} \qquad \forall t \in T_p \tag{5}$$

$$Q_t^{Tmax} = Q_t^T + Q_t^{SI} \qquad \forall t \in T_p \tag{6}$$

$$q_t^T \geq 0 \qquad \forall t \in T_p \tag{7}$$

where Q_t^{Tmax} is the total tertiary reserve required in the system at an hour t that calculated the used SI and the tertiary bought in the market. And q_t^T forces the variable quantity of tertiary reserve to be positive.

$$\sum_s^S \alpha_{t,s} \cdot P_p^S + \sum_l^L \beta_{t,l} \cdot P_p^L \leq SI^{max} \cdot \gamma_t \qquad \forall t \in T_p \tag{8}$$

$$\sum_s^S \alpha_{t,s} \cdot P_p^S + \sum_l^L \beta_{t,l} \cdot P_p^L \geq SI^{min} \cdot \gamma_t \qquad \forall t \in T_p \tag{9}$$

Eq. (8),(9) ensures that if the system uses SI, the total amount used has to be within limits. Besides, Eq.(10)-(13) limit the number of uses in the whole period of the auction and they include a parameter to vary these limits. Finally, (14),(15) ensure that a resource cannot be used more than K^T consecutive hours.

$$\sum_t^{t \in T_m} \alpha_{t,s} \leq K^{MS} \cdot B^M \qquad \forall s \in S_p, m \in M_p \tag{10}$$

$$\sum_t^{t \in T_m} \beta_{t,l} \leq K^{ML} \cdot B^M \qquad \forall l \in L_p, m \in M_p \tag{11}$$

$$\sum_t^{t \in T_p} \alpha_{t,s} \leq K^{YS} \cdot B^Y \cdot \frac{M_p}{12} \qquad \forall s \in S_p \tag{12}$$

$$\sum_t^{t \in T_p} \beta_{t,l} \leq K^{YL} \cdot B^Y \cdot \frac{M_p}{12} \qquad \forall l \in L_p \tag{13}$$

$$\alpha_{t-2,s} + \alpha_{t-1,s} + \alpha_{t,s} \leq K^T \qquad \forall s \in S_p, t \in T_p \tag{14}$$

$$\beta_{t-2,l} + \beta_{t-1,l} + \beta_{t,l} \leq K^T \qquad \forall l \in L_p, t \in T_p \tag{15}$$

3.5. Metrics

The potential impact and benefits arising from an optimal usage of the SI program are analysed based on the following metrics. The first approach is to understand the total cost of SI in the case of optimal usage. This cost collects both the fixed cost and the variable costs of the optimised program as shown in Eq (16). The second element to consider is the associated savings of the optimised SI program for the whole system. Eq. (17) presents the comparison between the current cost of providing the tertiary reserve acquisition with providing this service as a combination of the SI program and the tertiary reserve market.

$$TC_p^{SI} = CF_p + CV_p = (FC_p^S \cdot N_p^S + FC_p^L \cdot N_p^L) + \sum_t^T \left(\pi_t^{SI} \left(\sum_s^S \alpha_{t,s} \cdot P_p^S \cdot \Delta t + \sum_l^L \beta_{t,l} \cdot P_p^L \cdot \Delta t \right) \right) \tag{16}$$

$$S_p = \sum_{t}^{T_p} \left(\pi_t^T \cdot Q_t^T + \pi_t^{SI} \cdot Q_t^{SI}\right) - \sum_{t}^{T_p} \left(CV_t^{SI} + CV_t^T\right) \tag{17}$$

Regarding the efficiency of the program, Eq (18-20) present the weighted average cost per unit of energy used. Eq (18) presents the Levelised Cost of Energy € /MWh of the optimised SI program for the period p, while Eq (19) and Eq (20) disaggregate these costs for the small products and the large products, which have a different fixed cost FC_p^S, FC_p^L. These metrics serve as a way to compare the efficiency of the program with the costs of acquiring tertiary reserve in the market.

$$\bar{C_p} = \frac{TC_p^{SI}}{\sum_t^{T_p} \left(\left(\sum_s^S \alpha_{t,s} \cdot P_p^S \cdot \Delta t + \sum_l^L \beta_{t,l} \cdot P_p^L \cdot \Delta t\right)\right)} \tag{18}$$

$$\bar{C_p^S} = \frac{FC_p^S \cdot N_p^S + \pi_t^{SI} \left(\sum_s^S \alpha_{t,s} \cdot P_p^S \cdot \Delta t\right)}{\sum_t^{T_p} \left(\sum_s^S \alpha_{t,s} \cdot P_p^S \cdot \Delta t\right)} \tag{19}$$

$$\bar{C_p^L} = \frac{FC_p^L \cdot N_p^L + \pi_t^{SI} \left(\sum_l^L \beta_{t,l} \cdot P_p^L \cdot \Delta t\right)}{\sum_t^{T_p} \left(\sum_l^L \beta_{t,l} \cdot P_p^L \cdot \Delta t\right)} \tag{20}$$

To assess the efficiency of the program without considering the sunk costs, Eq (21) present the weighted average variable cost per unit of energy used.

$$C\bar{V}_p = \frac{CV_p^{SI}}{\sum_t^{T_p} \left(\sum_s^S \left(\alpha_{t,s} \cdot P_p^S \cdot \Delta t\right) + \sum_l^L \left(\alpha_{t,l} \cdot P_p^L \cdot \Delta t\right)\right)} \tag{21}$$

π_p^U represents the minimum tertiary price at which the SO triggers SI resources. These prices are the result of obtaining the minimum π_t^T at which the optimised SI program used DR resources in a given period.

As already mentioned, these metrics are useful to compare different scenarios such as the current situation with the optimal usage of the program, but also with new scenarios relaxing some constraints, such as the maximum and minimum capacity, and including a sensitivity analysis of the security coefficients.

4. Results and discussion

This section presents the results of the evaluation of the SI program and the potential of the optimised usage of it. We provide a general overview on how REE used this program and a comparison with the *ex-post* optimised case with a period by period analysis of the potential benefits and the main metrics analysed. Then we present a sensitivity analysis regarding both the security coefficients B^M and B^Y and the scenario of not considering maximum and minimum hourly constraints. Then, we compare the performance of optimised results of the program with and without maximum and minimum hourly capacity requirements. Due to extension considerations, when analysing detailed data of a period, we have included in the main body the 2017 period as an example, and we present the analogous figures for the rest of the periods in the Appendix.

