

From Vector-Level to Frequency-Wise Gaussian Mixture Modeling: A Footprint Analysis for Populating OV LV BPL Topology Class Maps

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Received May 25, 2026; Accepted June 27, 2026; Published August 6, 2026

In [1], the Gaussian Mixture Model (GMM) was introduced as an alternative population method for generating overhead low-voltage broadband over power lines (OV LV BPL) topologies, where a vector-level formulation was adopted to capture the joint statistical behavior of the channel attenuation error across the entire frequency range. This approach enabled the formation of clustered topology footprints on the OV LV BPL topology class maps, defined by the graphical combination of the average channel attenuation (ACA) and the standard deviation of the channel attenuation (SDCA).

Building upon this framework, the present short paper proposes a frequency-wise GMM population methodology, where the channel attenuation error is modeled independently at each frequency as a weighted sum of Normal Distributions (NDs). In contrast to the vector-level formulation, the proposed approach does not enforce a common latent component across frequencies, thus allowing increased flexibility in capturing frequency-dependent statistical variations.

The impact of the frequency-wise GMM parameters on the position, shape and dispersion of the resulting OV LV BPL topology footprints on the topology class maps is systematically investigated. The comparative assessment with the vector-level GMM of [1] is conducted through suitable Graphical Performance Indicators (GPIs), highlighting the fundamental trade-off between cross-frequency clustering and modeling flexibility. The results demonstrate that the frequency-wise GMM constitutes a versatile population mechanism, capable of approximating complex marginal distributions while altering the footprint structure on the topology class maps.

Keywords: Smart Grid; Broadband over Power Lines (BPL) networks; Power Line Communications (PLC); Distribution and Transmission Power Grids; Simulation; Modeling

Introduction

Overhead Low-Voltage (OV LV) Broadband over Power Lines (BPL) can be considered as a complementary last-mile communication solution that exploits existing electrical infrastructure to extend connectivity in smart grid and rural environments [1-7]. Since OV LV lines were originally designed for power delivery, their topological diversity and channel variability pose significant challenges for reliable data

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communication. The process of populating OV LV BPL topology classes with appropriate topologies has become a critical task, since accurately classifying and assigning topologies ensures network performance, improved channel estimation, stability and efficient resource allocation [8-10].

In [1], the Gaussian Mixture Model (GMM) was introduced as a transparent and analytically interpretable alternative to the Neural Network Topology Generator Methodology (NNTGM) [8-10] for populating OV LV BPL topology class maps. Adopting a vector-level formulation, the GMM of [1] captured the joint statistical behavior of the channel attenuation error across the entire frequency range, enabling the formation of clustered virtual topology footprints on the OV LV BPL topology class maps that are defined by the graphical combination of the average channel attenuation (ACA) and the standard deviation of the channel attenuation (SDCA). The impact of the GMM parameters, namely the mean μ , the standard deviation σ , the total count of Normal Distributions (NDs) and their assigned weights, on the relative position, dispersion and morphology of the resulting footprints for the vector-level GMM was systematically examined in [1]. Suitable Graphical Performance Indicators (GPIs) were also employed in [1] to further analyze the vector-level GMM virtual OV LV BPL topology footprints, providing complementary conclusions to those derived from the visual inspection of the topology class maps.

Building upon this foundation, the present short paper proposes a frequency-wise GMM population methodology, where the channel attenuation error is modeled independently at each frequency as a weighted sum of NDs. In contrast to the vector-level formulation of [1], the proposed approach does not enforce a common latent component across frequencies, thus allowing increased flexibility in capturing frequency-dependent statistical variations. The impact of the frequency-wise GMM parameters on the position, shape and dispersion of the resulting OV LV BPL topology footprints is systematically investigated and a comparative assessment with the vector-level GMM of [1] is conducted through the same GPIs, highlighting the fundamental trade-off between cross-frequency clustering and modeling flexibility.

The remainder of this paper is organized as follows. Section 2 briefly reviews the OV LV BPL topology class maps, GPIs and the vector-level GMM framework of [1]. Section 3 presents the proposed frequency-wise GMM methodology. The numerical results and GPI-based comparative assessment are discussed in Section 4, while Section 5 concludes the paper.

