Advanced Model-based Approaches to be Applied in the Context of a Bidding Zone Review

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Abstract — **This paper presents advanced model-based algorithms to be applied for identifying alternative configurations in the context of a bidding zone review process. Two main steps are foreseen in these approaches: in the first step, nodal indicators are computed for a sufficiently large set of power system scenarios; in the second step, nodes are grouped to form candidate bidding zones with the adoption of advanced clustering algorithms. In this paper, relevant proposals for improving existing methodologies are presented, with the aim of improving the reliability and robustness of the proposed alternative configurations. In particular, an advanced Security Constrained Unit Commitment algorithm is adopted for computing the Locational Marginal Prices. These prices are then processed using dedicated clustering algorithms to propose alternative bidding zones configurations. Relevant results are presented applying the proposed approach on a large-scale model and extended data set related to the Italian power system.**

Keywords — bidding zones, model-based, locational marginal process, power transfer distribution factors.

I. Introduction

The presence of congestions in the transmission network introduce a locational difference in the value of the energy among the nodes, requiring a dedicated approach to handle them [1]. *Nodal pricing* schemes consider all the constraints of the transmission network in each session of the electricity market, starting from the day-ahead one [2],[3],[4]. In the absence of congestions, the nodal prices should be basically the same in all the nodes, while the presence of congestions results in different nodal prices (Locational Marginal Prices, *LMP*s). On the contrary, *zonal pricing* schemes consider the aggregation of the network nodes into zones with uniform electricity prices. In this context, only predictable and structural congestions are considered in the day ahead clearing process. Ideally, the zones should be defined such that in the presence of transmission constraints, the electricity prices in all the nodes of the same zone are the same.

In the European Union, the internal electricity market has been progressively implemented since 1999, increasing competition at the wholesale level. The main goals of the process are: (i) maximising social welfare; (ii) optimal integration of renewable energy sources; (iii) maximising cross-border trade opportunities; and (iv) providing competitive energy prices [5][6]. To identify the optimal market clearing solution, complex optimisation algorithms are used, e.g., [7][7],[8] for the day-ahead market.

The structure of the European electricity market is based on zonal pricing [9]. A *bidding zone* is defined as the largest geographical area within which market participants can exchange energy without capacity allocation. The bidding zones should maximise economic efficiency and the opportunities for cross-zonal trading by maintaining security of supply. The Bidding zone borders shall be based on long-term, structural congestions in the transmission network [9].

On these bases, the identification of the bidding zones depends on the evolution of the transmission network and on the operating conditions in time. The bidding zones need to be continuously checked to confirm their effectiveness and revised when needed. This is even more true in the context of the energy transition: a significant evolution of the generation fleet, in terms of energy sources but also in terms of location, is expected in this decade. For this purpose, alternative bidding zone configurations are studied, to be considered in a bidding zone review process. The approaches adopted could be expert-based, considering the expertise of the transmission system operator (TSO) without using specific algorithms, or model-based, in which specific algorithms are executed based on selected information on the transmission network structure and operation. The expert-based approach is more suitable to apply incremental changes to the bidding zones with respect to the status quo considering a large set of criteria with complex interactions among them, while the model-based approach is suitable to conduct a "greenfield" analysis with no dependence on an initial solution.

In the European Union, a bidding zone review has been started by the Clean Energy Package [9] in 2019. In this context, the European Union Agency for the Cooperation of Energy Regulators (ACER) was asked to propose alternative configurations to be studied, based on discussions with the TSOs and use of data (including *LMPs*) provided by the TSOs [10]. The approach identified in [11] prioritises alternative bidding zone configurations defined by considering a step-wise process, in which (i) the network areas where the energy exchanges mostly contribute to the congestions are determined; (ii) alternative bidding zone configurations are found in these areas; and (iii) the configurations tending to improve economic efficiency and cross-zonal trading opportunities are selected and proposed as candidates for the review process.