4.1. *Overall results of the program*

Figure 4 presents the aggregated results of the program. During the five and a half years of the program under the Current Scenario (CS), the SI had a total fixed cost of 2,049.6 M€ with an almost nonexistent variable cost associated with the lack of use of it. During those years, the total cost that the Spanish SO paid for tertiary reserve added up to 707.4 M€ . Therefore, only the fixed costs of the SI program accounted for almost three times the total value of the tertiary reserve market, the market where SI is intended to operate for economic reasons. In this sense, it is clear that this DR program derives in a non cost-effective manner of delivering reserves due to the high fixed cost that it has. Nevertheless, if properly operated, the program could have reported over the years total savings of 163.2 M€ . With an economic optimal usage of the program by the SO, the cost of the program would add up to 2,049.6 M€ in fixed costs and 61.9 M€ of variable costs. The analysis does not intend to optimise the fixed costs, which are considered as a given parameter. The savings would represent up to 7.96 % of the fixed cost that representing the SI program and 23.07 % of the cost of using tertiary reserve during these last five and a half years.

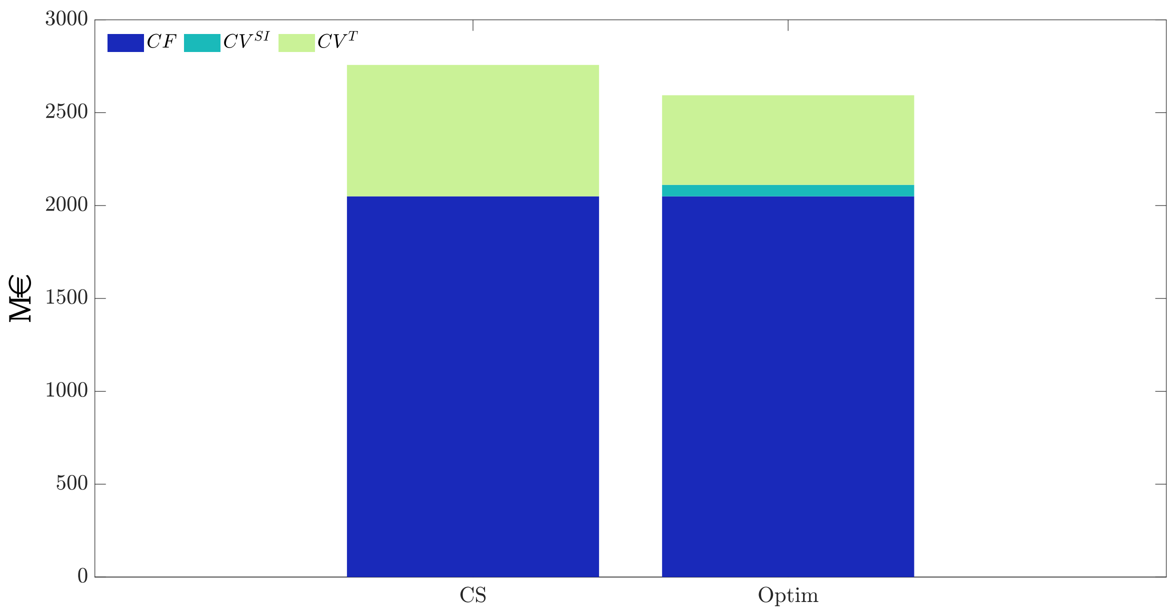

Figure 4: Summary of the potential benefits obtained with an optimised performance of the SI program.

When going to each period of the program, the differences in efficiency and savings largely differ. Figure 5 presents the results of the program by period. The results show how during 2015, 2017, 2018A, 2018B, 2019A, and 2019B the savings ranged from around 6 M€ to 52 M€ , while 2016 and 2020A only added up to around 0.5 and 3 M€ respectively. Focusing on the first group of six periods, we appreciate a similar optimum operation of the program, using DR to cap the higher costs of the tertiary reserve market with variable costs of the program lower than the market. The variations between these years refer to two main parameters, first differences between high tertiary prices and extreme price events, second the characteristics defining the SI's prices π_t^{SI}. Focusing on Figure 2, price differences in the tertiary market, and especially, with the extreme events that occur with tertiary prices above 100 € /MWh. For instance, 2017 presents a greater number of hours with extreme high prices while the second part of 2019 shows a lower mean and non existing extremely high events, thus a lower saving potential. Second, Table 1 presents the parameters k_p^{ref} and π_p^{ref} that define the SI price π_t^{SI}. From 2015 to 2017, SI prices were constant while in the last five periods these prices were linked to the hourly wholesale electricity price.

Therefore, under the optimised scenario, the variable costs of SI are higher in 2015 than in 2017, producing lower savings in the former. In contrast, the variable costs of the last five periods show that in these periods, the interplay among wholesale, SI, and tertiary prices triggers the usage of DR. In particular, during 2018B, the maximum benefit resulted from combining these parameters and obtaining usage prices per hour close to zero, with almost zero variable costs during the period. This results in low variable costs of the program with similar savings in comparison with other periods in the tertiary reserve acquisition, and in sum, higher total savings.

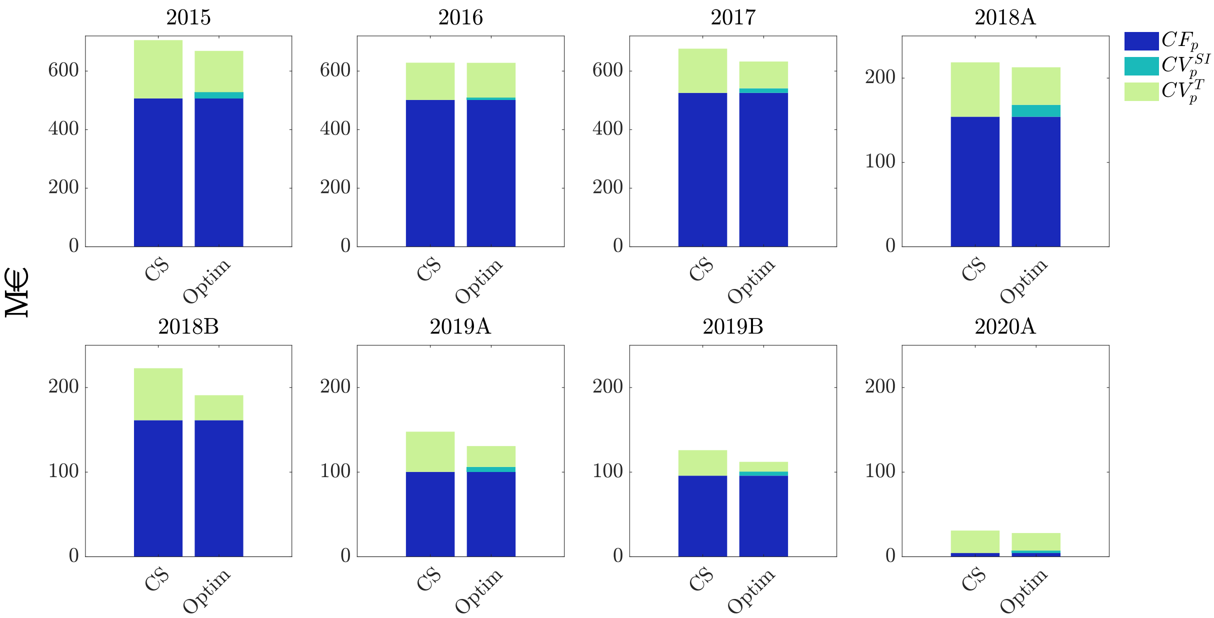

Figure 5: Summary of the potential benefits obtained with an optimised performance for each SI period.

