Alimisis V, Taylor PC. [Zoning evaluation for improved coordinated automatic voltage control](#). *IEEE Transactions on Power Systems* 2014

Copyright:

This work is licensed under a Creative Commons Attribution 3.0 License. For more information, see <http://creativecommons.org/licenses/by/3.0/>

DOI link to article:

<http://dx.doi.org/10.1109/TPWRS.2014.2369428>

Date deposited:

10/07/2015

This work is licensed under a [Creative Commons Attribution 3.0 Unported License](#)

Zoning Evaluation for Improved Coordinated Automatic Voltage Control

Varvara Alimisis, *Student Member, IEEE*, and Philip C. Taylor, *Senior Member, IEEE*

Abstract—Hierarchically structured automatic voltage control (AVC) architecture has attracted increased interest as networks operate closer to their capacity limits. Hierarchical AVC enables wide-area coordinated voltage regulation (CVR). Due to the inherent complexity of the task, it is based on reduced control models, i.e., simplified models of the system suitable for voltage control. It is a fact however that a single reduced control model (static RCM) cannot be optimal for all network configurations and operating conditions. In pursuit of an improved CVR, this paper investigates the applicability of zoning methodologies in adaptively determined RCM. It further argues that the selection of a zoning methodology affects not only the CVR operation, but also its robustness to erroneous data and proposes a comprehensive generic framework for evaluating its performance. Lastly, it extends and evaluates several zoning-based control model reduction methodologies: namely, hierarchical clustering employing two different proximity metrics, spectral k-way and fuzzy C-means, on both static and adaptive schemes.

Index Terms—Adaptive control model reduction (adaptive-RCM), automatic voltage control (AVC), coordinated voltage regulation (CVR), erroneous data, graph theory, pilot nodes.

I. INTRODUCTION

POWER systems are increasingly operated closer to their capacity limits, due to technical, economic and environmental drivers. Consequently there is an international trend towards advanced automatic voltage control (AVC) that involves some sort of coordination among reactive power resources and controllers [1], [2]. The adoption of an AVC strategy is tailored to the transmission grid to be controlled, i.e., network features, available control equipment, and market operation, hence different approaches have been exercised by TSOs and have been debated in the literature [3], [4].

Some power companies and TSOs use local automatic high side voltage control at power plants to a relatively fixed and flat schedule, combined with transmission-level switched capacitor banks with local and SCADA control, to deliver secure and economic power system operation [5]–[8]. Towards the same objective but featuring different control philosophy, AVC systems of hierarchical structure have originated in Europe and are

the subject of this paper. Hierarchical AVC architecture enables *wide-area closed-loop coordinated* voltage and reactive power control, however, due to the inherent complexity of the task relies on *zoning* based control model reduction (RCM). The approach allows sensitive coordinated reactive power dispatch of several plants in a *voltage control zone*, by regulating a *pilot node*, i.e., a central to the zone EHV load bus, rather than the power plant high side bus [4]. Such hierarchical control architecture has been put into operation in France [9], [10], Italy [11], and most recently in China [12], [13]. The accumulated experience reported from implementations but also from study cases [14]–[17] is highly encouraging.

Currently research into the *control model reduction* is developing in two directions. The first deploys heuristics to divide the system into weakly coupled zones and then places the pilot nodes in “the electric center” for each zone. This approach employs *zoning methodologies*. The second direction uses heuristics and artificial intelligence techniques to identify the most suitable pilot nodes by minimizing, in a system wide fashion, the linearized version of a particular CVR control objective function [18]. In this case, weak coupling requirement constitutes a static constraint of the optimization task. This paper is concerned with control model reduction that is 1) close to actual practices used in commercial AVCs and 2) can adapt to the network conditions in an online fashion, termed *adaptive RCM*. Approaches of the second research direction have received extensive academic interest but, unlike zoning methodologies, have not been deployed in actual implementations and cannot be incorporated in *adaptive RCM* schemes, due to their long execution times. Indicatively, evolutionary algorithms, that according to [19] are currently the best candidate solution, need several hours to converge. *Zoning methodologies* are thus examined, due to being both commercially applied and significantly fast.

A two-stage systematic approach reported in [20] has proved effective for determining voltage-control zones in the French hierarchical AVC implementation. The first stage involves calculating the electrical distance between the buses in the system. The second stage is to group the buses using hierarchical clustering. Work described in [21] and [22] can be thought of as variations of [20]. Authors of [21] used full Jacobian sensitivities for the formation of voltage control zones which are more robust but with increased computational cost. Research presented in [22] adds a pre-clustering stage to normalize the electrical distance that reduces the computational cost, which however possibly calls for meta-heuristics in cases where ranges of classification are not adequately narrow. Hierarchical clustering has also been followed in the Chinese

Manuscript received May 23, 2014; revised August 16, 2014 and October 27, 2014; accepted October 28, 2014. This work was supported by the Autonomic Power System project (APS)—EPSRC grant reference EP/I031650/1. Paper no. TPWRS-00708-2014.

The authors are with the School of Electrical and Electronic Engineering, Newcastle University, Newcastle, U.K. (e-mail: v.alimisi2@ncl.ac.uk; Phil.Taylor@ncl.ac.uk).

Color versions of one or more of the figures in this paper are available online at <http://ieeexplore.ieee.org>.

Digital Object Identifier 10.1109/TPWRS.2014.2369428

AVC implementation [12]. Unlike [20] they used the concept of “VAr control space” to quantify the distance between the buses, which considers the quasi-steady zonal control characteristics. A more intuitive clustering method has been proposed in [23], aiming to deliver zones that can dynamically adjust to topological and operational changes. Contradicting its motivation it uses geographical shortest paths as a distance metric between load nodes and generation, which is unsound and computationally prohibitive for realistic size networks. Fuzzy logic has also been used to identify voltage control zones [24], [25] where each node has a degree of belonging rather than belonging completely to one zone, prior to crisp clustering. An approach using fuzzy C-means is introduced in [25], and has demonstrated robustness for various operating conditions in the network. [26] applies spectral k-way clustering. It uses the eigenstructure of the network graph to form weakly coupled zones and is a computationally promising approach.

It is argued in literature that the selection of RCM affects the performance of the CVR control. While comparative studies exist for the approaches of the second research direction [19], [27], such an analysis has not been extended to *zoning methodologies*. This paper fills this gap and further argues that the selection of a zoning methodology affects not only the CVR performance, but also its robustness to erroneous data and the feasibility for *adaptive RCM*. All these three factors are a fundamental part of a future smart transmission grid [28], [29].

