Multiobjective Methodology for Assessing the Location of Distributed Electric Energy Storage

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Abstract. The perception of the associated impacts among possible management schemes introduces a new way to assess energy storage systems. The ability to define a specific management scheme considering the different stakeholder objectives, both technical and economic, will increase the perception of available installation options. This paper presents a multiobjective feasibility assessment methodology using an improved version of the Non-dominated Sorting Genetic Algorithm II, to optimize the placement of electric energy storage units in order to improve the operation of distribution networks. The model is applied to a case study, using lithium-ion battery technology as an example. The results show the influence of different charging/discharging profiles on the choice of the best battery location, as well as the influence that these choices may have on the different network management objectives, e.g. increasing the integration of renewable generation. As an additional outcome, the authors propose a pricing scheme for filling the present regulatory gap regarding the pricing scheme to be applied to energy storage in order to allow the exploitation of viable business models.

Keywords: Genetic algorithms · Energy storage · Power distribution networks · Energy profiles · Energy service · NSGAII

1 Introduction

The new electricity network challenges presented by the integrating of integrate distributed generation can lead to a more complex and less secure power system operation.

In the context of a microgrid environment, distributed electric energy storage systems(DEESS) are presented as an option to enable the optimization of resources, by providing the capability of effectively balancing supply and demand [1]. However, a methodology is needed to evaluate the best allocation of DEESS to provide the needed energy services to the network.

The proposed methodology allows the perception of the associated impacts from possible ESS management schemes, considering a potential pricing scheme for the energy delivered within the current legal framework for the ESS exploitation, and different objectives for the operation of DEESS representing different stakeholders.

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2 Electrical Energy Storage Systems

Previous research assessing the impact of energy storage systems (ESS) on the power system operation and economics has been focused on economic/optimal sizing.

As such, ESS has been modelled from the point of view of cost (economic models) or with a focus on the assessment of operational benefits, modelling the ESS response to power system disturbances at appropriate time scales (operational models) [2].

Some authors presented methodologies for evaluating the costs and benefits associated to energy storage [3, 4]. However none of those studies considered the ESS management scheme and its associated impacts.

Methodologies considering the use of electric vehicles (EV) may consider possible charging/discharging (C/D) schemes when providing specific energy service [5]. However this type of methodologies are more concerned with the unpredictability of the remaining energy available in the EVs than with their optimal grid distribution and associated impacts [6].

The storage management using intelligent C/D schemes is presented in [5] as a possible solution to release network capacity as well as to enable a more efficient operation. According to those authors, this approach may provide a basis to postpone grid reinforcements by investors, to decrease network losses, to avoid short interruptions and voltage quality problems, to shave power peaks and to smooth load curves.

A detailed literature review about the ESS operation, application, barriers and impact assessment was presented by the authors in Refs. [7, 8].

3 Definition of the Design Strategies

In order to fill the present regulatory gap regarding a possible pricing scheme to be applied to ESS the present methodology considers DEESS as special regime producers (SRP), thus benefiting from the same feed-in tariff used by renewable energy producers.

The pricing scheme proposed in this study considers that the electric ESS buys energy at the daily market price and sells it at SRP prices in high demand periods. This seems justifiable as the DEESS may play an important role to support the increased share of renewable energy (RE), avoiding the use of backup thermal generation. This study used an average SRP surplus tariff of 24.18€/MWh, corresponding to the available consumption data of 2008.

The strategy chosen for the current work was to optimize the location of each unit of the set of DEESS that would simultaneously maximize profits, minimize investment costs, network losses and voltage deviations. For that purpose, the authors chose to use an improved version of the Non-dominated Sorting Genetic Algorithm II (NSGAII).

The analysis was performed using daily profiles of demand, renewable generation and spot price obtained through clustering techniques applied to historical data. Network losses were determined by applying the demand and generation profiles as inputs to powerflow calculations, using Matpower and Matlab TM.

4 Methodology

To obtain the Pareto front representing the non-dominated solutions that represent the multiple optimization objectives, a previous characterization of the situation and a definition of the working objectives is needed, as presented in Fig. 1 for each scenario, using the iNSGAII in step 3. The algorithm was loaded with the network, technology characterization and service definition data block, defining this procedure as the first step of the methodology.