Model-based approaches consist of the following steps: (i) determine, by employing a complete model of the transmission network, electric grid-specific indicators related to optimal electricity market clearing and (ii) determine, using these indicators as inputs to tailor clustering algorithms, the bidding zones as consistent areas of the electric grid where the specified indicators present similar values. Clearly, since a bidding zone configuration must be stable over time and over a realistic range of network operating conditions, the clustering algorithms must process a significant number of network operating conditions.

In [12] the authors conducted a thorough bibliography analysis regarding calculation of the electric grid-specific indicators, while in [13] regarding the clustering algorithms for alternative bidding zones identification. On the indicators calculation side, it has been noticed that the adopted algorithms use a DC power flow (PF) model while rarely considering explicitly the N-1 security criteria and unit commitment (UC) of the conventional units. Generally, the N-1 security is strongly approximated through reducing the current limits of each element in N security conditions, while the absence of UC constraints can lead to large inaccuracies in the results due to the neglection of the inter-temporal constraints. Finally, adopting a DC PF model, means completely neglecting voltage-related problems due to high power transfers, which could appear in network areas characterized by long lines and poorly meshed structure, like the central part of Italy. In [15][15] the authors reduced the gap by proposing a calculation model that explicitly represented the N-1 security criteria: the results on a small set of snapshots of the Italian grid showed the clear impact of this representation on electric grid-specific indicators calculation.

The work in this paper continues to reduce the identified research gap. On the grid-specific indicators calculation side, it upgrades the model from [15][15] with UC constraints including specific constraints for hydro power units. The model is then applied to determine the inputs used in specific clustering algorithms aiming at grouping the nodes based on the relevant features. Tests are executed on an extended set of snapshots regarding the Italian Transmission grid.

The next sections of this paper are organised as follows. Section II provides a detailed description of the UC model, Section III illustrates the clustering-based procedure executed to form the candidate bidding zones, Section IV shows an example of application of the proposed procedure to the Italian Transmission grid on a large dataset and the last Section contains the concluding remarks.

II. Unit Commitment Model for Network Indicators Calculation

The algorithms developed for computing nodal indicators in [15] are based on a DC OPF where the grid is considered at nodal level and the N-1 security criteria is represented explicitly (including the corrective actions). However, it considered the temporal dimension as a set of independently optimized time intervals. This consideration is approximate, because the generation profile of the Production Units (PUs) is subject to intertemporal constraints such as minimum startup/shutdown time, ramp constraints, etc. To mitigate these issues, the DC OPF model has been updated with UC constraints of PUs, transforming it into an optimal UC algorithm with a daily optimization horizon (the same adopted in the day ahead electricity market) for computing nodal indicators. The algorithm is described in detail below.

A. UP Economic Model

Fig. 1 shows the structure of a PU. It consists of N_{UP} generators, each with production capacity limited between $P_{G,j}^{min}$ and $P_{G,j}^{MAX}$. Furthermore, according to the Italian market rules [16], economic bids are presented at PU level for a certain time interval and are characterized by quantity and price steps $<Q_{UP,k}^{m}, \pi_{UP,k}^{m}>$ presented in ascending order.

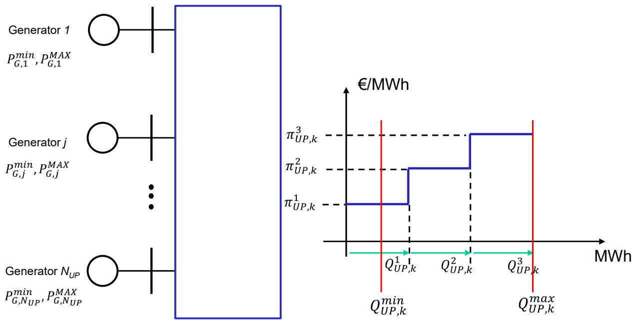

Fig. 1. PU model.