Robustness to erroneous data is a much desired property, due to the fact that pilot nodes substitute for key measurements. Any uncertainty in their values (such as imperfect prediction, noisy or corrupted data) significantly affects the zone they represent and to a lesser extent the neighboring control zones, in cases of a remaining, albeit weak, inter-zonal coupling. In this respect, investigation into different *zoning methodologies* is important due to the fact that they deploy different proximity metrics, clustering criteria and validation indices. At the same time, a single control model reduction, termed *static RCM*, cannot be optimum for all network configurations and operating conditions. Advances in substations communication and increased measurement availability allow for *adaptive RCM*. A novel AVC system based on online adaptive network zone division has been implemented in China and demonstrated voltage profile enhancement compared to *static RCM* [12], [13]. The above findings motivate the investigation of various zoning methodologies’ applicability in *adaptive RCM* schemes, from a theoretical point of view.

More specifically, the main contributions of this paper are:

- 1) It proposes a generic framework to assess the overall performance of CVR and has the following novel key attributes: It enables zoning methodologies comparative evaluation deploying full AC load flow equations within a probabilistic analysis, hence effectively extending [19], [27]. It can flexibly accommodate and evaluate any control implementation, e.g., [26], [30], [1], [31]. It further incorporates robustness to erroneous data and applicability in adaptive RCM in this comprehensive tool for CVR evaluation.
- 2) It formulates and extends a selective subset of the currently published zoning methodologies as clustering

Fig. 1. Generic hierarchically structured AVC architecture.

optimization problems and then integrates them into the framework, namely: Hierarchical clustering with single distance (HCS), hierarchical clustering in VAr control space (HCVS), spectral k-way (SKC) and fuzzy C-means (FCM). The first two have been deployed in actual implementations and no modifications are added. This paper effectively extends SKC and FCM methodologies with emphasis on the deployment of voltage sensitivity based proximity metrics, scale independence where possible and particular to each approach validation indices.

- 3) This is the first work to comparatively present quantitative results of zoning methodologies’ performance on the CVR problem. The extracted outcomes can be valuable in a number of ways, e.g., they can provide a benchmark for the development of other *control model reduction* techniques, facilitate the selection and design of a CVR control module, assess robustness of different filtering techniques and sensor technologies (e.g., PMU based CVR as proposed in [32]) or vulnerability to malicious attacks.
- 4) Last, it provides insight regarding the feasibility of adaptive CVR as well as of potential benefits, considering the CRM reconfiguration as a possible action before CVR reaches its limits [33] and emergency control takes place.

The rest of the paper is organized as follows. Section II contains a brief overview of a hierarchical AVC. Section III introduces the framework to assess the overall performance of CVR. Section IV formulates and extends the four zoning methodologies as clustering optimization problems. Lastly, Sections V and VI provide results and conclusions, respectively.

II. OVERVIEW OF A HIERARCHICAL AVC

This section presents the basic concepts of a hierarchical AVC architecture and elaborates on the required RCM. A generic hierarchically structured AVC architecture is shown in Fig. 1.

Towards achieving automatic real time voltage control, ideally one would optimize system-wide all control variables running a full AC optimal power flow. However, this is unrealistic and not compatible with real time requirements. [34] Owing to the inherent complexity of the task, reliable albeit suboptimal real time automatic control is delivered through a *zoning based reduced control model*. Zones are network subdivisions that demonstrate coherence to voltage control and are derived using the Jacobian matrix of the system. Within a

Fig. 2. Flowchart of the proposed generic framework.

zone, voltage is controlled on a pilot bus, i.e., a central EHV load bus whose voltage magnitude variation is representative of the zonal voltage profile. Analogously to the high-side voltage regulation, Secondary Voltage Regulation (SVR) counteracts slow and large voltage deviations occurring within a *control zone* by adjusting the set-points of primary voltage regulators (PVR) according to a PI law. The control resource is essentially based on the largest synchronous generators within the zone that have the maximum regulating sensitivity on the pilot node. Additionally, SVR operates on the local switching resources, only when needed, in accordance with the available margin of the generators reactive resources [11]. Effectively, the reduced control model is an approximation of the reactive power flow sub problem of a zone.

For optimization, emergency boosting and to avoid conflicting inter-zone control efforts, SVR set-points come from a tertiary loop, the tertiary voltage regulation (TVR) which coordinates the decentralized SVRs. TVR minimizes the differences between the actual field measurements and the reference values provided by a reactive OPF that uses as input the latest state estimation or alternatively deploys forecasts. The definition and the implementation of the SVR and the TVR vary from one TSO to another, as AVC is tailored to the features of the power grid to be controlled [10]–[12]. However, in principle, in all implementations TVR together with SVR deliver the co-ordinated voltage regulation (CVR).

III. FRAMEWORK

This section presents the generic framework to assess the overall performance of CVR control. The relevant flow-chart is shown in Fig. 2. At each iteration, blocks A and C effectively generate a system state, while blocks B, D, and E solve and evaluate the performance for that state. More specifically:

A. Block A

First a random system state is generated by sampling a load duration curve. Then a system-wide optimal power flow (OPF) is solved which minimizes system losses while considering security constraints. This block provides system state information (P, Q, V) to blocks B and C and reference voltage and reactive power level values (V_{ref}, Q_{ref}) and respective control limits ($V_{max}, V_{min}, Q_{max}, Q_{min}$) to block D.

B. Block B

This block integrates a zoning methodology into the framework. A zoning methodology consists of a zoning algorithm that divides the network into weakly coupled control zones, and an algorithm for pilot node selection within the zones. These are discussed in detail in Section IV. The zoning methodology using the state information received from block A provides to the CVR of Block D pilot nodes to base the control on and the set of available reactive resources to regulate a zone's voltage profile. It should be noted that for comparison purposes in our implementation this block can switch between four different zoning algorithms but of course the approach can work with just one.

C. Block C

This block creates voltage deviations and provides the CVR with the voltage deviation vector-target to act upon. This vector is generated as follows:

- Reactive load is perturbed around its nominal value by sampling a probability distribution. Perturbations are assumed to be instantaneous. Randomly selected line trips are also considered. This system perturbation approach could be extended to account for any possible system contingency.

— Steady-state AC load flow equations are used to derive mid-term voltage values assuming that the transient response of generators has reached steady state when CVR acts. This gives the values of the $\Delta V [N \times 1]$ voltage deviation vector all across the network of N buses, as the difference between the voltage magnitude from Block A, V_{ref} , and the voltage magnitude after disturbance V_{ad} as in (1):

$$\Delta V = V_{ref} - V_{ad}. \quad (1)$$

— The CVR controller has knowledge of the voltage deviation vector only at the pilot nodes ΔV_P as well as of the reactive power Q_g produced by those control resources that participate in the CVR, as can be seen in Fig. 1. To account for erroneous data, the controller is considered to act in the general case based on the information $\{\Delta V_P, \hat{Q}_g\}$. The relation between the latter and $\{\Delta V_P, Q_g\}$ is further clarified in Section V. The source of error can be any of the following: noisy measurements; imperfect predictions or corrupted data.