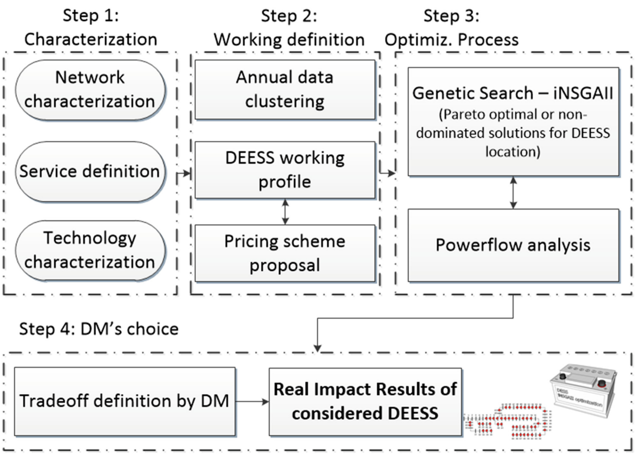

Fig. 1. Methodology definition for DEESS location assessment

The technology characterization block includes the technical characteristics of the considered ESS (battery plus power converter), since solutions depend on the technology and its working limits. This block provides information to define the working periods of the C/D profile in the DEESS working profile block and the capacity limits to be used in the optimization process and power flow analysis performed in the genetic search block INSGAII.

The network characterization block includes the daily demand diagram of the distribution substation and combines the active and passive elements of the studied electricity grid. Though the proposed methodology aims to study the best ESS location within a distribution network, considering different management schemes, it may be applied to any type of grid provided that the correct characterization is done.

The first step, the service definition is settled in this study with three main objectives, societal objectives, such as network power losses reductions and RE generation integration and private investor objectives, namely the maximization of income from buying and selling in different time periods.

The DEESS working profile block, within step 2, represents an intermediate stage for definition of the C/D schedule considering the ESS technology and the main proposed objectives. Therefore, it combines the objective of the DM with the technical limits of the considered ESS.

In order to define a C/D profile the storage elements and to evaluate the economical value of the operation, prototypes of daily load demand profiles (DLDp), as well as energy market rates profiles (EMRp) and renewable wind generation profiles (RWGp) were needed.

For solving this problem in step2: *Annual data clustering*, the authors developed a process to obtain such profiles using cluster analysis, namely through a competitive neural networks method, confirmed with a hierarchical clustering approach.

The output of this process was the definition of 5 clusters of daily diagrams for each data type from which a prototype could be derived as well as its representativeness in one year of data. The definition of the number of clusters was assessed by analyzing the tree dendogram and the distance between the centers of each cluster.

The step3 *iNSGAII* block uses the genetic algorithm to search for non-dominated solutions. The tool uses a "Binary Tournament Selection" based on the rank and crowding distance to choose the best individuals for the evolution process. Namely, an individual is selected in the rank is lesser than the other or if crowding distance is greater than the other for individuals in the same rank, as shown in Fig. 2.

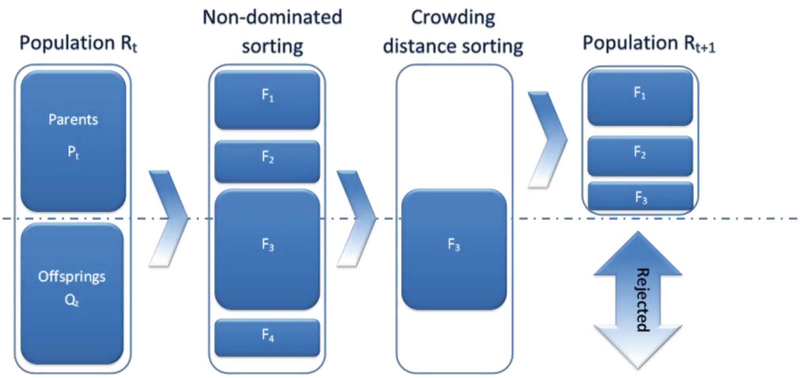

Fig. 2. Binary tournament selection in the improved NSGAII

For the considered case study, the iNSGAII population of possible solutions was assumed to be composed of 150 individuals while a maximum number of 100 generations was defined, both values that were consistently above those needed for convergence to be attained.