OV LV BPL Topology Class Maps and Vector-Level GMM Framework

In this Section, the OV LV BPL topology class maps and GPIs are presented as the reference framework for the representation and assessment of topology populations, based on the ACA and the SDCA as defined in [1, 8]. Within this context, the vector-level GMM framework of [1] is briefly revisited, where the channel attenuation error is modeled jointly across all frequencies, leading to clustered topology footprints on the maps. For consistency and benchmarking purposes, the GPIs of [9] are also adopted to quantify the position and dispersion of the resulting footprints.

OV LV BPL Topology Class Maps and GPIs

The OV LV BPL topology class maps of [1, 8-10] are adopted as the reference framework for the graphical representation and assessment of topology populations. These maps are defined in terms of the ACA and the SDCA, which form the horizontal and vertical axes, respectively. Within this framework, each indicative OV LV BPL topology is associated with a characteristic location on the class map, while its corresponding virtual realizations form a footprint that captures its dispersion and variability.

Following [1, 8-10], the class boundaries are approximated by the median lines between neighboring indicative OV LV BPL topologies, thus providing a practical separation between rural, suburban and urban topology classes. In addition, $\pm 10\%$ ACA / SDCA regions are defined around each indicative topology, serving as reference areas that reflect moderate variations of their nominal characteristics. These graphical elements facilitate the interpretation of the footprint structure and enable a consistent evaluation of topology behavior under different population mechanisms.

To quantitatively assess the distribution of the resulting topology footprints, the GPIs introduced in [9] and applied in [1] are also employed in this short paper. In particular, the “inside the class” and “inside the box” metrics are used to measure the extent to which virtual topologies remain within their expected class and within the predefined $\pm 10\%$ ACA / SDCA regions, respectively. The combined use of topology class maps and GPIs establishes a consistent and comparable evaluation framework, which is utilized in the following Sections for the analysis of the considered GMM-based population approaches.

Vector-Level GMM Population Methodology

The vector-level GMM methodology has been introduced in [1] as a principled alternative to the NNTGM for generating virtual OV LV BPL topologies under controlled stochastic variability, while preserving methodological continuity with prior topology-classification studies. To ensure consistency and comparability, the vector-level GMM framework adopts the established channel attenuation metrics of ACA and SDCA together with the OV LV BPL topology class maps of the previous subsection. It further reports these metrics and class-map placements both for indicative OV LV BPL topologies and for their corresponding GMM-derived virtual OV LV BPL topologies, enabling benchmark-oriented evaluation. In addition, the framework incorporates the GPIs to quantify how GMM parameter changes shift the relative position and footprint size of virtual topologies across the predefined topology classes.

At the modeling core, the vector-level GMM methodology builds on the notion that a virtual transfer function is constructed by superimposing (in the dB domain) a stochastic difference term onto the DHM-based theoretical response across the set of flat-fading subchannels in the examined band as similarly made in practical measurement campaigns where differences between the theoretical coupling-scheme transfer function and the measured response have been adopted [11-14]. In particular, for subchannel frequencies $f_q, q = 1, \dots, Q$, the virtual coupling-scheme transfer function is generated as

$$H_{\text{virtual}}(f_q) = H_{\text{theor}}(f_q) - e^D(f_q), q=1, \dots, Q \quad (1)$$

where $[\cdot]^D$ denotes the applied difference distribution —i.e., either Continuous Uniform Distribution (CUD) or ND—, $H_{\text{theor}}(f_q)$ is the DHM-derived theoretical coupling

scheme transfer function, $e^D(f_q)$ denotes the random measurement-difference process (in dB) and Q is the number of subchannels over the considered frequency range.