D. Block D

This block contains the CVR strategy. CVR regulates the voltage at the pilot buses PN_{set} through the coordinated control of the synchronous resources that participate in CVR in each zone. The synchronous generators that have control capability above a threshold are selected in each zone, as in (2):

$$QR_g \cdot C_{pg} \geq a_{ck} \quad (2)$$

where QR_g is the reactive capability of the generator, C_{pg} is the sensitivity of the zone's pilot node to the control generator, and a_{ck} is the allowed minimum control capability in the zone k . A quadratic programming model, similar to the EDF CSVR [10] is used here. It should be noted however that any other control implementation could have been used, without loss of generality. The primary goal of CVR is to control the voltages at the pilot buses PN_{set} to follow the optimal forecasted reference values as updated by the OPF of Block A. The secondary goal (with lower priority) is to align the MVar distribution among the participating generators in each control zone to enhance security of supply. For the latter, a reference value for the reactive power level is specified for each area, e.g., for the J th area

$$Q_{refJ} = \frac{\sum_{g \in SVR_J} Q_g}{\sum_{g \in SVR_J} Q_{g,max}} \quad (3)$$

where SVR_J is the set of generators participating in SVR for area J . Then the following quadratic programming problem is solved:

$$\min \left\{ \sum_{i \in PN_{set}} (\Delta V_P)^2 + \mu \cdot \sum_{J \in k} \left(\sum_{g \in SVR_J} \left(Q_{refJ} - \frac{Q_g + \Delta Q_g}{Q_{g,max}} \right)^2 \right) \right\} \quad (4)$$

subject to the following inequality constraints:

$$V_{P,min} \leq V_P + C_{pg} \cdot \Delta Q_g \leq V_{P,max} \quad (5)$$

$$V_{G,min} \leq V_G + C_{vg} \cdot \Delta Q_g \leq V_{G,max} \quad (6)$$

$$Q_{g,min} \leq Q_g + \Delta Q_g \leq Q_{g,max} \quad (7)$$

where μ is the weighting factor between the two objectives, Q_g denotes the current reactive power output vector of control generators, ΔQ_g denotes the regulation amount to be determined by this iteration of control, V_P and V_G denote the voltage of pilot buses and the power plants voltage, respectively, and C_{pg} and C_{vg} are the voltage sensitivity matrices. Equations (5) and (6) are the voltage operation limits. Equation (7) shows the reactive power operation limits of the controlled generators, which are dependent variables with respect to the active power output.

E. Block E

This block evaluates the control decisions. At each CVR cycle a correction ΔQ_g vector is computed, based on the implementation discussed in block D.

— The performance PI_i of one iteration of the CVR is assessed based on the average absolute relative error for the N load buses:

$$PI_i = \frac{1}{N} \cdot \sum_{i=1}^N \left| 1 - \frac{V_{ac}(i) - V_{ad}(i)}{\Delta V(i)} \right| \quad (8)$$

where ac index signifies the voltage value after control and ad the voltage value after a disturbance. All values are computed by full AC load flow. ΔV values are computed as in (1). It should be noted that voltage dynamics are neglected, based on the assumption that the associated control loops are time dynamically decoupled, i.e., the time constant of the power plant reactive power control loop is chosen to be sufficiently higher than that of the primary voltage control loops and sufficiently lower than that of the secondary voltage regulation. For the interested reader adequate justification of the above can be found in [30].

— The performance PI_i is compared to a threshold PI_{thres} . A performance PI_i lying below the desired threshold calls for reconfiguration of the zones and pilot nodes, provided that the examined zoning methodology allows for adaptive RCM. In this case, the analysis returns to *Block B* and the PI_i value of performance for this cycle is updated.

As a probabilistic performance measure the expected value of the PI is used, i.e.,

$$OPI = 1 - E \{PI\}. \quad (9)$$

This is updated at the end of each iteration. Effectively our approach is equivalent to a non-sequential Monte Carlo method [35].

A lower OPI value indicates a worse CVR control performance. Hence, based on this index the proposed comprehensive framework can be used to evaluate and compare CVR performance for any configuration of its components in Blocks A, B, C, D, and E. This framework is used in this paper to investigate how the selection of a zoning methodology affects CVR performance. A thorough investigation based on various zoning methodologies is carried out which additionally considers 1)

data accuracy and 2) possibility of CRM reconfiguration; while the CVR control law remains unchanged.

IV. ZONING METHODOLOGIES

This section formulates four zoning methodologies as clustering optimization problems, and contributes some extensions where necessary. In principle, a *zoning methodology* comprises of two modules: 1) a *zoning algorithm* that divides the network into areas appropriate for CVR control and 2) a *pilot node selection algorithm* that identifies a bus per zone so that its voltage magnitude variation represents adequately the zone's voltage profile.

A. Zoning Algorithms for Network Division

In graph theory, the engineering term *zoning* is referred to as *clustering*. It is an optimization problem that requires the definition of: 1) a *proximity measure*, i.e., an “electrical distance” that represents the degree of similarity for any two nodes; 2) a *clustering criterion*, i.e., a cost function or some other type of rule to form a number of zones utilizing the proximity measure; and 3) *cluster validation*, i.e., a way to assess the relative appropriateness of clustering solutions proposed by an algorithm.

1) *Hierarchical Clustering With Single Electrical Distance (HCSD)*: This approach along with the concept of *electrical distance* was first introduced in [20].

Proximity Measure: The degree of coupling in terms of voltage between two nodes, m and n , can be quantified by the attenuation of voltage variations, defined as

$$a_{mn} = \frac{\left[\frac{\partial V_m}{\partial Q_n} \right]}{\left[\frac{\partial V_n}{\partial Q_n} \right]}. \quad (10)$$

To obtain symmetrical distances and move from a product to a sum, the following quantity is used as a proximity measure:

$$D_{mn} = -\log(a_{mn} \cdot a_{nm}). \quad (11)$$

Clustering Criterion: Agglomerative clustering (bottom-up) is used to merge nodes into clusters. At each iteration, the *complete linkage criterion* in (12) defines the proximity of any two clusters C_I, C_J :

$$ICD_{I,J} = \max \{D_{mn} : m \in C_I \text{ and } n \in C_J\}. \quad (12)$$

Then clusters are merged, based on (13):

$$C_I \cup C_J : \min \{ICD_{I,J}\}. \quad (13)$$

The result of the iterative algorithm is a tree of clusters, called dendrogram, which shows how the clusters are related.