The tool evaluation functions were integrated in the algorithm using powerflow analysis to evaluate the impact of each individual solution on the network performance.

The final preferred solution must be chosen from the Pareto front resulting from step 3, by the DM, in step4: *DM's choice*, considering its own perception and assumed tradeoffs between the objectives. The resulting impact will finally be attained considering the DM's choice.

4.1 Improved NSGAII

As a tool to solve the multi-objective problem formulated in the current work, the authors chose an improved version of the NSGAII (iNSGAII) which has proven to be efficient, especially in power distribution operation and planning problems when compared with conventional algorithms and particle swarm optimization (PSO) [9, 10].

The iNSGAII draws on the work developed in [11], replacing the fixed genetic operators of conventional NSGAII with dynamic adaptation of crossover (pc) and mutation (pm) probabilities, according to the genetic diversity in the population.

This feature avoids premature convergence by maintaining the genetic diversity of the population (G_{div}) using the following heuristic updating principles:

1. Use large pc and small pm when G_{div} in the current generation is large;
2. Use reduced pc and large pm when G_{div} in the current generation is reduced.

The genetic diversity of one population is determined by the genetic variability of individuals being responsible for the dispersion of solutions in the feasible space. To measure the resemblance of individuals they must be regarded as a multidimensional vector using a distance vector.

If the distance is below a predefined threshold (Dth), we may assume the two individuals are similar; else, the two individuals are dissimilar [10].

$$d(i,j) = \sqrt{(g_i(1) - g_j(1))^2 + \cdots + (g_i(N) - g_j(N))^2} \tag{1}$$

Where g_i is the chromosome of individual "i" and g_j the chromosome of individual "j".

To measure the genetic diversity (Gdiv), the following equation is used:

$$G_{div} = \left(\frac{\sum_{i=1}^{Nind} \sum_{j=i+1}^{Nind} 1_{\{d(i,j) > Dth\}}}{N_{ind} \times C_2} \right) \times 100 \tag{2}$$

G_{div} it is a variable in the range [0, 100] meaning that when the value is zero all individuals are similar and when it is 100 all individuals in the population are dissimilar.

For the optimization process, the authors used four multi criteria evaluation parameters presented in the following paragraphs as objective functions to be optimized simultaneously.

The first evaluation function to be minimized is the sum of the network power losses (PL) in all the n branches of the MV distribution network during the whole day. The elementary time interval is a quarter-hour (tj = 0.25 h) so the data set has 96 values (m = 96).

$$NEL = \sum_{i=1}^{n} \sum_{j=1}^{m} \frac{PL_{ij}}{t_j} \tag{3}$$

The second evaluation function to be minimized is the network voltage quadratic mean deviation (*NVqmd*), for all individual voltage deviations (*VD*) in the *N* network buses compared with the voltage reference value (V_{ref}), during each elementary time interval.

$$NVqmd = \frac{\sqrt{\frac{\sum_{k=1}^{N}\left(VD_k^2 - V_{ref}^2\right)}{N}}}{\sum_{j=1}^{m} t_j} \tag{4}$$

The third evaluation function to be minimized is the network storage annualized cost (*NSAC*) for installing *x* units of DEESS, with an individual capital cost (*Cac*). The C_{ac} is calculated considering the global capital costs (c_c) and the capital recovery factor (*CRF*) as presented in Eq. 5, where *d* is the dimensionless discount rate and *y* the expected life of the equipment, measured in years;

$$\mathrm{NSAC} = x \times C_{ac} = x \times c_c \times CRF = x \times c_c \times \frac{d(1+d)^y}{(1+d)^y - 1} \tag{5}$$

The fourth evaluation function is the network energy rate benefit (*NERB*) considering the energy tariff (*C*) and the required energy (*E*) to charge (*ch*) and discharge (*dch*) in one day.

$$NERB = \sum_{j=1}^{m} \left(E_{dch} \times C_{dch} - E_{ch} \times C_{ch}\right)_j \tag{6}$$

4.2 Network Characterization

The case study made use of the IEEE 69 bus three-phase balanced 12.66 kV RDS [12], a well-documented network, often used for research purposes.

The network was comprised by an 8 MVA substation and 69 nodes from which 48 are load-points (distribution transformers), with a total load of 3.8 MW and 2.69 MVAr (peak period). The network in its radial configuration had all the boundary tie-switches in the open position.