The production limits of the PU are defined with respect to the limits of the individual generators of PU as:

$$Q_{UP,k}^{min} = \sum_j P_{G,j}^{min} \tag{1a}$$

$$Q_{UP,k}^{max} = \sum_j P_{G,j}^{MAX} \tag{1b}$$

By defining $\Omega_{UP,k,t}^{m}$ as the quantity accepted by the market for each bid step m and for each time interval t, the total quantity produced by the PU is:

$$Q_{UP,k,t} = \sum_m \Omega_{UP,k,t}^{m} \tag{2a}$$

$$\Omega_{UP,k,t}^{m} \leq Q_{UP,k,t}^{m} \tag{2b}$$

$$Y_{UP,k,t} \cdot Q_{UP,k,t}^{min} \leq Q_{UP,k,t} \leq Y_{UP,k,t} \cdot Q_{UP,k,t}^{max} \tag{2c}$$

where $Y_{UP,k,t}$ is a binary variable representing the PU status.

Just like in the DC OPF problem [15][15], the total cost of accepting the bids is minimized, but now, the objective function is calculated over all the optimization horizon:

$$C_{UP} = \sum_t C_{UP,t} = \sum_{(t,k,m)} \pi_{UP,k.t}^{m} \cdot \Omega_{UP,k,t}^{m} \tag{3}$$

The total accepted quantity for the PUs is distributed among the generators of the PU, proportionally to the maximum power:

$$P_{G,j,t} = \frac{P_{G,j}^{MAX}}{\sum_j P_{G,j}^{MAX}} \cdot Q_{UP,k,t} \tag{4}$$

Since (1a), (1b) and (2c) already consider the capability of the generating units of the PU, there is no need to impose additional constraints on the variable $P_{G,j}$. This reduces considerably the number of constraints and binary variables.

B. Constraints of the UC Model

The PUs have a ramp constraint that limits the amount of power variation between two consecutive time intervals:

$$Q_{UP,k,t+1} - Q_{UP,k,t} \leq RAMP_{UP,k}^{\uparrow} \cdot Y_{UP,k,t} + Q_{UP,k,t}^{max} \cdot (1 - Y_{UP,k,t}) \tag{5a}$$

$$Q_{UP,k,t-1} - Q_{UP,k,t} \leq RAMP^{\downarrow}_{UP,k} \cdot Y_{UP,k,t} + Q^{max}_{UP,k,t} \cdot (1 - Y_{UP,k,t}) \quad (5b)$$

where $RAMP^{\uparrow}_{UP,k}$ *and* $RAMP^{\downarrow}_{UP,k}$ represent the maximum power variation that each PU can deliver in the upward and downward direction, respectively, during a defined time. In (5a), $Q^{max}_{UP,k,t}$ terms avoids the unit produces more than its capacity when turned ON; the same mechanism should be used in (5b) with $Q^{min}_{UP,k,t}$ to turn the unit OFF from minimum production. However, since the time window considered is one hour, the plant's dynamics are neglected, and the (5b) is relaxed by using $Q^{max}_{UP,k,t}$ instead.Each unit is characterized by constraints related to being in or out of service. If the market changes the status of a unit, it is necessary to maintain the generator in that state for at least a certain number of hours, according to its technical specifications, to ensure the feasibility of such transition [17]:

$$T^{ON,0}_{UP,k} = min(N^{time}, TMIN^{ON}_{UP,k} - UON^{0}_{UP,k}) \quad (6a)$$

$$Y_{UP,k,t} = 1, \ \forall\, t = 1, \dots, T^{ON,0}_{u} \quad (6b)$$

$$\sum_{time=t}^{t+TMIN^{ON}_{UP,k}-1} Y_{UP,k,time} \geq TMIN^{ON}_{UP,k} \cdot (Y_{UP,k,t} - Y_{UP,k,t-1}) \quad (6c)$$
$$\forall t = T^{ON,0}_{u} + 1, \ \dots, N^{time} - TMIN^{ON}_{u} + 1$$

$$\sum_{time=t}^{N^{time}} Y_{UP,k,time} \geq (N^{time} - t + 1) \cdot (Y_{UP,k,t} - Y_{UP,k,t-1}) \quad (6d)$$
$$\forall t = N^{time} - TMIN^{ON}_{u} + 2, \dots, N^{time}$$

where $T^{ON,0}_{UP,k}$ is the number of initial periods that the unit must remain in service; $TMIN^{ON}_{UP,k}$ is the minimum time for the unit to stay in service; $UON^{0}_{UP,k}$ is the number of hours the unit has been online prior to the start time window and N^{time} is the number of time windows within the considered time horizon.