In contrast, 2016 had high variable prices for the usage of SI, which resulted in a small usage of the resource during optimal operation, as it was not efficient to use it compared with the tertiary reserve market. This price, set by REE, was between 3 and 4 times higher than in 2015 and 2017 due to the high value of k_p^{ref}. When *ex-post* optimising the SI resource, this high price leads to in not using the total DR capacity during the available hours, which means savings are around one hundred times lower compared with other periods. Finally, the sixth group of columns, 2020A, differs from the others since it covers six months and REE contracted around half of the small products compared to the rest of the periods and no large products. This resulted in lower total costs, but also lower absolute savings.

4.2. Economic efficiency and usage of the program

To analyse the potential efficiency of the program, we compare in Figure 6 the average cost of the optimised program with the average price that the tertiary reserve market had during the reference period. In this sense, we see that even considering an optimised usage of the service, the SI program had an average cost ranging from five to ten time higher than the average tertiary reserve price during the periods 2015, 2017, and both periods in 2018 and 2019. In 2016 this cost adds up to more than 90 times higher while in 2020A the cost is only 1.6 times higher. The variability between these metrics largely relies on the initial fixed costs paid to the availability of these resources. While during the first years of the program the fixed cost meant the impossibility of having competitive costs with the traditional market, during the last periods of the SI these fixed costs are sensibly reduced, resulting in a resource with lower differences within the market and even competitive with the price spikes during 2020A. As previously discussed, 2016 is an an anomaly since the optimisation of the program does not generate a relevant improvement of the efficiency of the program due to the high variable costs.

The other logical but relevant result is the comparison between the large and small products. While large products provide more power, their cost once optimised is between 50% to 100 % times higher than the cost of small products. The large products became more cost-competitive once they reduced the power provided from 90MW to 40MW in the period 2018B. The variability of costs is mainly related to two elements. First, providing on the one hand more power, which is more valuable for the system. Second, fewer consumers can provide larger quantities of power, which results in lower competition in the assignation of these products. These two elements result in higher prices as regards the large capacity products, as Figure 6 shows for six of the periods analysed. 2019B is the only period with different results due to a higher usage of large products with lower variable prices and a lower gap between the fixed costs of the small and large products. Thus, if the SO now has the capacity to better control and coordinate resources due to the digitalisation of the grid, having a myriad of smaller resources will be more cost-effective than having large resources, which are scarce and less competitive with each other.

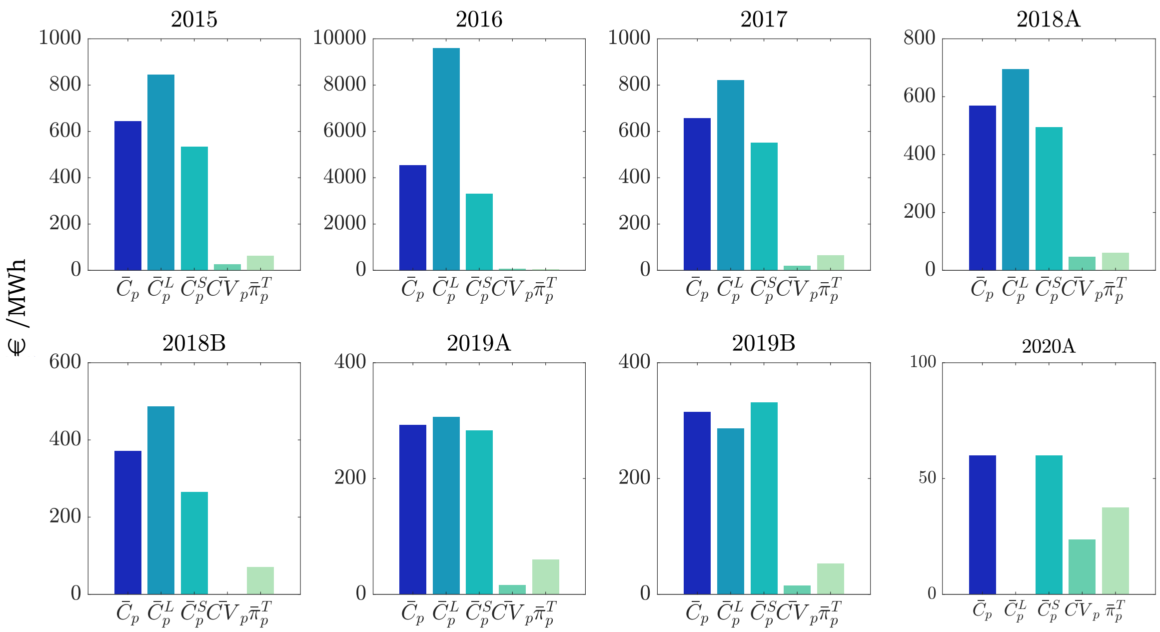

Figure 6: Summary of the main economic metrics obtained with an optimised performance for each SI period.

Figure 7 shows the minimum triggering price of the SI program (π_p^U) at which REE should have used the resource and the average tertiary prices with their standard deviation during each period. Thus, during the hours when prices were higher than the reference price, the SO should have considered using the SI to reduce costs to provide tertiary reserve. While during some periods the reference price is above the average of the tertiary reserve price, the trend shows that SI usage can be interesting for the SO at several times of day and during some periods in practically every time period, as the variable costs are reduced or almost non-existing.