Cluster validation: To obtain the most appropriate, k number, disjoint groups the dendrogram is cut at a desired level, based on the relative diameter criterion. The diameter of a cluster $diam_C$ in (14) is the maximum distance between any two points in the cluster, while the relative diameter of k clusters is obtained from (15):

$$diam_C = \max \{D_{mn} : m, n \in C\} \quad (14)$$

$$RD = \frac{\sum_{i=1}^k diam_{C_i}}{k}. \quad (15)$$

The changes in the slope of the relative diameter curve RD correspond to a deterioration of the quality of the groupings. Ultimately, the most appropriate number of zones k within $[1, k_{\max}]$ is derived from the following equation:

$$k : \max \{|RD_2 - RD_1|, \dots, |RD_{k_{\max}} - RD_{k_{\max}-1}|\}. \quad (16)$$

2) *Hierarchical Clustering in VAR Control Space (HCVS)*: For a network with g reactive power sources and l nodes to be classified and S_{ij} , the sensitivity of the i th node's voltage with respect to the j th reactive power source's VAR output, the “VAR control space” is defined in [12] as a g -dimensional Euclidean space where each load node can be described by a coordination vector $\{x_{i1}, x_{i2} \dots x_{ig}\}$ with x_{ij} defined as

$$x_{ij} = -\log(|S_{ij}|). \quad (17)$$

Based on the above definition, each component of a node's coordination vector represents how much the node is coupled with a specified reactive power source.

Proximity Measure: For two load nodes $m\{x_{m1}, x_{m2} \dots x_{mg}\}$ and $n\{x_{n1}, x_{n2} \dots x_{ng}\}$, the electrical distance D_{mn} is defined by (18):

$$D_{mn} = \sqrt{|x_{m1} - x_{n1}|^2 + \dots + |x_{mg} - x_{ng}|^2}. \quad (18)$$

Clustering Criterion: Similarly to the HCSD approach, agglomerative clustering is used, however singletons are merged iteratively to construct the *dendrogram*, based on the *average linkage criterion*:

$$ICD_{I,J} = \frac{1}{\sum_{m \in C_I} (C_I) \cdot \sum_{n \in C_J} (C_J)} \sum_{m \in C_I} \sum_{n \in C_J} (D_{mn}). \quad (19)$$

It follows that nodes strongly coupled with the same set of reactive resources would be placed in the same cluster.

Cluster Validation: The average inter-cluster distance (AD) is used to determine the most appropriate number of clusters k , within the examined range $[1, k_{\max}]$:

$$AD = \sqrt{\frac{\sum ICD_{I,J}^2}{k}} \quad I = 1, \dots, k; \quad J = I+1, \dots, k. \quad (20)$$

It follows that the greater the AD , the weaker the coupling between the clusters. Thus, k is determined as follows:

$$k : / \max \{AD\}. \quad (21)$$

3) *Spectral k-Way Clustering (SKC)*: The approach presented in this paragraph is based on [26]. Unlike [26], this paper's formulation uses strictly voltage sensitivity based proximity metrics and concludes with a clustering validation stage. Spectral-based analysis extracts global information about the structure of the graph from eigenvalues of graph matrices.

Proximity Measure: A weighted adjacency matrix: $A(G) = [w_{ij}]$ is associated to the network graph G . Weight w_{ij}

accounts for the cost of putting nodes i, j in separate clusters and are derived from (11), provided that node i is adjacent to node j in G .

The degree matrix of the graph $D(G) = [d_{ij}]$ is defined as

$$d_{ij} = \begin{cases} 0 & \text{if } i \neq j \\ \sum_{k=1}^n w_{ik} & \text{if } i = j. \end{cases} \quad (22)$$

The Laplacian of graph G is the $N \times N$ symmetric matrix $L(G) = D(G) - A(G)$. The normalized Laplacian is used in this paper, which is scale independent [36]:

$$L_n = D^{-(1/2)} \cdot L \cdot D^{-(1/2)}. \quad (23)$$

The Normalized Laplacian is singular, it has rank at most $n - 1$ and it has 0 as eigenvalue. The rest of the eigenvalues would be positive. The multiplicity of zeroes represents the number of connected sub-graphs. For a spectral k -way classification the k top eigenvalues are used to assign coordinates to the nodes of the graph in R^k . Vector $x = \{x_1, \dots, x_N\}$ is normalized to have length 1 in R^k :

$$U_i = \frac{x_i}{\|x_i\|} \quad 1 \leq i \leq N. \quad (24)$$

This amounts to a radial projection onto the $k - 1$ sphere.

Clustering Criterion: At this stage k -means is used to assign the N nodes into k clusters. K -means iteratively minimizes the objective function:

$$J = \sum_{j=1}^k \sum_{i=1}^N \|U_i^j - C_j\|^2 \quad (25)$$

where $\|U_i^j - C_j\|$ accounts for the distance between a node and a cluster centroid C_j . This optimization iterates until the movement of the k -centroid points falls below some minimum threshold or a maximum number of iterations is reached.

Clustering Validation: Eigengap analysis is used in this paper to identify the most appropriate clustering decision, as in [36]. Eigen gap is the difference between two consecutive eigenvalues. The eigenvalues of L_n are sorted in an ascending order and the relative eigengap γ is examined:

$$\gamma = \frac{v_{k+1} - v_k}{v_k}. \quad (26)$$

A number of clusters k within the range $[1, k_{\max}]$ which maximizes γ indicates that the network admits a good decomposition in k -clusters and this is revealed by the spectral embedding in dimension k . It is noteworthy, that the relative eigengap criterion can identify the most appropriate number of clusters before one proceeds to k -means optimization. This significantly reduces the computational cost of the SKC methodology and is further discussed in Section V-B.

4) *Fuzzy k-Means (FCM):* The approach presented in this paragraph is based on [25]. Unlike [25] this paper's formulation uses strictly voltage sensitivity based proximity metrics and concludes with a clustering validation stage, using fuzzy statistics.

Proximity Measure: Variable x_{ij} accounts for the voltage coupling of load nodes i, j and is calculated as in (11).