Constraints like (6) can be formulated also for the minimum downtime of each PU.

C. *Constraints for Managing Hydroelectric and Pumped-Storage Hydroelectric Power Plants*

Hydroelectric and pumping plants have their production capacity limited over time by the capacity of the reservoir or the water flow for run-of-river plants. Fig. 2 depicts the generic model adopted. Each plant *k* is characterized by the capacity of its reservoir, $E_{UP,k,t}$, which is increased by $Fill_{UP,k,t}$ at the end of time window *t* due to natural reservoir filling. The algorithm can choose between producing energy $Q^{prod}_{UP,k,t}$ and utilizing a portion of $E_{UP,k,t}$ at efficiency η^{prod}_{UP}, or absorbing energy $Q^{pump}_{UP,k,t}$ and increasing $E_{UP,k,t}$ at efficiency η^{pump}_{UP}. This is described by (7a), while (7b) represents the actual production of the PU, i.e., $Q_{UP,k,t}$. A PU cannot simultaneously present a production bid and an absorption bid in the market, so the existence of only one of them will force one of the positive variables, $Q^{pump}_{UP,k,t}$ or $Q^{prod}_{UP,k,t}$, to zero. The reservoir capacity $E_{UP,k,t}$ is constrained by (i) upper and lower bounds (7c) of the technical limits of the reservoir and (ii) by a minimum level to be maintained at the end of the analyzed period (7d). Furthermore, constraint (7e), where the positive variable $\epsilon_{UP,k,t}$ is present in the objective function multiplied by a high penalty cost, aims to prevent any of the constraints (7a)-(7d) from becoming infeasible due to a rigid value of the $Fill_{UP,k,t}$ parameter:

$$E_{UP,k,t} = E_{UP,k,t-1} - \eta^{prod}_{UP} \cdot Q^{prod}_{UP,k,t} + \frac{Q^{pump}_{UP,k,t}}{\eta^{pump}_{UP}} + Fill_{UP,k,t} \quad (7a)$$

$$Q_{UP,k,t} = Q^{prod}_{UP,k,t} - Q^{pump}_{UP,k,t} \quad (7b)$$

$$E^{min}_{UP,k} \leq E_{UP,k,t} \leq E^{max}_{UP,k} \quad (7c)$$

$$E_{UP,k,end} \geq E^{min,end}_{UP,k} \quad (7d)$$

$$Fill_{UP,k,t} = Fill^{max}_{UP,k,t} - \epsilon_{UP,k,t} \quad (7e)$$

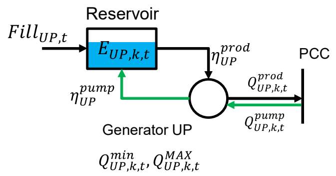

Fig. 2. Hydroelectric and Pumped-storage hydroelectric power plant model

Model (7), as is, represents the pumping plant model. But neglecting the variable $Q^{pump}_{UP,k,t}$ in (7) leads to the model of a traditional hydroelectric plant, capable only of power generation. To model a run-of-river plant it suffices to limit the variable $Q^{prod}_{UP,k,t}$ to the value $\eta^{prod}_{UP} \cdot Fill^{max}_{UP,k,t}$.