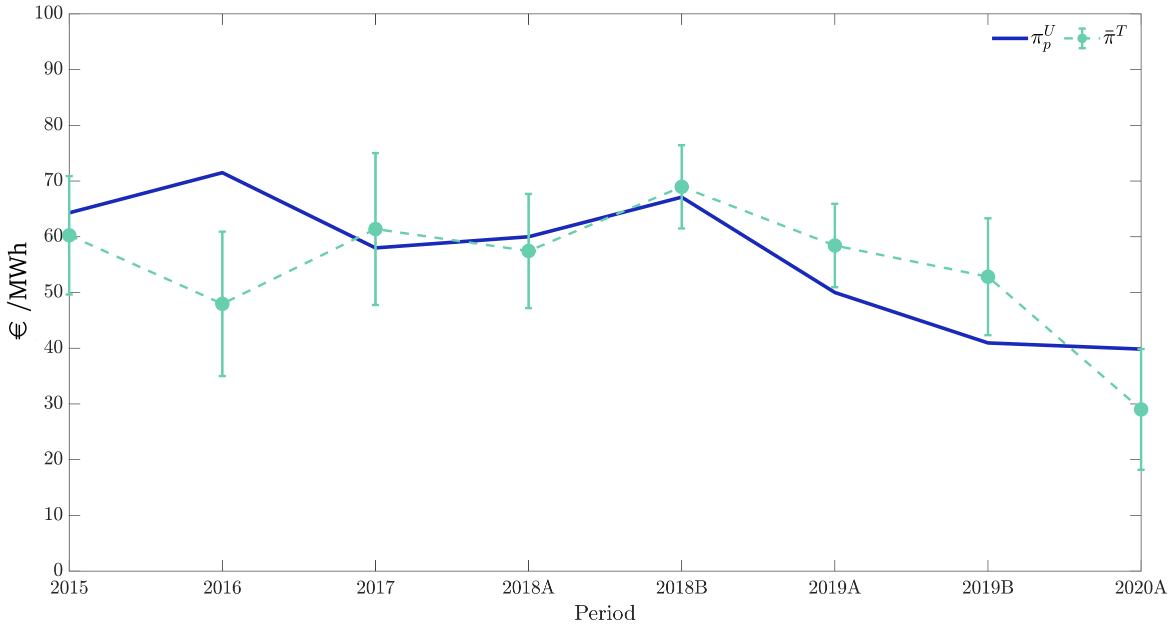

Figure 7: Minimum tertiary price per period where SI is used.

4.3. Sensitivity of the security

coefficients

As the SI program also has the objective of being an emergency resource for the SO, we considered different security coefficients of usage for economic reasons to leave part of the available resource as an emergency resource to the SO. Figure 8 shows how the economic efficiency of the program evolved based on different yearly and monthly security coefficients during 2017. In the annex, there is a similar figure for each period. B^Y represents the percentage of total hours of the year used for economic reasons while B^M represents the monthly hours available, which are constant throughout the period. In this sense, the right side shows how the most critical element to economically optimise the usage of SI is the yearly constraint, to say, the total number of hours that the program can be used. In contrast, while increasing B^M helps to improve the performance, it is not that critical as price hours are spread throughout the year.

In other words, while limiting B^Y caps the potential benefits of the economic usage of the program, B^M does so but not in such a critical way, especially once you range 0.5 of the monthly usage, when increasing this parameter does not affect at all the final optimum savings. The figure shows how increases in the B^Y parameter achieve diminishing improvements in the economic efficiency of the optimised program. When reducing B^Y the economic efficiency improves at a diminishing ratio with more important but declining variations of B^M when increasing B^Y. Thus, while the economic efficiency improvement from B^Y at 0.1 to 0.2 moves from around 4,030 € /MWh to 2,020 € /MWh, moving from 0.5 to 0.6 only implies a reduction from 800 € /MWh to 665.5 € /MWh. In the case of B^M this only occurs until a certain level. While Figure 8 shows the 2017 period, the rest of the years present a similar trend.

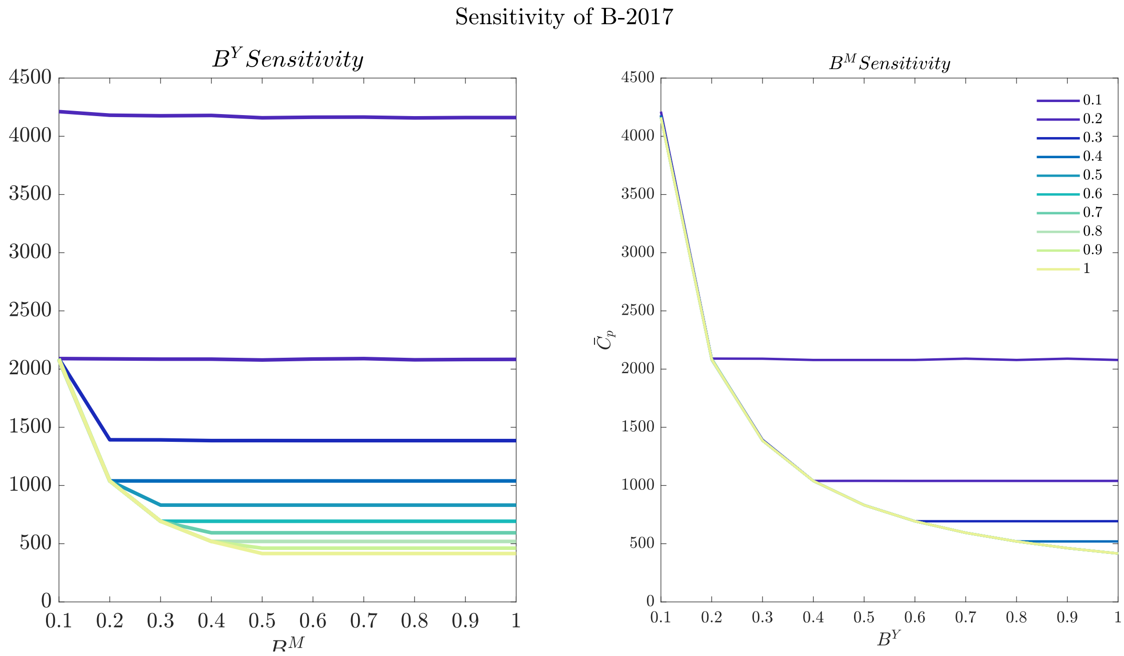

Figure 8: Sensitivity analysis of the economic efficiency of the SI program regarding B^Y and B^M metrics

In this sense, we argue that if REE aims to reduce the initial cost, the yearly and monthly restrictions of the program can be reduced to use the program less but during the hours when the program provides the most benefits to the system. Specially, having the program monthly constraints above 0.5 from the actual constraint does not provide added value to the economic optimisation. The DR resource never reaches the maximum constraint level in any particular month. Thus, if reducing this constraint implies reductions in the fixed cost, the SO must consider this option as it does not affect the final optimum. Moreover, if reducing the total amount of yearly hours also implies a reduction in the fixed cost, the SO can obtain an improvement of the economic efficiency of the program. A trade-off exists between the marginal benefits of using the SI program for economic purposes and a reduction of the fixed costs of the program. Therefore, the last resources of DR used by the SO do not provide such benefits as the marginal savings obtained are considerably reduced after shaving the highest tertiary prices.