Clustering Criterion: Fuzzy k -means is used to assign the N load nodes into k clusters. It is based on minimization of the following objective function:

$$J_m = \sum_{i=1}^N \sum_{j=1}^k u_{ij}^m \cdot \|x_i - C_j\|^2 \quad 1 \leq m < \infty \quad (27)$$

Where u_{ij} is the degree of membership of x_i in the cluster j . The fuzzifier m determines the level of cluster fuzziness. A large m results in smaller memberships and hence fuzzier clusters. In the limit $m = 1$, the memberships u_{ij} converge to 0 or 1, which is the simple k -means. Fuzzy clustering is carried out through an iterative optimization of the objective function in (27) with the update of membership u_{ij} and cluster centroids C_j :

$$u_{ij} = \frac{1}{\sum_{t=1}^k \left(\frac{\|x_i - C_t\|}{\|x_i - C_j\|} \right)^{2/(m-1)}} \quad \text{and} \quad C_j = \frac{\sum_{i=1}^N u_{ij}^m \cdot x_i}{\sum_{i=1}^N u_{ij}^m}. \quad (28)$$

This procedure converges to a local minimum or a saddle point of J_m when

$$\left\{ \left| u_{ij}^{(\text{iter}+1)} - u_{ij}^{(\text{iter})} \right| \right\} < \varepsilon \quad \text{or} \quad \max\{\text{iterations}\} \quad (29)$$

where ε is a termination criterion between 0 and 1.

Clustering Validation: The appropriateness of a clustering decision based on a value k can be validated using Xie and Beni index [37]:

$$V_{XB}(k) = \frac{\sum_{j=1}^k \sum_{i=1}^N u_{ij}^m \cdot \|x_i - C_j\|^2}{N \cdot \min_{ij} \|C_i - C_j\|}. \quad (30)$$

A smaller value for the V_{XB} index signifies a more appropriate clustering decision that provides compact clusters that are adequately separated.

B. Pilot Node Selection Within Zones

It is neither practical nor economic to monitor and control all buses in a zone, thus a pilot node is selected for each zone to represent the load nodes voltage profile. The electrical centre of the zone is used as a pilot node, due to the fact that such measurement points provide a good image of the changes in the voltages taking place within the zones, as discussed in [20], [38]. The index L_m denotes the proximity of node m to all other nodes belonging in the same zone C in terms of electrical distance and is defined as

$$L_m = \sum_{m,n \in C} D_{mn} \quad (31)$$

where D_{mn} accounts for the electrical distance between nodes m and n and is derived from (10) and (11). The load bus that minimizes the L_m norm is selected as pilot node. Such centroids are normally well connected buses and strong with respect to load perturbations within the zone they belong. Hence, this allows system operators to monitor the system load perturbations more accurately and maintain the voltage deviations within a reasonable range. The number of pilot nodes equals the number of zones that a clustering validation index has indicated as most

Fig. 3. Topology of the 3-area system [40]. Note that all zoning methodologies produce the same zoning result as illustrated in this figure.

appropriate. A bigger number of pilot nodes would result in more homogeneous clusters, however at the same time would increase the coupling among the zones and would require more complex control laws to deal with closed-loop interaction and dynamic instability risk. A judiciously designed zoning methodology has to reach an appropriate trade-off among those two contradictory control objectives.

V. SIMULATION RESULTS AND DISCUSSION

Results are organized as follows: Section V-A tests and discusses zoning methodologies' generalities of interest for the CVR application, Section V-B investigates the applicability of the zoning methodologies in *adaptive RCM*, while the next four paragraphs deal with the evaluation of the zoning methodologies using the proposed framework on a network with non-obvious boundaries. More specifically: Section V-C presents a base case comparison which provides sufficient reasoning for the zoning methodologies evaluation (HCSD, HCVS, SKC, and FCM); Section V-D investigates how well each of the zoning methodologies serves the CVR objective assuming accurate measurements; Section V-E introduces errors to measurements and assesses the robustness of CVR control performance for each of the zoning methodologies. Note that Sections V-D and V-E deal with *static RCM*. Lastly, Section V-F extends the results to *adaptive RCM* and demonstrates its significance when topological changes occur to the network.

A. Zoning Methodologies- Discussion on Basic Properties

All zoning methodologies use proximity metrics that require as input only the Jacobian matrix of the system, which is readily available and is updated periodically as the conditions vary. Due to this input, it follows that all zoning methodologies are structure and state dependent. A well designed zoning methodology is expected to have the ability to identify obvious boundaries. To prove the latter, similar to [39], the IEEE-96 system [40] is

used. This system is framed by replicating the IEEE RTS-24 network three times and with few interconnections. A 72-mile 230-kV line connects area 2 to area 3 and a 67-mile 230-kV line connects area 1 to area 3. The grouping results for this system are presented in Fig. 3 and are identical to all zoning methodologies when three clusters are requested. The above outcome validates their basic ability to identify obvious boundaries.

B. Zoning Methodologies Applicability in Adaptive RCM

This paragraph investigates whether a zoning methodology can be incorporated in an adaptive RCM scheme and what are the prime factors to allow this to happen. A desirable property of such a scheme would be the ability to quickly update the RCM based on the new calculated Jacobian. Ideally RCM would be carried out fast enough, in order to also allow CVR to act upon it within its first cycles of operation, i.e., in less than 1 min [1]. To get an answer for a realistic size network, for this investigation, the 2383-bus Polish system is used [41]. Times reported in this section are calculated on a PC with 3.2-GHz quad core CPU and 8 GB of RAM. HCSD and HCVS methodologies are based on agglomerative hierarchical clustering and their computational complexity depends only on the number of nodes to be clustered. In light of the above in order to improve computation time, the examined network is reduced to 1733 nodes prior to the agglomerative clustering, by collapsing leaf-nodes. These would in any case cluster within their immediate upstream neighbors.

The computational complexity of SKC and FCM methodologies is $O(nki)$ and $O(nk^2i)$, respectively [42]. Parameter n accounts for the number of buses to be classified, k is the number of clusters and i the number of maximum iterations. To allow faster convergence, parameter k can be bounded within a range $\{k_{\min}, k_{\max}\}$ that makes sense from an engineering point of view. The upper limit applied in here accounts for number of reactive resources that have a reactive margin above 20 MVar. The range examined is $\{10, 151\}$. For the SKC methodology,

Fig. 4. Relative eigengap heuristic to determine number of clusters for SKC.

Fig. 5. Scalability of FCM for various numbers of clusters.

the relative eigengap heuristic introduced in Section IV.A3 can be deployed to specify the most desirable number of clusters k within the range $\{10, 151\}$ and thus speed up computation time. An investigation into the relative eigengap for the 2383-bus Polish system is shown in Fig. 4 and reveals 17 zones as the optimum answer for SKC. For the FCM methodology the whole $\{10, 151\}$ range of values needs to be examined, in absence of any relevant heuristic. Fig. 5 shows how the FCM methodology scales over this range. It is noteworthy that even at $k_{\min} = 10$ zones, computation time exceeds the 60-s threshold.

Fig. 6 comparatively presents the zoning methodologies computational cost. In the FCM methodology, clustering for the various k values within the range $\{10, 151\}$ can be parallelized. Hence, the computational cost of the overall process is represented by the classification towards the $k_{\max}$ number of clusters. HCSD, HCVS, and SKC methodologies can determine the control model reduction in an online fashion, contrary to FCM. Methodologies based on agglomerative hierarchical clustering appear to have the best potential. SKC was found to solve the classification problem adequately fast (~ 8 s) however the calculation of eigenvalues significantly increases the computational cost.