D. *Tertiary Reserve Constraints*

One of the criteria for the security of the network is the existence of a minimum level of generation reserves to address power imbalances in the network, providing the capability to keep the network frequency close to its nominal value of 50 Hz. According to the dispatching rules of the Italian power system, these minimum reserve levels must be ensured at bidding zone level (considering reserve sharing) and for the whole network control area level. Thus, for a generic area that contains *M* PUs that must ensure a minimum downward reserve $Q^{res\downarrow}_{Area,t}$ and a minimum upward reserve $Q^{res\uparrow}_{Area,t}$, the following constraints must be satisfied:

$$\sum_{k=1}^{M} (Q_{UP,k,t} - Y_{UP,k,t} \cdot Q^{min}_{UP,k,t}) \geq Q^{res\downarrow}_{Area,t} \quad (8a)$$

$$\sum_{k=1}^{M} (Y_{UP,k,t} \cdot Q^{MAX}_{UP,k,t} - Q_{UP,k,t}) \geq Q^{res\uparrow}_{Area,t} \quad (8b)$$

E. *Constraints for Network Security*

To ensure network security in N and N-1 conditions, it is necessary to add the DC PF equations and the branch flow constraints in N and in N-1 condition for each contingency. The structure of these equations can be found in [15][15].

The Lagrange multipliers associated with the DC power flow equations provide the Locational Marginal Prices (*LMP*s) at each bus of the network, which are then used by the clustering algorithms indicated in the next section to group the network buses, providing useful information to the determine the bidding zone configurations.

III. Clustering-Based Procedure

Dedicated clustering procedures have been further improved in the framework of this study. These are meant to derive alternative bidding zone configurations starting from a set of *LMP*s and grid topology data.

The main issues for applying clustering algorithms to the problem under study are the need to consider the network topology with the connections among nodes, and the need to determine relatively uniform clusters. With this prospect, clustering algorithms aimed at identifying outliers are not suitable and topology checks are needed, either embedded in the calculation process or applied to the clusters formed. The research carried out by the authors has tested various options based on traditional clustering algorithms, such as kmeans or hierarchical clustering with different linkage criteria that consider different ways to determine the conventional distances among clusters [18]. These options used individually are insufficient to carry out the entire grouping, because of the limitations due to the absence of topology-based information included in these algorithms. Because of that, these algorithms can be considered in a first phase of the analysis, while the topology-based considerations are included in a further phase by applying suitable algorithms.

The procedure is summarized in Fig. 3. The number of clusters is chosen based on practical considerations, in a range (e.g., 4-8) around the present number of bidding zones.

The square adjacency matrix **A** is constructed, with binary entries corresponding to the connections of pairs of nodes in the row and column (0 = not connected; 1 = connected).

The *LMP*s are used as features for clustering and are included in the matrix $\mathbf{D}_{\mathrm{LMP}}$, with nodes in the rows and scenarios in the columns. Each scenario has the same probability of occurrence. For each scenario, a clustering algorithm is executed to find a node partitioning with the given number of clusters. From the clustering results, a similarity matrix **P** is constructed, in which the entries contain, for each pair of nodes, the similarity index assessed based on the number of times the selected nodes belong to the same cluster. The nodes are then grouped by using the Spectral Clustering algorithm [19] with the matrix **P** as an input. The last step is the execution of a connectivity check based on the information provided by the adjacency matrix.

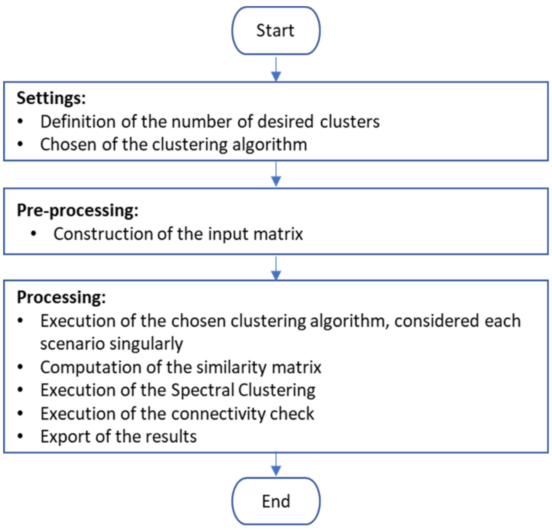

Fig. 3. Clustering algorithm.