The key extension introduced by the Vector-Level GMM methodology is the replacement of simpler difference models (e.g., single NDs or CUDs) with a Gaussian mixture that can represent heterogeneous, multi-cluster deviation behavior through a weighted superposition of multiple normal components. Letting $e^{\text{GMM}}(f_q)$ denote the GMM-driven difference random variable, its probability density function is defined by

$$p[e^{\text{GMM}}(f_q)] = \sum_{k=1}^K w_k \mathcal{N}[e^{\text{ND}}(f_q) | \mu_k, \sigma_k], \quad q = 1, \dots, Q \quad (2)$$

where $\mathcal{N}[e^{\text{ND}}(f_q) | \mu_k, \sigma_k]$ denotes the ND component with mean μ_k and standard deviation σ_k , and the mixture weights satisfy $\sum_{k=1}^K w_k = 1$. This parameterization enables systematic control of the closeness of virtual-topology attenuation behavior to that of a given indicative topology while still permitting structured deviations by tuning the number of components K , their statistics (μ_k, σ_k) , and the weights w_k . Consequently, the framework offers a flexible yet analytically tractable means of generating diverse virtual OV LV BPL topologies and assessing their class-map footprints using ACA / SDCA and GPs under consistent evaluation criteria.

In summary, the vector-level GMM methodology models the error process over the entire frequency range as a single random vector governed by a shared latent mixture component, thereby imposing a coherent cross-frequency structure on the generated realizations. Denoting $e^{\text{GMM}} = [e^{\text{GMM}}(f_1) \ \dots \ e^{\text{GMM}}(f_Q)]^T$, the vector-level GMM assumes that one of K ND components is selected once per realization and then used to generate error samples across all Q flat-fading subchannel frequencies. This mechanism naturally yields clustered realizations where each cluster corresponds to a distinct ND component. The vector-level GMM methodology supports interpretable global spectral-shape behaviors that remain consistent across the examined frequency band, because a single latent mixture component governs the generation mechanism over all subchannels. Consequently, the resulting virtual OV LV BPL topologies, generated from an indicative topology through the adopted GMM-based construction, tend to exhibit spectrum-wide attenuation patterns that are coherent across frequency and therefore lead to clustered virtual-topology realizations. From a topology-class population perspective, this cross-frequency coupling is advantageous because it produces virtual topologies with stable, class-consistent signatures, facilitating the systematic population of OV LV BPL topology classes with realizations that preserve the macroscopic characteristics of the indicative case. However, the same coupling may limit the diversity of the generated class population when the target class requires frequency-localized variability or more heterogeneous spectral features; this motivates the frequency-wise GMM formulation introduced next, which enables finer-grained shaping of virtual topology footprints on the OV LV BPL topology class maps.

Frequency-Wise GMM Methodology

Building upon the vector-level GMM paradigm, this short paper introduces the frequency-wise GMM to obtain a more flexible representation of the error process by modeling the error distribution independently at each frequency. Let $f_q, q = 1, \dots, Q$, denote the flat-fading subchannel frequencies over the examined band, and let $e^{\text{FW}}(f_q)$

denote the frequency-wise GMM error random variable at frequency f_q . The virtual coupling scheme transfer function is constructed by superimposing (in dB) the modeled error onto the DHM-derived theoretical response:

$$H_{virtual}(f_q) = H_{theor}(f_q) - e^{FW}(f_q), q=1, \dots, Q \quad (3)$$

In contrast to the vector-level GMM methodology, frequency-wise GMM does not enforce a shared latent component across frequencies. Instead, each marginal error variable $e^{FW}(f_q)$ follows its own mixture distribution.

For each frequency f_q , the frequency-wise GMM models the marginal density of the error as a mixture of K ND components:

$$p[e^{FW}(f_q)] = \sum_{k=1}^K w_{k,q} \mathcal{N}[e^{FW}(f_q) | \mu_{k,q}, \sigma_{k,q}], q = 1, \dots, Q \quad (4)$$