C. Base Case Comparison

The New England 39-bus test network [41] is used as a case study. It is an adequately meshed network and is often used in CVR studies. It features 9 synchronous generators and one interconnection to the New York power system. HCSD, HCVS, SKC, and FCM methodologies are called to suggest the most appropriate reduction of the control problem for a single network state (maximum load). Each of them is represented by the zoning outcome that optimizes

Fig. 6. Zoning methodologies' computational cost for the 2383-bus Polish system.

Fig. 7. Zoning outcomes and pilot node identification.

its validation index. The parameters that optimize the clustering validation are listed in Table I. Fig. 7 presents the zoning decisions made by each of the zoning algorithms. The selected pilot nodes within the zones are also identified and highlighted: $\{\text{HCSD}: [4, 20, 21, 28]\}$, $\{\text{HCVS}: [1, 6, 16, 26]\}$, $\{\text{SKC}: [6, 20, 21, 26]\}$, and $\{\text{FCM}: [1, 6, 16, 20, 28]\}$. As can be seen, different methodologies, sharing the same control objective and network, make different decisions, and a natural question is which is the most appropriate for CVR.

D. Evaluation- Static RCM and Accurate Measurement

This paragraph compares the performance CVR achieves with respect to the four zoning methodologies. Static RCM is considered on the New England 39-bus test network [41] and accurate measurements; $\{\widehat{\Delta V}_P, \widehat{Q}_g\} = \{\Delta V_P, Q_g\}$ in block C of Section III. MATPOWER software is used as a load flow engine [41]. The probabilities associated with the system

TABLE I
FEATURES OF CLUSTERING VALIDATION

Zoning methodologies	Validation criteria – $f(x)$	$optimum\{f\}$	$x:f optimum$
HCSD	$\max\{\Delta RD(k)\}$	0.0265	4
HCVS	$\max\{AD(k)\}$	7.0612	4
SKC	$\max\{\gamma(k)\}$	0.4498	4
FCM	$\min\{V_{XB}(k)\}$	0.0961	5

Fig. 8. Load duration curve.

Fig. 9. Cumulative probability distribution for load deviations.

load level and load deviation are expected to be obtained from available system data. In absence of such data for the test system, the different load levels (as percentage of maximum) are assumed to follow the cumulative probability distribution of Fig. 8, similar to [43]. Deviation cases over base-case load are assumed to follow the cumulative probability distribution of Fig. 9, similar to [19].

Simulation results for the case of accurate measurement are presented in Table II. The CVR algorithm is common to all zoning methodologies and the measurements introduce no uncertainty to the problem. However, results reveal that the selection of the zoning methodology affects the performance the voltage control algorithm achieves. As can be seen in Table II, HCVS and SKC methodologies achieve the highest performance for this case study. While all zoning methodologies allow the controller to achieve acceptable performance, a higher performance is very much desirable as signifies reduced losses and enhanced voltage profile.

TABLE II
ZONING METHODOLOGY EVALUATION

Zoning Methodology	HCSD	HCVS	SKC	FCM
OPI (%)	86.91	92.09	91.23	89.88

Fig. 10. Zoning methodologies comparison under various measurement errors.

E. Evaluation –Static RCM and Noisy Pilot Bus Measurements

This paragraph is concerned with the robustness of a zoning methodology to measurement errors. The analysis described in Section V-D is repeated (exact network and probabilistic modelling). However, this time CVR acts upon a voltage deviation vector which bears an error ε , as in

$$\widehat{\Delta V}_P = |1 - \varepsilon| \cdot \Delta V_P. \quad (32)$$

In the general case, ε can follow any distribution. In this example, error ε follows uniform distribution with same magnitude for all pilot node measurements. This error is initially set at 2% and gradually increased to 10%. Fig. 10 presents the OPI performance of each zoning methodology with respect to the measurement error. Obviously, increasing the level of measurement errors deteriorates the zoning methodologies OPI performance. The final OPI curves are quite linear for the error range examined. A smaller curve slope indicates a more robust zoning methodology. Zoning methodologies demonstrate different degrees of robustness to measurement errors. Based on the slope of their corresponding OPI curves, HCSD appears to be the most robust to measurement errors, while FCM the least robust. It is noteworthy that for increasing errors SKC methodology outperforms the HCVS. The above indicate that a zoning methodology should be selected in accordance to the expected accuracy of the voltage measurements CVR receives.

F. Adaptive RCM in Presence of Topological Changes

This paragraph demonstrates the significance of adaptive RCM on the New England 39-bus network [41]. Adaptive RCM is very much desirable when topological changes occur to the network, as a change in topology can affect zones' homogeneity to control and both inter- and intra-zone coupling. The performance of a zoning methodology in conjunction with CVR with perfect measurement is assessed for the most stressed state (maximum loading and 20% perturbation all across the load nodes). Worst state is re-evaluated when certain lines are tripped. Only tie lines and no generation disconnection

Fig. 11. Benefits of adaptive RCM in presence of topological changes.

is considered, that is 32 topology states. Assessing these 32 states, results in the $\Delta(OPI)_{static}$ score for each of the zoning methodologies.

In practice, certain contingencies can be quite severe to the voltage control algorithm performance. For HCSD, HCVS, and SKC methodologies—which Section V-B suggested are applicable in adaptive RCM—the deterioration of the performance calls for a new RCM decision. This happens when the reported deterioration lies below a pre-determined threshold, as in block E of Section III. For FCM results are presented only for the static case.

Fig. 11, compares the performance deviation $\Delta(OPI)$ the four zoning methodologies exhibit in the presence of topological changes. Black columns indicate scores under static RCM, while grey ones include adaptive RCM for various $\Delta(PI)_{thres}$ thresholds [20%, 10% and 1%] provided that this is feasible by the zoning methodology. A negative $\Delta(OPI)$ signifies deterioration. Results in Fig. 11 indicate that the potential of adaptive RCM by a zoning methodology, allows the CVR to avoid significant performance deterioration. The achieved benefits depend on the selected $\Delta(PI)_{thres}$ value. Lower values for this threshold would allow better performance, but would require increased availability of measurements. For the case $\Delta(PI)_{thres} = 1\%$ a slight improvement in the CVR performance is observed, for the methodologies applicable in adaptive RCM scheme (HCSD, HCVS, and SKC). This is due to the fact that some new RCM decisions were found to exceed initial performance OPI_{static} and certain topological changes slightly improve the inter-zone coherence and subsequently control performance.