IV. Application to the Italian System

A. Description of the System Under Analysis

The power system considered is the Italian High Voltage (HV) transmission (Fig. 4). The Sardinia Island is not included as its connection with continental Italy is in HVDC (not synchronous). The resulting network is characterized by 1086 nodes, 1300 branches and 420 generating units [20].

The described procedure is applied on a significant number of operating scenarios. The year 2019 is considered and, for simplification, each day is reduced to six significant hours, namely 4:00, 8:00, 12:00, 16:00, 18:00 and 22:00. Thus, considering that the data for three hours is missing, and the corresponding days neglected, a total of 2172 scenarios are obtained. The nodal real and reactive power demands have been set according to the actual data provided by the TSO. They present three components: (i) the net demand at HV substation level seen as the difference between the total demand and the total generation present at lower voltage levels; (ii) the import from DC cables, and (iii) the import of Italy from neighboring countries at the North border. The evolution of the three components is shown in Fig. 5. Two periods where the demand is highest can distinguish: beginning of the year (winter), and middle of summer.

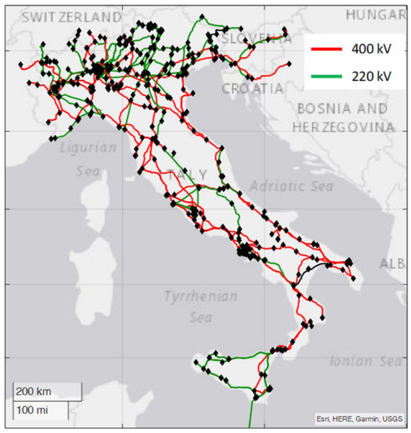

Fig. 4. Italian HV Transmission Grid with cross-border connections.

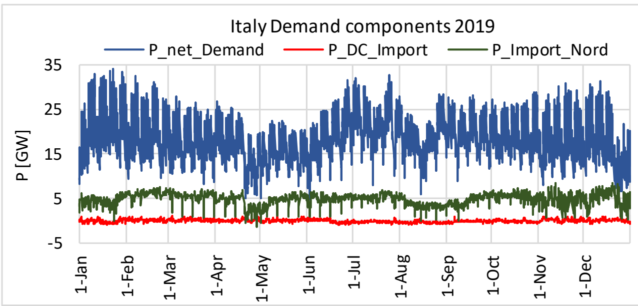

Fig. 5. Italian HV Transmission Grid demand components.

Fig. 6 shows the residual demand to be satisfied by PU connected in the HV grid, hence the demand covered through the market clearing algorithm of Section II. It is calculated as the difference between the net demand and the imports.

For each generating unit connected to the HV grid (Fig. 1), the actual market bids corresponding to the considered scenarios have been used; the data is available at [21]. The technical data of the PUs in terms of ramp rates, minimum time of operation etc., has been provided by the Italian TSO.

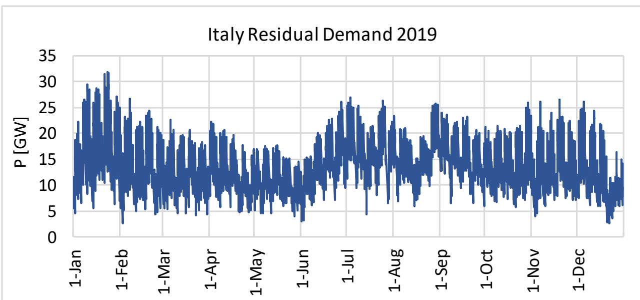

Fig. 6. Italian HV Transmission Grid residual demand.

B. UC Results

The optimization model that represents the nodal market with UC constraints has been run on all the considered scenarios, with the UC constraints being applied on a daily basis. The algorithm converged within a well-contained calculation time: about one minute for each day, which shows the capability of the proposed methodology to potentially process a very large dataset.