4.4. Scenario without maximum and minimum capacity constraints

To not only analyse the *statu quo*, we also considered removing the regulatory parameters that force the SO to use the SI program between the range of 200 MW and 500 MW. We call this scenario Optimised Unconstrained (Optim - UC) and we compare it with the Constrained scenario. In this case, the optimal usage of SI concentrates in the hours with the larger price differences between supplying the tertiary reserve with the current market mechanisms and generation capacity.

Figure 9 shows the hourly distribution of the usage of the SI program during 2017 under the constrained scenario. The usage never goes above 500 MW or below 200 MW and concentrates in the morning hours associated with the demand ramp at the start of the working day and during the colder months at the end of Autumn and Winter. The annex shows an hourly distribution of the SI of each period.

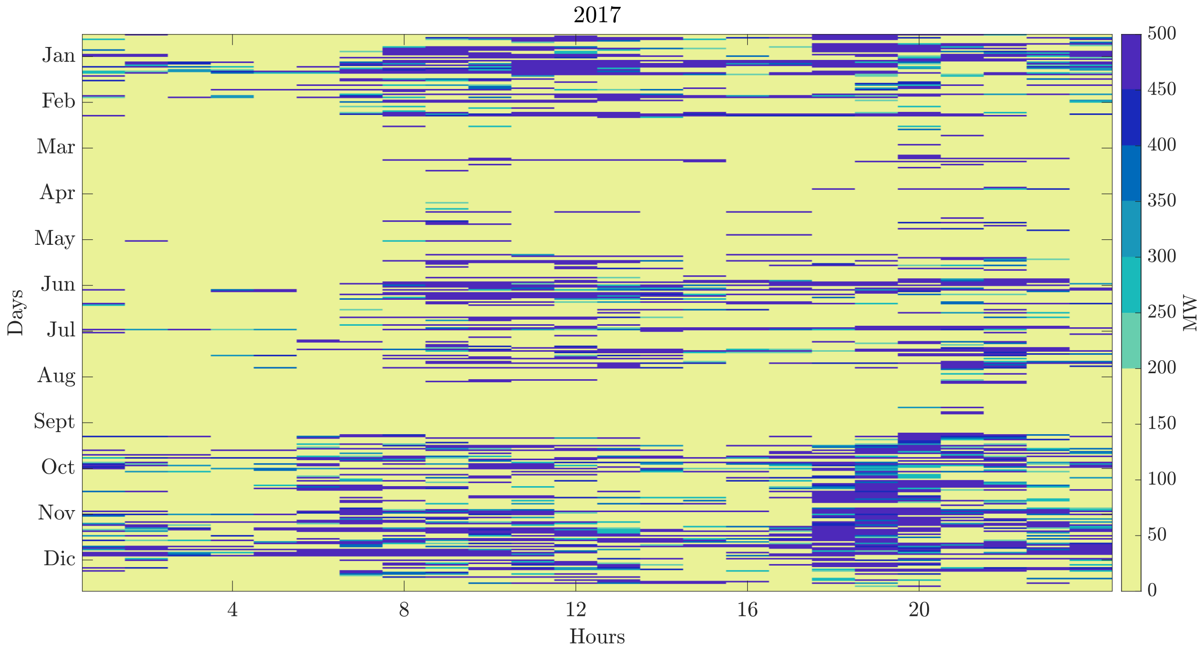

Figure 9: Hourly capacity of the optimised SI program used in 2017

In contrast, when no maximum hourly capacities are considered, during some hours, the SI program supplies all the needed capacity of tertiary reserve. Consequently, as the total capacity is the same, the SI resources concentrate in fewer hours but provide more capacity. Figure 10 shows the hourly distribution of the usage of the optimised SI program during 2017. Compared with Figure 9, the usage is more concentrated in fewer hours and the SO ends up using up to 3,000 MW in an hour, five times more than the maximum capacity stated by the program.

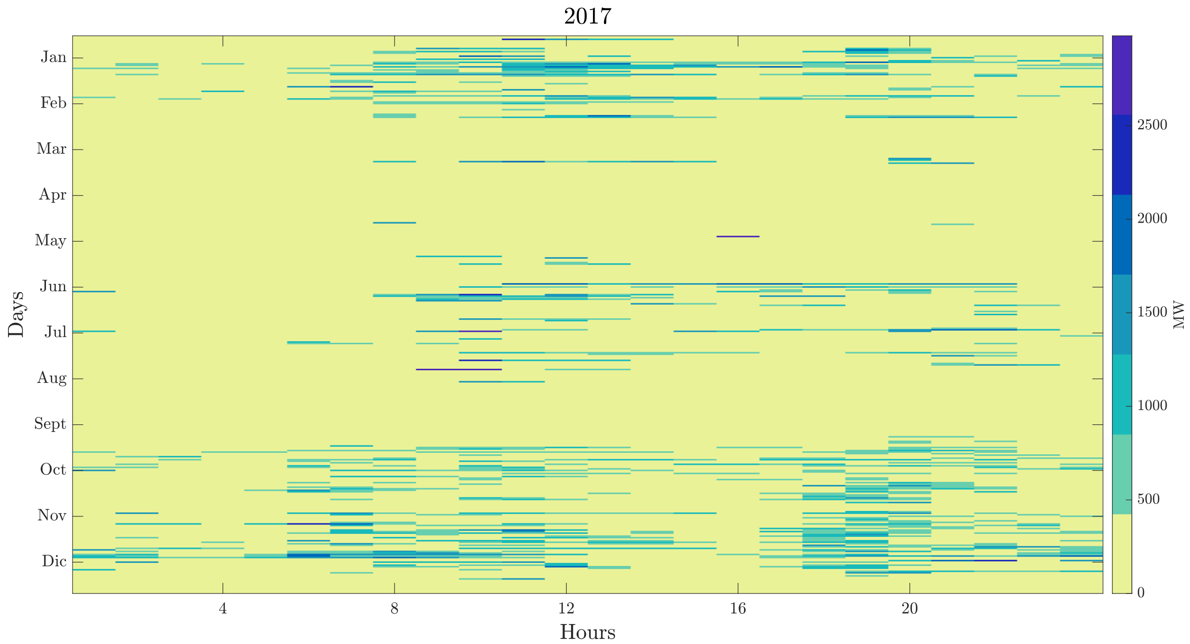

Figure 10: Hourly usage of the optimise SI program without capacity constraints in 2017