VI. CONCLUSIONS AND FUTURE WORK

In pursuit of improved coordinated automatic voltage control, this paper proposed a novel generic framework to evaluate various configurations of CVR components. This framework has been used in this paper to facilitate the selection of the required control model reduction among various existing candidate solutions. This investigation goes beyond the evaluation of regular operation, and it is the first to consider robustness against erroneous data, which in the presented results comes from noisy measurements on the pilot nodes. Even though the presented results focus on the performance of four examined

zoning methodologies—HCSD, HCVS, SKC, and FCM—with respect to CVR, the proposed framework is generic and may accommodate any possible control model reduction methodology, data acquisition technique or control scheme.

An additional aspect examined is zoning methodologies applicability in adaptive RCM scheme. It can be concluded that three out of the four examined zoning methodologies—HCSD, HCVS, and SKC—are adequately fast to determine the reduction of the control model in an online fashion and this allows for improved performance when topological changes occur in the network. For SKC methodology the relative eigengap heuristic is of great value in its online applicability. This applied heuristic needs the calculation of the eigenvalues that correspond to the examined system state, but can judiciously indicate the most appropriate number of clusters, prior to the iterative k-means optimization. In principle, adaptive RCM does not jeopardize the desired engineering simplification of online automatic control that CVR is designed to deliver. It does however rely upon increased sensing and telecommunication capabilities. The latter are becoming available through the online remote sensing and command infrastructures being deployed by the utilities under the umbrella of smart grids. Future work would focus on techno-economic evaluation of most appropriate thresholds for the RCM reconfiguration and the implications for measurements from a planning perspective.

ACKNOWLEDGMENT

The authors would like to thank the reviewers, whose comments significantly helped to improve and clarify the paper.

REFERENCES

- [1] J. Y. Wen, Q. H. Wu, D. R. Turner, S. J. Cheng, and J. Fitch, "Optimal coordinated voltage control for power system voltage stability," *IEEE Trans. Power Syst.*, vol. 19, no. 2, pp. 1115–1122, May 2004.
- [2] C. Taylor, D. C. Erickson, K. Martin, R. Wilson, and V. Venkatasubramanian, "WACS-wide-area stability and voltage control system: R&D and online demonstration," *Proc. IEEE, Special Issue on Energy Infrastructure Defense System*, vol. 93, no. 5, p. 892, 906, May 2005.
- [3] C. W. Taylor, "Line drop compensation, high side voltage control, secondary voltage control—why not control a generator like a static VAR compensator?," in *Proc. IEEE Power Eng. Soc. Summer Meeting*, Seattle, WA, USA, 2000.
- [4] Coordinated Voltage Control in Transmission Networks, CIGRE Task Force, 2007, C4.602.
- [5] S. Koishikawa, S. Ohsaka, M. Suzuki, T. Michigami, and M. Akimoto, "Advanced control of reactive power supply enhancing voltage stability of a bulk power transmission system and a new scheme of monitor on voltage security," in *Proc. CIGRE*, 1990, 38/39-01.
- [6] S. Noguchi, M. Shimomura, J. Paserba, and C. Taylor, "Field verification of an advanced high side voltage control at a hydro power station," *IEEE Trans. Power Syst.*, vol. 21, no. 2, pp. 693–701, May 2006.
- [7] P. Nedwick, A. Mistr, and E. B. Croasdale, "Reactive management a key to survival in the 1990s," *IEEE Trans. Power Syst.*, vol. 10, no. 2, pp. 1036–1043, May 1995.
- [8] E. C. Starr and E. J. Harrington, "Shunt capacitors in large transmission networks," *Trans. AIEE, Part 3, Power App. Syst.*, vol. 73, no. 2, p. 146, 1953.
- [9] J. P. Paul, J. T. Leost, and J. M. Tesserion, "Survey of the secondary voltage control in France: Present realization and investigations," *IEEE Trans. Power Syst.*, vol. 2, no. 2, pp. 505–511, May 1987.
- [10] H. Lefebvre, D. Fragnier, J. Y. Boussion, P. Mallet, and M. Bulot, "Secondary coordinated voltage control system: Feedback of EDF," in *Proc. IEEE Power Eng. Soc. Summer Meeting*, Seattle, WA, USA, 2000.
- [11] S. Corsi, M. Pozzi, C. Sabelli, and A. Serrani, "The coordinated automatic voltage control of the Italian transmission grid – Part I: Reasons of the choice and overview of the consolidated hierarchical system," *IEEE Trans. Power Syst.*, vol. 19, no. 4, pp. 1723–1732, Nov. 2004.