with mixture weights satisfying $\sum_{k=1}^K w_{k,q} = 1$, $w_{k,q} \geq 0$ for all q . Here, $\mu_{k,q}$ and $\sigma_{k,q}$ denote the mean and standard deviation of the k -th ND component at frequency f_q and $w_{k,q}$ controls its relative contribution. Allowing the parameters $\{w_{k,q}, \mu_{k,q}, \sigma_{k,q}\}$ to vary with q enables the model to capture frequency-dependent heterogeneity in the error statistics. Crucially, frequency-wise GMM selects $e^{FW}(f_q)$ independently across frequencies which implies that mixture-ND-component selections can vary from one frequency to the next. The frequency-wise GMM differs fundamentally from the vector-level GMM in how it treats cross-frequency dependence. In the vector-level GMM, the entire error vector e^{GMM} is generated under a single latent component shared across all frequencies, thus inducing clustered, spectrum-wide behavior. By contrast, frequency-wise GMM performs component selection per-frequency. As a result, frequency-wise GMM can represent complex, locally varying distributions across the spectrum without enforcing global structure; however, it no longer produces inherently clustered realizations across frequencies, since no common latent component ties the spectrum together. Hence, the choice between the two approaches reflects a principled trade-off: vector-level GMM emphasizes global structure and clustering via a shared latent mode, whereas frequency-wise GMM prioritizes flexibility by independently shaping the frequency-dependent marginals.

Under the proposed frequency-wise GMM, the generation of each virtual OV LV BPL topology is explicitly aligned with the broader task of populating OV LV BPL topology classes with appropriate and statistically consistent topologies. In this context, frequency-wise GMM builds on the prior use of NDs as statistical models of measurement differences, extending this experience through a structured mechanism that supports class-consistent virtual-topology generation [1]. Concretely, for each frequency f_q , an error sample $e^{FW}(f_q)$ is drawn from its frequency-specific mixture and then incorporated into the virtual transfer-function construction via subtraction in the dB domain. By enabling frequency-dependent error statistics, the frequency-wise GMM can more effectively accommodate non-uniform deviations across the spectrum and, consequently, can yield virtual topologies whose attenuation behavior is suitably tailored to match the characteristics of targeted topology classes. The resulting populated footprints can then be assessed within the same evaluation pipeline (ACA / SDCA topology class maps and GPIs), thereby preserving methodological consistency while improving the representational adequacy of the class population process and supporting downstream objectives such as reliable channel estimation, stable operation, efficient resource allocation and the adoption of adaptive modulation and coding strategies [8-10].

As far as the frequency-wise GMM default operation settings are concerned, these can be listed as follows in accordance with the ones of NNTGM and vector-level GMM of [1, 8, 9]:

- *Topology segmentation and indicative classes:* OV LV BPL networks are typically represented as a cascade of OV LV BPL topologies with a characteristic span of about 1000m, while a representative topology layout is illustrated in Fig. 1 of [8]. Each topology is delimited by a transmitting and a receiving end and along the transmission corridor N open-circuited branches of various lengths may be encountered. Following [8, 15, 16], the key structural parameters (e.g., branch count and branch-length patterns) for the three indicative cases —rural, suburban and urban— are summarized in Table 1 of [8]. These three indicative topologies act as representative realizations of the corresponding main OV LV BPL topology classes, as further elaborated in [1, 11, 12, 17].
- *LOS cutoff for physical consistency:* The Line-Of-Sight (LOS) case (also included in Table 1 of [8]) exhibits the lowest attainable attenuation among the OV LV BPL topologies under consideration. Therefore, the vector-level and frequency-wise GMM-generated values in eqs. (1) and (3), respectively, are restricted so that, at any given frequency, the attenuation of the virtual OV LV BPL topology produced of eqs. (1) and (3) cannot fall below the LOS attenuation level. This LOS cutoff constraint enforces a physically meaningful lower bound, ensuring that the stochastic error modeling does not yield unrealistically “better-than-LOS” channel conditions.
- *Frequency grid:* The GMM operation is assumed over 1–30MHz, employing an 1MHz flat-fading subchannel spacing. Under this configuration, the number of subchannels is $Q=29$. For methodological consistency and to support a direct, fair comparison between frequency-wise GMM and vector-level GG, the same frequency range and subchannel spacing are also used here, so that observed differences can be attributed to the modeling approach rather than to discrepancies in the frequency-domain parametrization.