Figure 11 presents the Monotone usage curve of the SI program during the 2017 period. As mentioned above, the usage is concentrated in lower hours but with a larger application by the SO. While the SO uses fewer hours of the program, during more than 250 hours the program delivers more than 1,000 MW, achieving up to 3,000 MW at the maximum hours. If the constrained application uses SI resources 1,850 hours, the unconstrained optimisation reduces this to only 1,230 hours. Nevertheless, relaxing this constraint does not imply substantial improvements in the total performance of the program. In total, relaxing the constraints implies 14 M€ . Figure 12 shows the resulting savings of each year under this scenario. During the years when all the SI resources are used to optimise the system costs (2015, 2017, 2018, 2019, and 2020), savings relate to shifting DR resources to the most profitable hours. On average, relaxing these constraints results in a 10% improvement in the total savings. In 2016, when the profitable hours are less due to the high variable costs of the year, savings are doubled as the usage of the resource is increased from the constrained scenario. In contrast, during the first half of 2020 savings only increase by 3 %. This results from an initial lower availability of resources that results in not being able to use much more capacity per hour than the 500 MW set by the regulation.

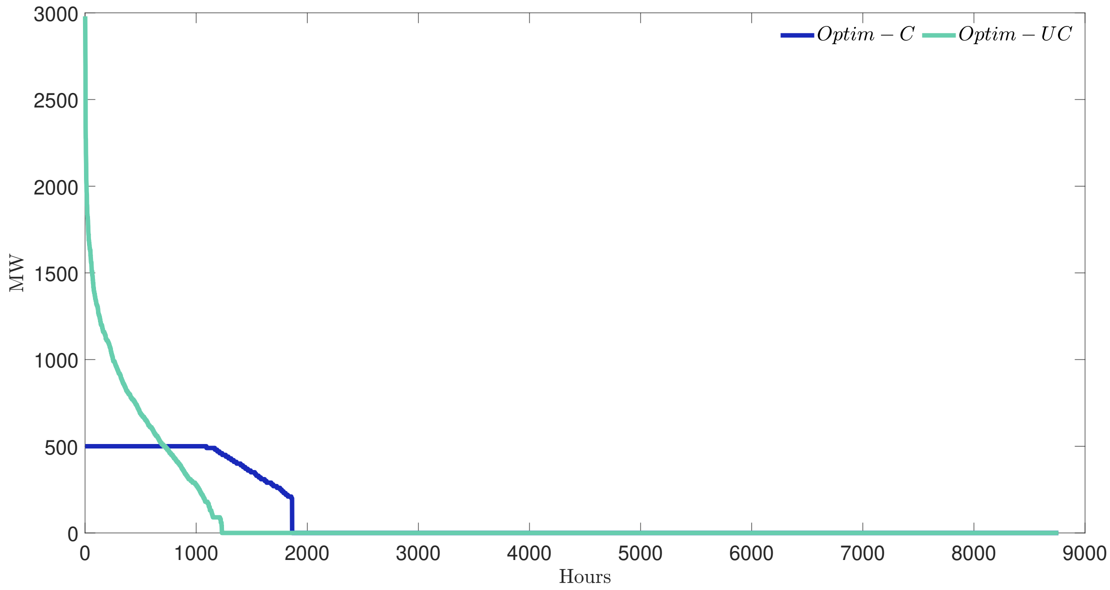

Figure 11: Monotone SI usage curve with and without constraints in 2017

Figure 12: Hourly usage of the optimise SI program without capacity constraints in 2017

4.5. Policy recommendation for IL programs

The analysis of the Spanish SI program reveals several key elements to consider when designing and operating IL programs for both economic and security reasons from a SO perspective. These programs combine the DR usage in AS markets with DR as a capacity or last resort resource. Fixed costs are the principal burden to have cost efficient resources. If IL programs coexist with market prices of other services, a weighted fixed cost to obtain the demand reduction capacities is key in order to compete with other market resources. Mechanisms to quantify the real costs incurred by consumers participating in these programs are crucial to reduce the initial capital cost prices. Therefore, policy instruments such as resource specific auctions (only DR) and service auctions (DR and generation) can be seen as potential elements to improve programs' efficiency.

IL programs are profitable to use during critical hours, using fewer resources of the market and thus generating savings for the system as a whole. These resources cap the usage of more expensive resources when prices rise above certain levels. In this sense, having an analysis of price triggering elements results in a valuable policy tool for SO. These reference prices are a guide to help operators in their daily operation. When reserve prices are above these levels, they should consider the usage of IL resources. In this sense, future studies should consider how using these resources in reserve markets with marginal price structures can provide further savings as they reduce the price of the whole market.

5. Conclusions

This paper presents an *ex-post* evaluation of the Spanish Interruptible Load program regarding its economic efficiency, real impact, and specific parameters associated with an optimal usage it. The method used consists in an Mixed Integer Linear Problem optimisation formulation that consider the physical and regulatory constraints of these types of programs. To compare and evaluate the efficiency we also present a set of economic metrics that permit the comparison with complementary resources.

We use the method to analyse five and a half years of the SI program in the Spanish power system. The optimisation shows that under the current conditions of the program, the economic efficiency of the DR resources largely differs from obtaining tertiary reserve resources from the market. After the Demand Response optimisation, these resources are four to ten times more expensive than the average tertiary reserve procured in the market. Only in 2020, when the fixed cost was largely reduced and the SO procured less Demand Response resources did these become cost competitive with the most expensive hours of tertiary reserve. The efficiency parameters are also highly dependent on the usage. Reductions of the amount of the SI resources used for economic purposes to save some resources for technical constraints show how the last elements of capacity are the least valuable for the system. In other words, the usage of DR resources for economic purposes has decreasing marginal savings.

In sum, the results show how the Spanish system operator did not operate to optimise the economic performance of the program. Thus, the specific economic objective of the program has failed to deliver its potentialities.

If used under a cost minimisation strategy, this resource would have saved the system a total of 163 M€. If the current constraints of maximum and minimum hourly usage capacity are relaxed, savings would increase by 14 extra M€. Both savings represent a small fraction of the historical total fixed costs of the program but around a quarter of the tertiary reserve needs of the system.