Fig. 7 shows the obtained average *LMP* calculated over all the grid buses, for each scenario. Compared to Fig. 6, it is clear that the variation shown in Fig. 7 follows well the trend of the residual demand. This is in-line with the expected results, as in the ideal case (no congestions, price invariance, etc.), the *LMP* perfectly follows the demand.

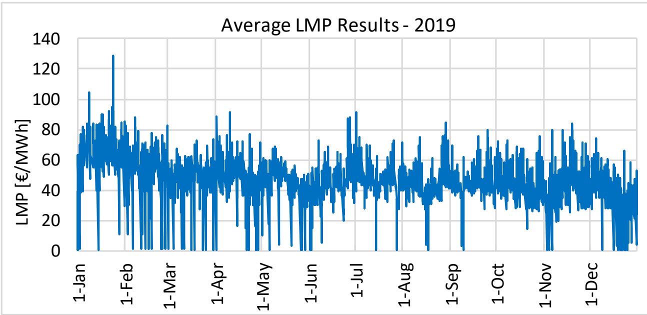

Fig. 7. Average *LMP* over all network buses for each considered scenario.

Fig. 8 shows the total number of branches congested in each considered scenario and in N-1 security conditions; the figure also shows the trend of the daily average number of congestions. In some scenarios, few congestions occured in N security conditions, hence they are not considered relevant. Clearly, the highest concentration of congestions is in the midsummer period (one of the periods with highest demand and lower conductor ampacity) suggesting that this is the period of higher sparsity in the *LMP* values.

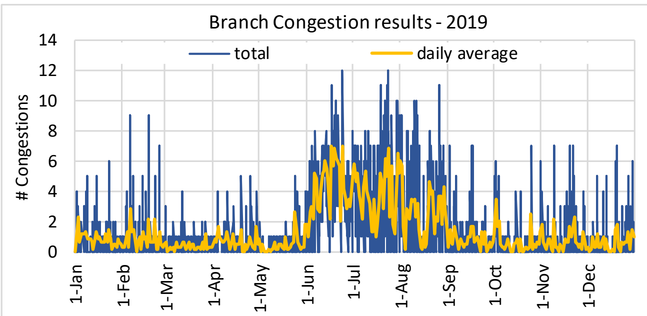

Fig. 8. Branch congestions statistics in N-1 security conditions.

As explained in [14], the optimization model also contains a flow limit on a set of branches in the grid that is the Center North (CN)-Center South (CS) interface, where the flow is limited due to potential voltage problems. Fig. 9 shows the evolution of the interface's congestion together with the cumulative average to better track its dynamic. The cumulated average suggests a concentration of interface congestions at the beginning of the year, i.e., in the other period with highest demand. Thus, the "price separation" at the interface of Italy occurs more often here, leading to higher values of *LMP*s (see Fig. 7).

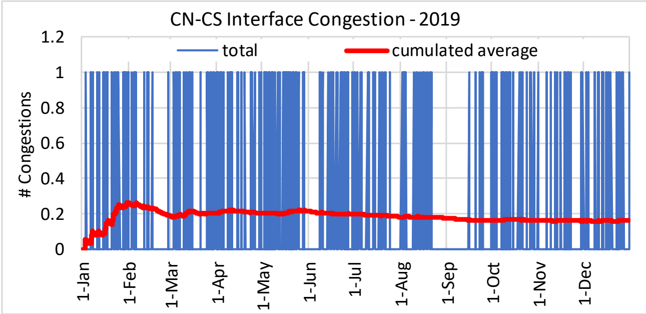

Fig. 9. CN-CS interface congestion statistics.

C. Clustering Results

Fig. 10 and Fig. 11 show the clustering results obtained by considering different input data to the clustering algorithms, corresponding to successive phases of development of the model-based activity, taking 7 clusters as an example.