The combined use of OV LV BPL topology class maps and GPIs provides a robust and interpretable framework for evaluating how alternative GMM-based population mechanisms shape the footprints of virtual OV LV BPL topologies on the class maps. In the present work, these tools are employed comparatively to quantify the impact of adopting a frequency-wise GMM instead of the vector-level GMM formulation, focusing on differences in: (i) the relative placement of the virtual OV LV BPL topology footprints with respect to the OV LV BPL topology class regions; and (ii) the footprint dispersion / extent within and across classes. By applying the same class map representation and the same GPIs to both modeling strategies, the analysis isolates the effect of the population mechanism itself, ensuring a consistent and meaningful comparison. On this basis, the next Section presents the simulation results and the accompanying comparative analysis, providing a concise quantification of the differences between the two GMM population frameworks in terms of their induced footprint population behavior.

The Effect of GMM Parameter Variation on the Frequency-Wise GMM Virtual Topology Footprints

In this short paper, the sensitivity analysis focuses on GMM parameters that differentiate the frequency-wise GMM methodology from the vector-level one, and therefore can alter the resulting virtual topology footprint population on the OV LV BPL topology class maps. The effects of the ND mean μ and standard deviation σ are not revisited, because under the adopted GMM operation settings they act as global shift and spread controls applied uniformly across the entire frequency range, i.e., they affect the generated attenuation profile in an essentially frequency-agnostic manner. Consequently, for the same (μ, σ) configuration, the induced changes in attenuation metrics and footprint placement are identical in the frequency-wise and vector-level GMM methodologies, differing only in the mechanism by which mixture components are selected across frequency. Since these (μ, σ) -driven effects have already been fully characterized in [1], repeating them here would not provide additional insight into the population mechanism. Therefore, the analysis concentrates on the remaining parameters, namely the mixture composition (e.g., the number of components K) and the mixture weighting whose interaction with frequency-wise versus vector-level component selection can materially change footprint dispersion and coverage on the OV LV BPL topology class maps.

Total Count of NDs and its Impact on GMM Virtual Topology Footprints and GPIs

Following the parameterization established in [1], this short paper adopts the same scenario-based GMM constructions in order to examine the effect of the number of ND components incorporated into the mixture, while maintaining full comparability with the vector-level baseline results. Since the influence of the ND mean μ and ND standard deviation σ has already been systematically characterized in [1] under the same operating assumptions, the analysis herein focuses on the mixture composition (i.e., the total count of NDs). Accordingly, the following GMM scenarios are considered:

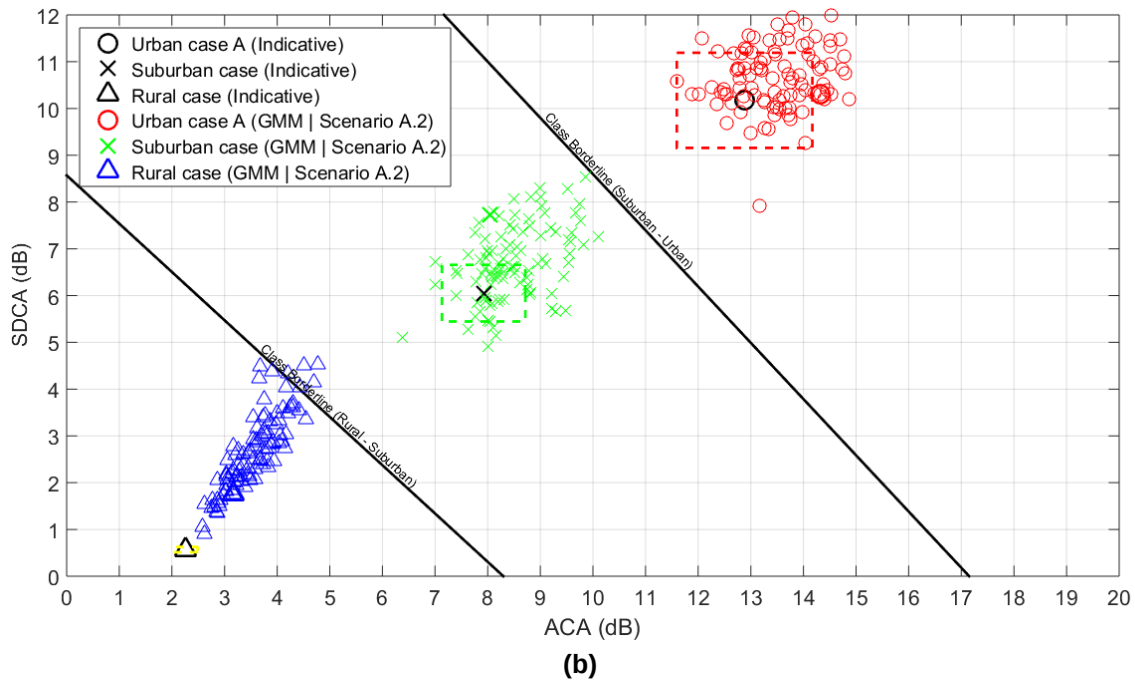
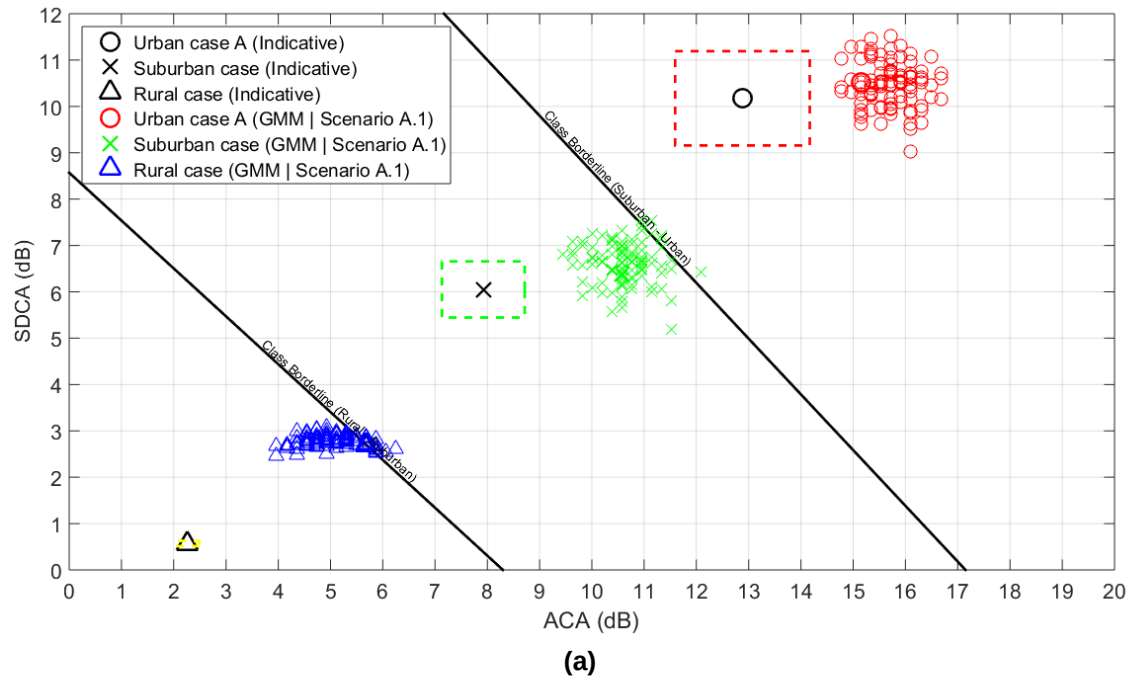
- *Scenario A.1:* GMM of Scenario A.1 consists of 2 ND components. The first ND of this scenario is characterized by its mean $\mu_{A.1.1}$ and standard deviation $\sigma_{A.1.1}$ that are equal to 0dB and 0.5dB, respectively, –see Figure 2(a) of [1]– with weight $w_{A.1.1} = 0.5$. The second ND of this scenario is characterized by its mean $\mu_{A.1.2}$ and standard deviation $\sigma_{A.1.2}$ that are equal to 5.5dB and 0.5dB, respectively, –see Figure 2(e) of [1]– with weight $w_{A.1.2} = 0.5$.
- *Scenario A.2:* GMM of Scenario A.2 consists of 3 ND components. The first ND of this scenario is characterized by its mean $\mu_{A.2.1}$ and standard deviation $\sigma_{A.2.1}$ that are equal to 0.2dB and 0dB, respectively, –see Figure 3(a) of [1]– with weight $w_{A.2.1} = 0.34$. The second ND of this scenario is characterized by its mean $\mu_{A.2.2}$ and standard deviation $\sigma_{A.2.2}$ that are equal to 0.2dB and 3dB, respectively, –see Figure 3(c) of [1]– with weight $w_{A.2.2} = 0.33$. The third ND of this scenario is characterized by its mean $\mu_{A.2.3}$ and standard deviation $\sigma_{A.2.3}$ that are equal to 0.2dB and 7dB, respectively, –see Figure 3(e) of [1]– with weight $w_{A.2.3} = 0.33$.
- *Scenario A.3:* GMM of Scenario A.3 consists of 2 ND components. The first ND of this scenario is characterized by its mean $\mu_{A.3.1}$ and standard deviation $\sigma_{A.3.1}$ that are equal to 3dB and 0.5dB, respectively, –see Figure 2(d) of [1]– with weight $w_{A.3.1} = 0.5$. The second ND of this scenario is characterized by its mean