Interruptible Load programs provide a valuable resource for the system as a whole, but detailed and systematic analysis of their potential benefits and optimal operation in real environments are lacking in the literature. The method hereby presented shows a usage strategy and a detailed analysis of a specific program and then presents a set of conclusions to apply to the design and usage of these types of programs. From a system perspective, Interruptible Load resources present savings that diminish with their usage. Topics for further research are the impact of these resources in marginal price markets, comparisons of the costs of capacity payments to demand and generation resources, and the co-optimisation of these resources in several markets such as secondary and tertiary reserve with a system optimisation perspective.

CRediT authorship contribution statement

David Ribó-Pérez: Conceptualization, Methodology, Software, Data Curation, Writing - original draft, Writing - review & editing. Alicia Carrión: Methodology, Data Curation, Writing - review & editing. Javier Rodríguez-García: Methodology, Data Curation, Writing - review & editing. Carlos Álvarez-Bel Conceptualization, Writing - review & editing, Supervision.

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Appendix

All case studies have been solved using Gurobi under Julia.JuMP [60], while the data treatment has been performed in MATLAB. We have used an Intel (R) Core (TM) i7 computer at 1.99 GHz and 16 GB of RAM. Each simulation takes between a couple of minutes up to less than one hour depending on the amount of variables, period and security coefficients. All optimisations are performed with a MIPGap of 1e-3