- [12] H. Sun, Q. Guo, B. Zhang, W. Wu, and B. Wang, "An adaptive zone-division-based automatic voltage control system with applications in China," *IEEE Trans. Power Syst.*, vol. 28, no. 2, pp. 1816–1828, May 2013.
- [13] H. Sun, Q. Guo, B. Zhang, and W. Wu, "Development and applications of system-wide automatic voltage control system in China," in *Proc. IEEE PES General Meeting*, 2009.
- [14] S. Corsi, F. De Villiers, and R. Vajeth, "Power system stability increase by secondary voltage regulation applied to the South Africa transmission grid," in *Proc. Bulk Power System Dynamics and Control (iREP) – VIII (iREP)*, Rio de Janeiro, Brazil, 2010.
- [15] Q. Guo, H. Sun, J. Tong, M. Zhang, B. Wang, and B. Zhang, "Study of system-wide automatic voltage control on PJM system," in *Proc. IEEE Power and Energy Soc. General Meeting*, Minneapolis, MN, USA, 2010.
- [16] J. L. Sancha, J. L. Fernandez, A. Cortes, and J. T. Abarca, "Secondary voltage control: Analysis, solutions and simulation results for the Spanish transmission system," *IEEE Trans. Power Syst.*, vol. 11, no. 2, pp. 630–638, May 1996.
- [17] G. N. Taranto, N. Martins, D. M. Falcao, A. C. B. Martins, and M. Santos, "Benefits of applying secondary voltage control schemes to the Brazilian system," in *Proc. IEEE Power Eng. Soc. Summer Meeting*, Seattle, WA, USA, 2000.
- [18] M. Ilic-Spong, J. Christensen, and K. L. Eichorn, "Secondary voltage control using pilot point information," *IEEE Trans. Power Syst.*, vol. 3, no. 2, pp. 660–668, May 1988.
- [19] T. Amraee, A. Soroudi, and A. M. Ranjbar, "Probabilistic determination of pilot points for zonal voltage control," *IET Gen., Transm., Distrib.*, vol. 6, no. 1, pp. 1–10, 2012.
- [20] P. Lagonotte, J. C. Sabonnadiere, J. Y. Leost, and J. P. Paul, "Structural analysis of the electrical system: Application to secondary voltage control in France," *IEEE Trans. Power Syst.*, vol. 4, no. 2, pp. 479–486, May 1989.
- [21] M. K. Verma and S. C. Srivastava, "Approach to determine voltage control areas considering impact of contingencies," *IEE Proc., Gen., Transm., Distrib.*, vol. 152, no. 3, pp. 342–350, 2005.
- [22] J. Zhong, E. Nobile, A. Bose, and K. Bhattacharya, "Localized reactive power markets using the concept of voltage control areas," *IEEE Trans. Power Syst.*, vol. 19, no. 3, pp. 1555–1561, Aug. 2004.
- [23] H. Kai, G. Shan, and G. Quan, "Research on partition for automatic voltage/var control based on electrical distance to generator," in *Proc. IEEE ISGT-Asia*, Tianjin, China, 2012.
- [24] X. Gang, Q. Zhou, and Y. Feng, "Comprehensive sensitivity-based reactive power optimization under the hierarchical and regional in transmission network," in *Proc. 11th Int. Conf. Environment and Electrical Engineering (EEEIC)*, 2012.
- [25] H. Mehrjerdi, E. Ghahremani, S. Lefebvre, M. Saad, and D. Asber, "Authenticated voltage control of partitioned power networks with optimal allocation of STATCOM using heuristic algorithm," *IET Gen., Transm., Distrib.*, vol. 7, no. 9, pp. 1037–1045, 2013.
- [26] H. Mehrjerdi, S. Lefebvre, M. Saad, and D. Asber, "A decentralized control of partitioned power networks for voltage regulation and prevention against disturbance propagation," *IEEE Trans. Power Syst.*, vol. 28, no. 2, pp. 1461–1469, May 2013.
- [27] A. Conejo and M. J. Aguilar, "Secondary voltage control: Nonlinear selection of pilot buses, design of an optimal control law, and simulation results," *IEE Proc. Gen., Transm., Distrib.*, vol. 145, no. 1, pp. 77–81, 1998.
- [28] V. Alimisis, C. Piacentini, J. King, and P. C. Taylor, "Operation and control zones for future complex power systems," in *Proc. IEEE Green Technologies Conf.*, Denver, CO, USA, 2013.
- [29] F. Li, W. Qiao, H. Sun, H. Wan, J. Wang, Y. Xia, Z. Xu, and P. Zhang, "Smart transmission grid: Vision and framework," *IEEE Trans. Smart Grid*, vol. 1, no. 2, pp. 168–177, 2010.
- [30] M. Eremia and M. Shahidehpour, *Handbook of Electrical Power System Dynamics: Modeling, Stability and Control*. New York, NY, USA: Wiley–IEEE Press, 2013.
- [31] H. Mehrjerdi, S. Lefebvre, M. Saad, and D. Asber, "Coordinated control strategy considering effect of neighborhood compensation for voltage improvement in transmission systems," *IEEE Trans. Power Syst.*, vol. 28, no. 4, pp. 4507–4515, Nov. 2013.
- [32] H. Y. Su and C. W. Liu, "An adaptive PMU-based secondary voltage control scheme," *IEEE Trans. Smart Grid*, vol. 4, no. 3, pp. 1514–1522, 2013.
- [33] S. Corsi, "Wide area voltage protection," *IET Gen., Transm., Distrib.*, vol. 4, no. 10, pp. 1164–1179, 2010.
- [34] R. Marconato, *Electric Power Systems*. Milan, Italy: CEI, 2004.
- [35] R. Billinton and W. Li, *Reliability Assessment of Electric Power Systems Using Monte Carlo Methods*. New York, NY, USA: Plenum, 1994.
- [36] R. J. Sanchez-Garcia, M. Fennelly, S. Norris, N. Wright, G. Niblo, J. Brodzki, and J. W. Bialek, "Hierarchical spectral clustering of power grids," *IEEE Trans. Power Syst.*, vol. 29, no. 5, pp. 2229–2237, Sep. 2014.
- [37] X. L. Xie and G. Beni, "A validity measure for fuzzy clustering," *IEEE Trans. Pattern Anal. Machine Intell.*, vol. 13, no. 8, pp. 841–847, 1991.
- [38] L. Mili, T. Baldwin, and R. Adapa, "Phasor measurement placement for voltage stability analysis of power systems," in *Proc. 29th IEEE Conf. Decision and Control*, Honolulu, HI, USA, 1990.
- [39] I. Kamwa, A. Pradhan, and G. Joos, "Automatic segmentation of large power systems into fuzzy coherent areas for dynamic vulnerability assessment," *IEEE Trans. Power Syst.*, vol. 22, no. 4, pp. 1974–1985, Nov. 2007.
- [40] C. Grigg, P. Wong, P. Albrecht, R. Allan, M. Bhavaraju, R. Billinton, Q. Chen, C. Fong, S. Haddad, S. Kuruganty, W. Li, R. Mukerji, D. Patton, N. Rau, D. Reppen, A. Schneider, M. Shahidehpour, and C. Singh, "The IEEE reliability test system-1996. A report prepared by the Reliability test system task force of the application of probability methods subcommittee," *IEEE Trans. Power Syst.*, vol. 14, no. 3, pp. 1010–1020, Aug. 1999.
- [41] R. D. Zimmerman, C. E. Murillo-Sanchez, and R. J. Thomas, "MATPOWER: Steady-state operations, planning, and analysis tools for power systems research and education," *IEEE Trans. Power Syst.*, vol. 26, no. 1, pp. 1088–1096, Feb. 2011.
- [42] S. Ghosh and S. K. Dubey, "Comparative analysis of k-means and fuzzy c-means algorithms," *IJACSA Int. J. Adv. Comput. Sci. Applicat.*, vol. 4, no. 4, pp. 35–39, 2013.
- [43] T. Guo and J. Milanovic, "Probabilistic framework for assessing the accuracy of data mining tool for online prediction of transient stability," *IEEE Trans. Power Syst.*, vol. 29, no. 1, pp. 377–385, Jan. 2014.

Varvara Alimisis (S'12) received the Diploma in electrical and computer engineering from NTUA, Athens, Greece, in 2010. Currently, she is pursuing the Ph.D. degree at Newcastle University, U.K.

Her research interests include smart grids, complex systems and networks, voltage optimization and control, and artificial intelligence techniques.

Philip C. Taylor (M'01–SM'08) received the Engineering Doctorate in the field of intelligent demand side management techniques from the University of Manchester Institute of Science and Technology (UMIST), U.K., in 2001.

He is a Professor of electrical engineering at Newcastle University, U.K. He currently holds the DONG Energy Chair in Renewable Energy. He carries out research that focuses on the challenges associated with the widespread integration and control of distributed generation in electrical distribution networks.