$\mu_{A.3.2}$ and standard deviation $\sigma_{A.3.2}$ that are equal to 0.2dB and 5dB, respectively, –see Figure 3(d) of [1]– with weight $w_{A.3.2} = 0.5$.

To investigate the impact of the total count of NDs in the frequency-wise GMM operation, Figure 1(a) depicts the OV LV BPL topology class map along with the frequency-wise GMM virtual topology footprints for the rural, suburban and urban indicative cases under the default GMM operation settings when the mixture follows Scenario A.1. Each footprint comprises 100 GMM virtual topologies per indicative OV LV BPL topology. Figures 1(b) and 1(c) present analogous class-map projections for Scenario A.2 and Scenario A.3, respectively. The same GPIs employed for the evaluation of footprint placement and dispersion in [1] are then applied to the frequency-wise GMM virtual OV LV BPL topologies of the three OV LV BPL topology classes in Figures 1(a)-1(c), and the resulting GPI values are reported in Table 1.

Observing Figures 1(a)-1(c), the impact of the number of NDs participating in the frequency-wise GMM construction is investigated under various scenarios of ND components, namely:

- As far as Scenario A.1 is concerned, the two NDs derived from Figure 2(a) and Figure 2(e) of [1] were combined with equal weights ($w_{A.1.1} = 0.5$ and $w_{A.1.2} = 0.5$). Based on this approach, the corresponding Scenario A.1 footprints are obtained and presented in Figure 1(a). As can be observed, incorporating multiple NDs into the GMM enables the formation of virtual topology footprints through the weighted averaging of the participating NDs. In this case, the footprint center undergoes a horizontal displacement approximately calculated as $0.5 \times \mu_{A.1.1} + 0.5 \times \mu_{A.1.2} = 0.5 \times 0 + 0.5 \times 5.5 = 2.75$ dB given that $\sigma_{A.1.1} = \sigma_{A.1.2} = 0.5$ dB. Furthermore, the SDCA dimension now exhibits a substantially broader graphical extent compared to the highly constrained coverage of the component NDs illustrated in Figures 2(a) of [1] and 2(e) of [1]. It is important to emphasize that the frequency-wise GMM of Scenario A.1 retains the characteristic horizontal displacement along the ACA axis already identified in the ND components of [1]. This behavior is consistently observed across the frequency-wise GMM virtual topology footprints of both the suburban and urban cases A, whereas in the rural case, the effect emerges primarily due to a persistent SDCA shift. Furthermore, through the comparison of Figures 1(a)-1(c), it is evident that the mixing of the two NDs produces footprints that shift toward intermediate ACA values relative to their original indicative cases. Comparing the vector-level (Figure 4(a) of [1]) and frequency-wise (Figure 1(a) herein) results for Scenario A.1 makes clear that, while both methodologies are anchored to the same mixture-defined “intermediate” ACA tendency, they differ in the footprint population mechanism: the vector-level GMM yields more clustered, globally coherent footprints due to its shared latent component across frequencies, whereas the frequency-wise GMM produces more dispersed, frequency-localized footprint clouds due to independent component selection per frequency thereby enabling controllable trade-offs between class-consistent clustering and within-class diversity in topology-class map population.