Additional figures

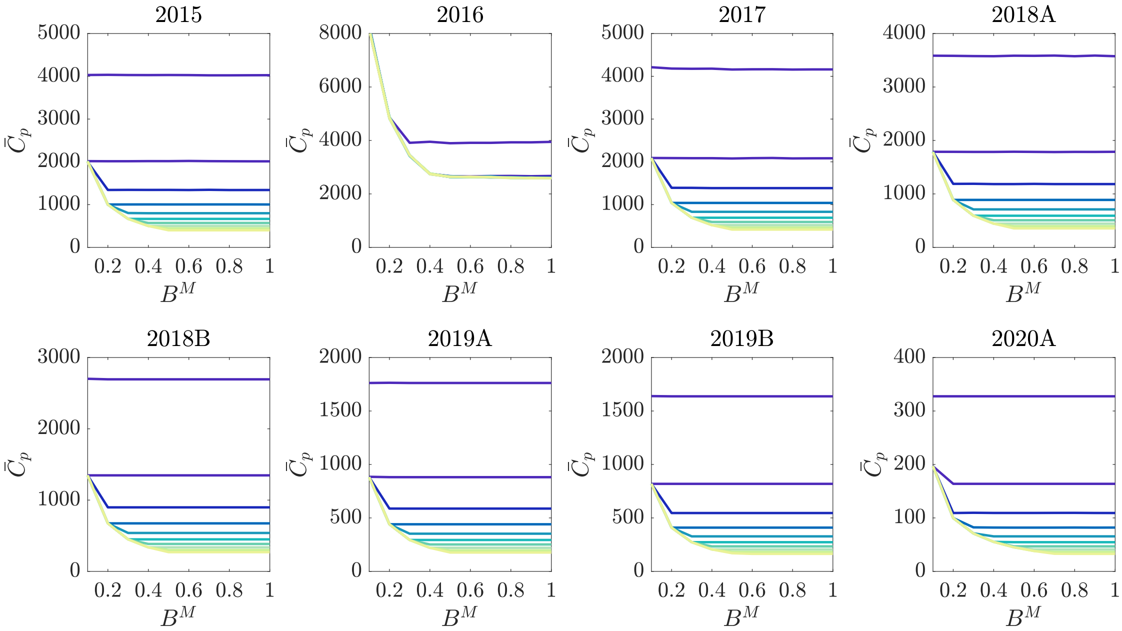

Figure 13: Sensitivity analysis of the SI program regarding B^M metrics

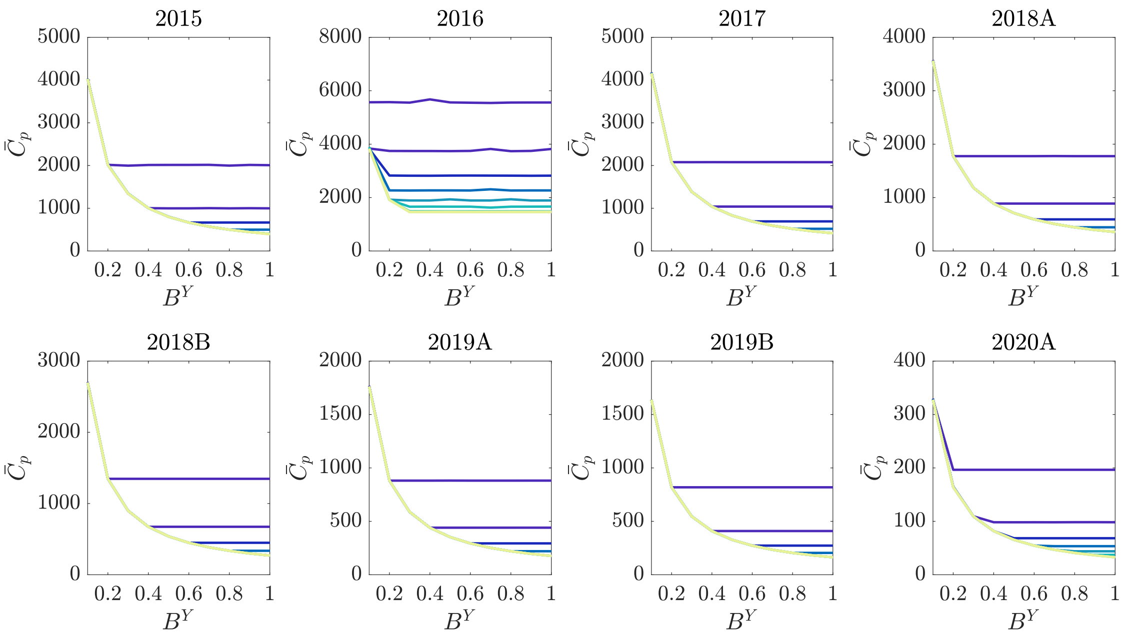

Figure 14: Sensitivity analysis of the SI program regarding B^Y metrics

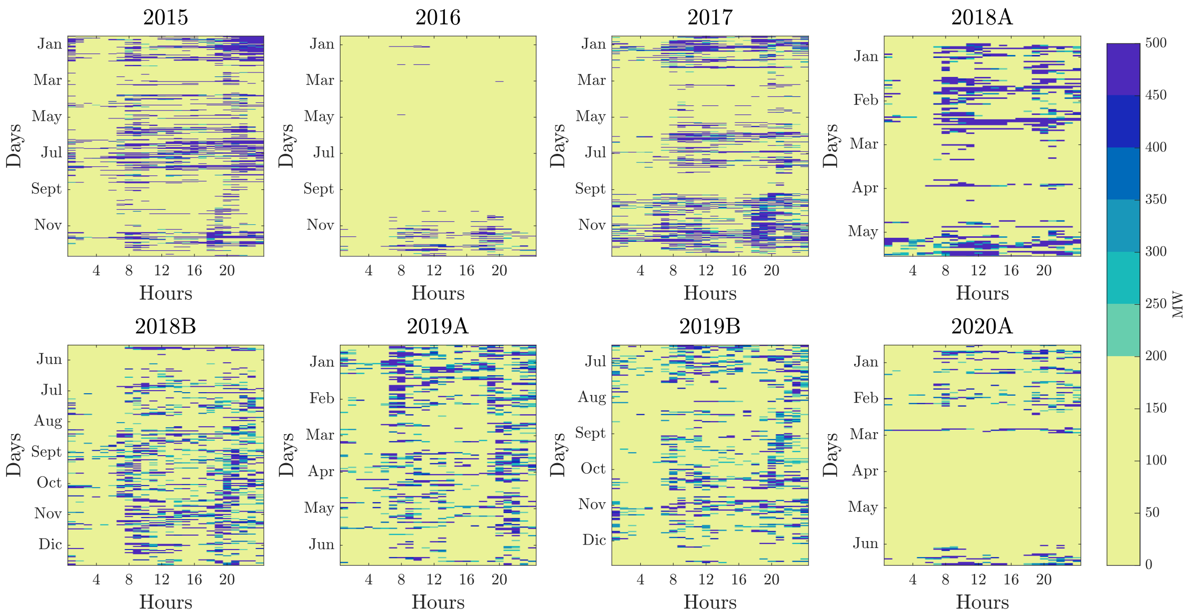

Figure 15: Hourly usage of the optimised SI program during the eight periods of study

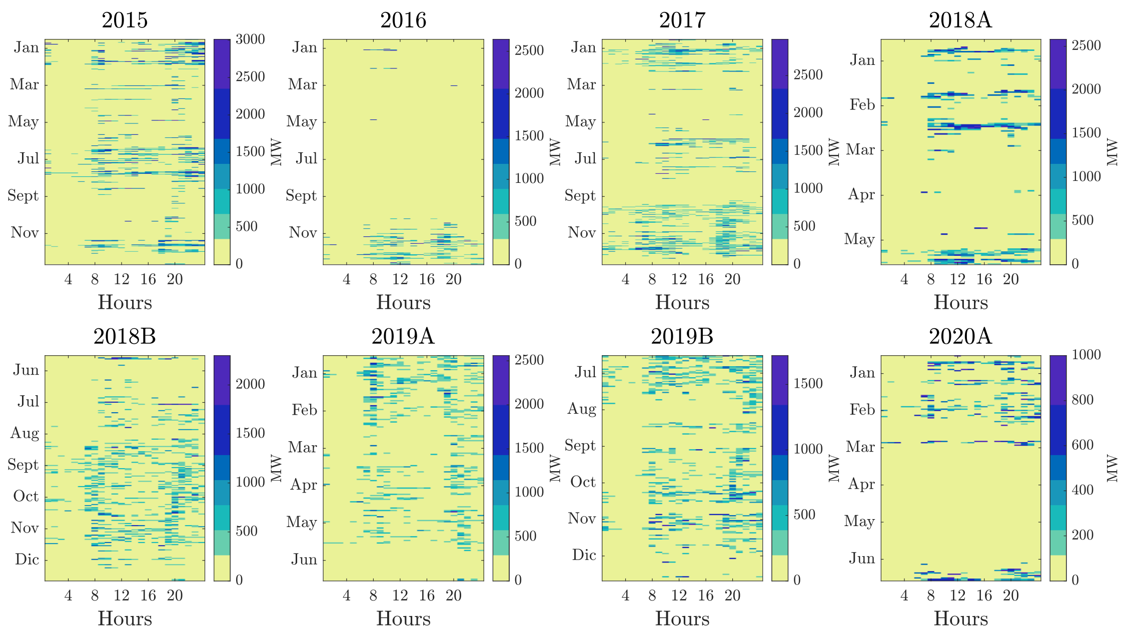

Figure 16: Hourly usage of the optimised unconstrained SI program during the eight periods of study

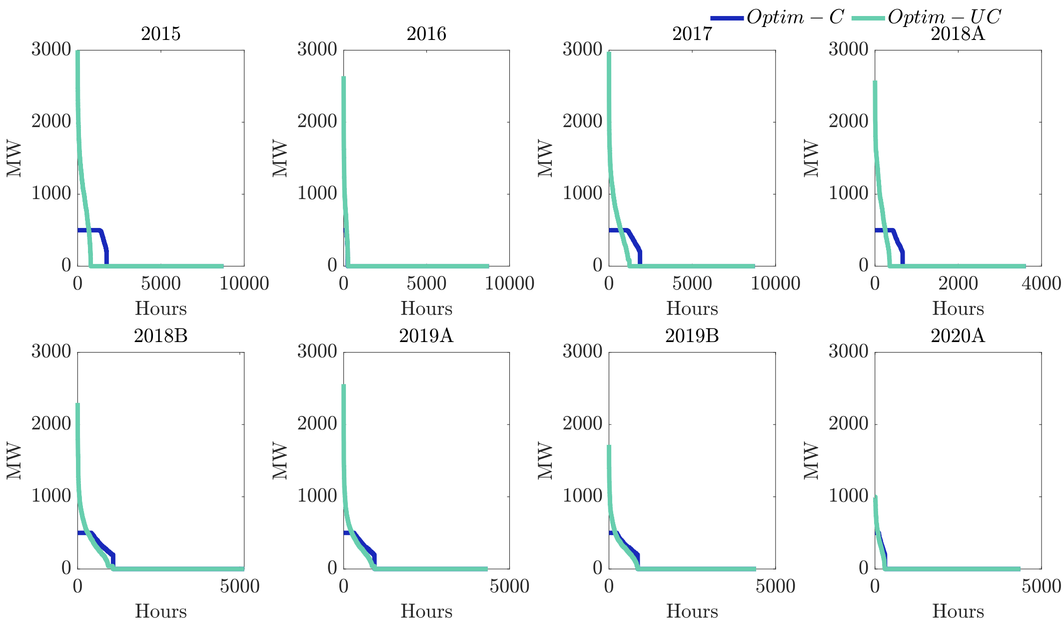

Figure 17: Monotone curves of the SI program during the eight periods of study

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