The starting point (Fig. 10) is the solution presented in [22]. In this case, the clusters were identified through a multi-scenario methodology: the analysed *LMP*s were obtained through a DC OPF executed for 100 scenarios considered singularly. In the algorithm, the N-1 security criteria were incorporated, and historical load and generation profiles were considered [15]. Moreover, a weight to each of the 100 scenarios was assigned by the TSO to consider the probability of occurrence estimated according to historical data. As can be noticed in the figure, some clusters were characterised by a relatively low number of nodes.

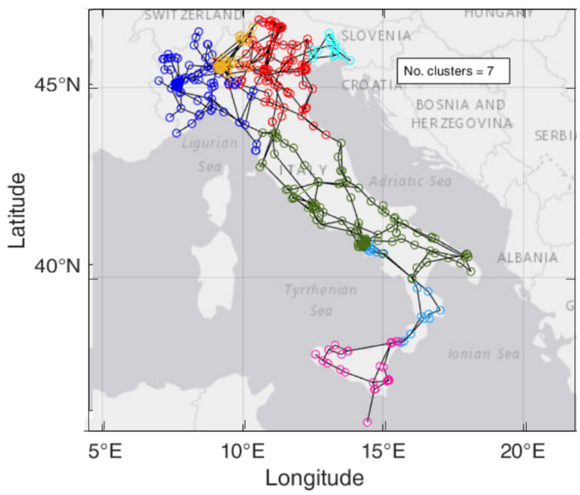

Fig. 10. Solution presented in [22].

Considering the same methodology but with a more representative dataset characterized by 2172 scenarios and the execution of the UC model, the clusters depicted in Fig. 11 were identified. With reference to the previous results, more uniform groups were created, reflecting particular conditions. For example, a specific cluster appears in the South-East of Italy – the green points), which identifies a zone with particular characteristics of the generation, with a large share of production from renewable energy sources in wind and photovoltaic power plants.

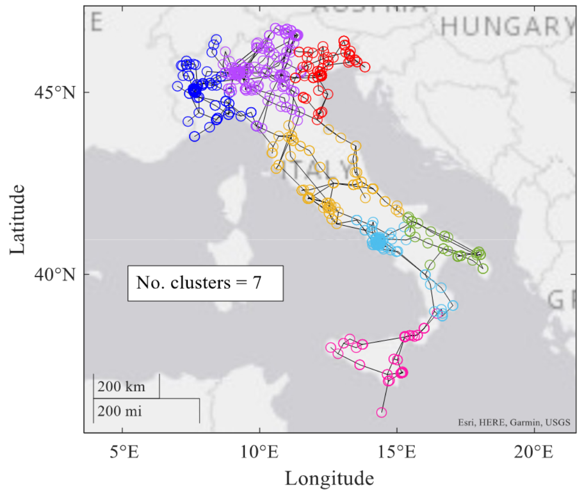

Fig. 11. Clustering results obtained by using the *LMP*s determined starting from the DC-OPF with Unit Commitment.

CONCLUDING REMARKS

To assist the bidding review process, this paper has proposed the application of specific algorithms for calculating the *LMP*s, considered as the features of interest for grouping the nodes of the HV network by considering the effects of network congestions in different time periods. The analysis has been carried out by adopting advanced procedures specifically formulated for both OPF calculation, with the inclusion of unit commitment in the DC OPF, and a combination of clustering algorithms that enables the incorporation of network topology-based information in a framework targeted for the application of the spectral clustering. The results confirm the applicability of the proposed methodology on a large-scale power system such as the Italian one.

More generally, the definition of the bidding zones should consider further aspects related to generation availability, foreseeable evolution of the network, uncertainty of the future generation and demand, and other aspects of the network operation that can be revealed through a more detailed study, e.g., by using an AC OPF. The authors are working in this direction with the aim to reflect voltage constraints in the *LMP*s obtained from the market clearing algorithm and to introduce a probabilistic approach able to increase the representativeness of the *LMP* scenarios in the clustering algorithms. In parallel, stopping criteria for the clustering procedure are under investigation.

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