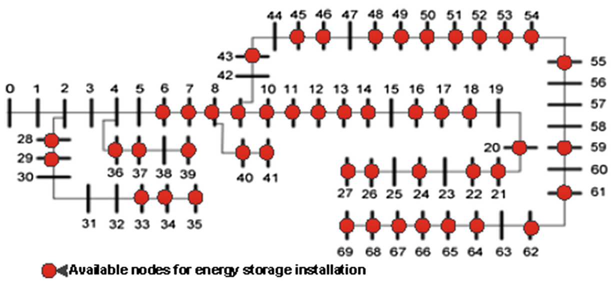

Fig. 3. 12.66 kV radial distribution systems

As shown in Fig. 3, the proposed RDS included 48 distribution transformers, which the DM considers as possible locations for the installation of the ESS units.

The decision maker can easily define the availability of a specific node for ESS installation using a binary number (1 or 0) (Table 1).

Table 1. Example of coding technique for identification of available buses

Node number	1	2	3	4	…	n − 1	N
Availability Status	0	1	1	0	…	1	0

This information will be used to compose a reference vector in order to translate bus references into chromosomes and back. This technique will assure that all possible chromosomes correspond only to admissible solutions, also reducing their size to the maximum number of allowed storage sites (Table 2).

Table 2 Example of the reference chromosome

Reference chromosome	Node number	2	3	…	z
	Availability status for GA	1	1	…	1

4.3 Technology Characterization

The assessment of the DEESS evaluation impact is dependent of the considered technology. Therefore, the simulations were performed using data available from a manufacturer of nanophosphate lithium ion batteries.

The selected battery with the respective power converter were characterized according to the data available at the manufacturer website and technical publications [13, 14]. According to these data, a total energy of 64,35 Wh/cell was assumed to correspond to one hour of charging with 100 % of depth of discharge (DoD).

From the definitions of the battery manufacturer, the “1CA” (Cranking amperes) discharging profile was chosen, corresponding to a discharging current of 19.50 A, with 3.30 V per cell, or 64.35 W per cell. The proposed solution required roughly 0.1 m^3 for the battery systems (a battery pack of two Rows of 180 cells) without power converter (PC), a volume that could be easily integrated in any power transformer (PT) facility.

According to several manufacturers, a plausible 90 % PC efficiency [13] can be expected, with a nominal charging power of 23.17 kW and a discharging capacity of 20.85 kW per PT.

Considering the total of 360 cells and a unitary cell price of roughly 51.70 € [15], the capital cost is 18 612.00 €. Regarding the PC, an estimated cost of 6 949.80 € was obtained from [16]. The total cost of the storage system is estimated in 25 561.80 €.

Assuming an interest rate of 8 % and a lifetime of 15 years, the resulting annualized capital cost was 2 986.37 €.

4.4 Working Profile Definition

The proposed approach used three scenarios, regarding plausible objectives for the energy storage:

- Objective 1 – To maximize profit from daily energy spot market rates;
- Objective 2 – To minimize daily energy distribution network losses;
- Objective 3 – To maximize profit from renewable wind generation.

These objectives establish three possible C/D profiles to be evaluated under each defined prototype, during the optimization process, in terms of return on investment, grid losses, voltage deviation and net benefit of energy buying and selling operations in different time periods.

For objectives 1 and 2, the charging periods were established to use the periods of lowest rates and minimum network power losses, respectively, while the discharging periods were defined for the highest rates and maximum power losses, respectively.

Regarding scenario 3, the methodology intended to compare the average daily load diagram with each of the five wind energy production daily prototype diagrams, obtained during the data clustering stage.

In order to control the amount of RE supplied to the grid, a comparison was made between normalized profiles of wind generation and the average annual load demand (LD).

The C/D profiles were derived from the difference between the average LD profile and the five wind generation prototypes. Namely, a negative difference result represents a potential excessive wind generation and positive results represent the periods when stored energy should be delivered because demand is less likely to be supplied by RE generation.

For each objective, twenty-five simulations were performed as a result of combining the following prototypes:

- Set 1: The five EMRp combined with the five DLDp for Objective 1 and 2;
- Set 2: The five RWGp combined with the five EMRp for objective 3.

All the C/D profiles were gathered into an input binary matrix that defines the daily C/D periods to be used in the optimization process.

5 Results

The DEESS management scheme, which depends strongly on the fact that the DM has to balance his choices among three different objectives, has a marked influence on results. Different management schemes of wind integration lead, as depicted in Fig. 4, for a sub-set of input scenarios, to a variation of daily losses between 8416.87 kWh and 8473.22 kWh. For the sake of alleviating the computational burden, a single annual average LD profile was used, in the case of objective 3, instead of five different profiles. Nevertheless, five different profiles were preserved in the calculations, both for renewable (wind generation) production and for market energy rates.

The impact results for objectives 1 and 2 are similar, both presenting possible NEL reduction and NERB improvement among simulations, in which different management

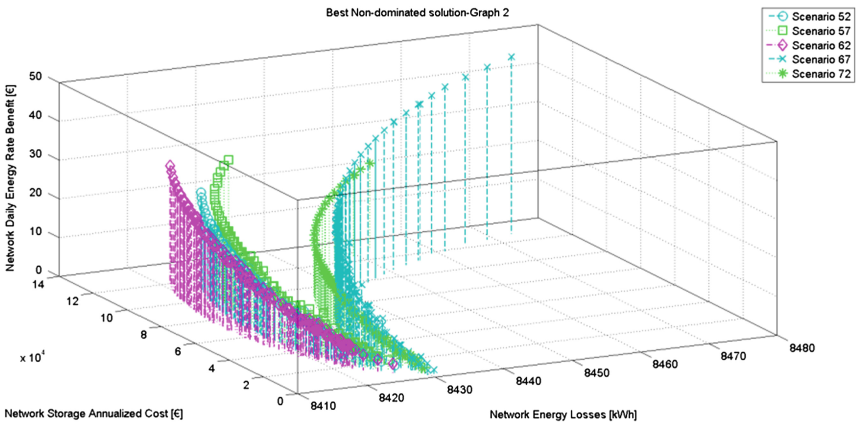

Fig. 4. Simulation results under objective 3

schemes influence the Pareto-fronts. However, depending on the considered LD prototype profile, different variations were obtained, showing that network operating conditions should be accounted for the DEESS assessment, as presented in Fig. 5.

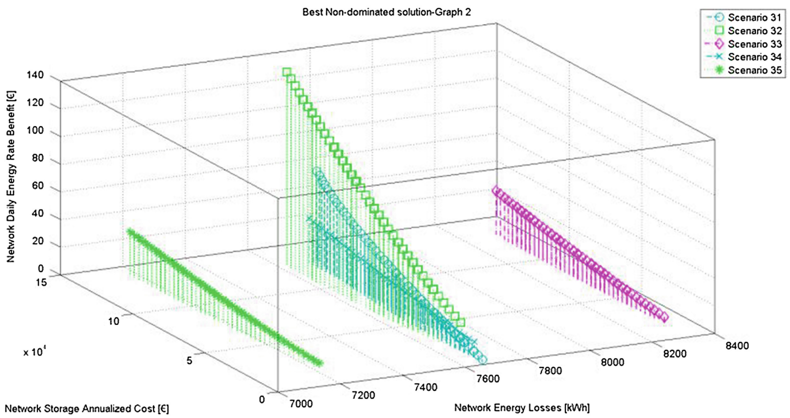

Fig. 5. Simulation results under objective 2

Figure 6 shows that the increase of investment in ESS units not necessarily contribute to the NEL reduction. It also shows that the management scheme may have an important influence in the final NEL. A possible future development that might prove useful consists on comparing the overall impacts of DEESS and of the conventional thermal backup to RE production.

Different evolution gradients are observable in Fig. 7, of NERB as regards to NSAC, pertaining to objective 3. This may prove useful to the decision maker when establishing tradeoffs between costs and revenues.

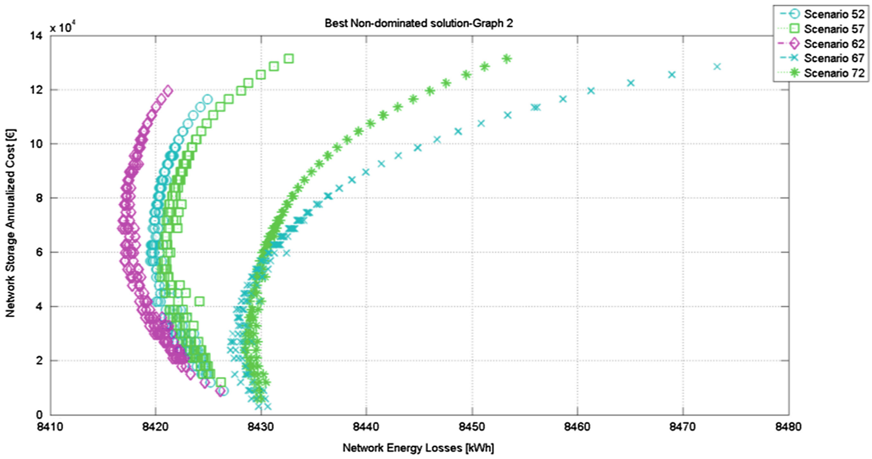

Fig. 6. NSAC vs NEL simulations under objective 3

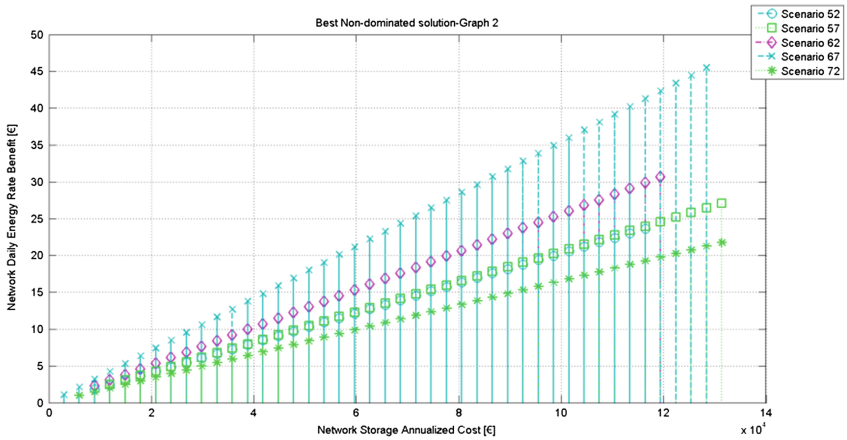

Fig. 7. Relation between NERB and NSAC among objective 3 performed simulation results

The methodological proposal presented in the paper, combining technical and economic evaluation parameters, is directed at facilitating the decision making process, especially when it aims to consider the combined preferences of societal and private stakeholders. In this context, the proposed tool can also play an assisting role in the definition of a regulating framework for deployment of DEESS and market integration.

6 Conclusions

The search for an optimal location of DEESS aiming the minimization of power losses, voltage deviation and investment, simultaneously maximizing the net income resulting from the difference between energy sale revenue and energy purchase cost in different time periods, required the use of a multiobjective optimization method. In this context, a genetic algorithm proved to be a suitable choice to assess non-correlated objectives.

The method chosen was an improved NSGAII algorithm as explained in [8], avoiding the need of a previous definition of fitness weight factors by the DM and using dynamic crossover and mutation probabilities, depending on the genetic diversity of the population of solutions. It becomes thus possible not to present an “optimal solution” to the DM but provide the opportunity to choose his/her preferred solution from the highest quality set of non-dominated solutions presented by the search tool, according to assumed tradeoffs between the objectives.

The present work also proposes a possible pricing scheme to be used for promoting DEESS exploitation since the existence of a regulatory framework may stimulate the existence of market players intending to invest on energy storage. As one of the main objectives is balancing the surplus/deficit periods of RE availability, the authors assumed that the energy recovered from energy storage should be rewarded on an equivalent basis to the energy that is displaced.

The stakeholders that can benefit from the developed methodology are the DSO and the SRP or any authority acting on behalf of societal interest.

Considering the different stakeholder interests the proposed methodology intends to provide a set of non-dominated solution instead of defining a single final solution. The definitive solution will depend of the DM final choice.

Increasing the flexibility of the C/D cycles of the storage medium could modify the economic results of the energy storage model. In fact, different algorithms used to determine the C/D cycle could lead to a different relation between the optimization objectives, being this a direction of study that the authors intend to pursue.

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