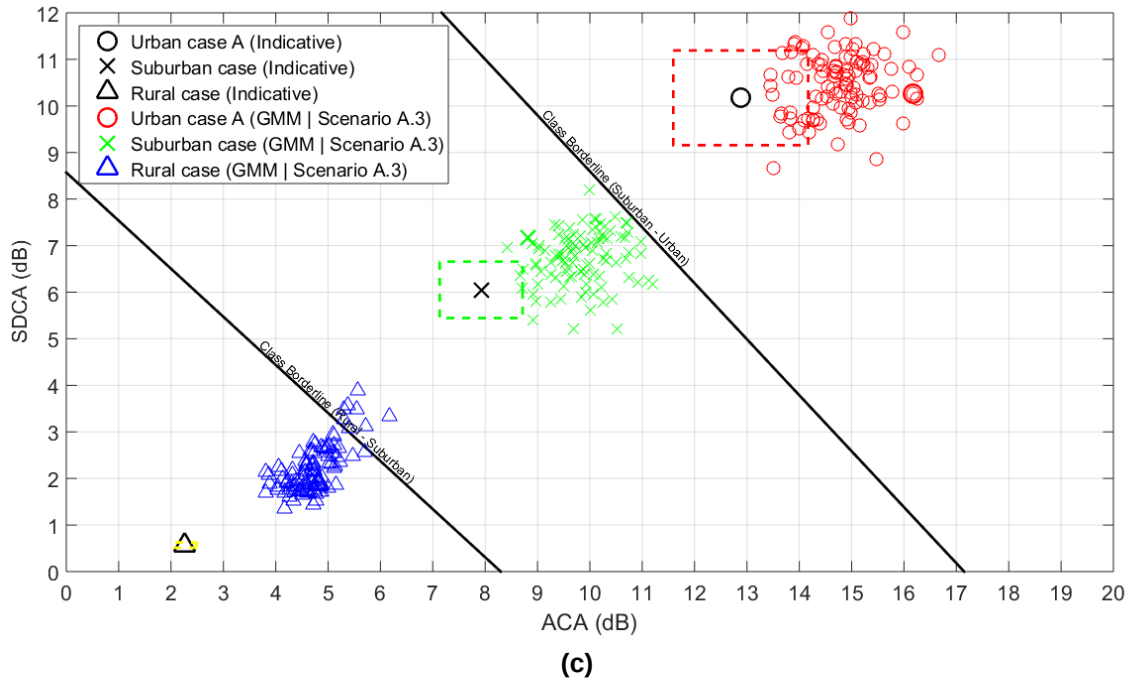


Fig. 1. OV LV BPL topology class map with frequency-wise GMM virtual topology footprints of the three indicative OV LV BPL topologies for various total counts of NDs. **(a)** Scenario A.1 (2 NDs). **(b)** Scenario A.2 (3 NDs). **(c)** Scenario A.3 (2 NDs).

Table 1. GPIs of the frequency-wise GMM OV LV BPL topologies of the three OV LV BPL topology classes for different scenarios of total count of NDs (GMM default operation settings are applied).

Scenario A.1 (2 NDs)			
GPI	OV LV BPL topology class		
	Rural case class	Suburban case class	Urban case A class
Inside the class (%)	84	93	100
Inside the box (%)	0	0	0
Scenario A.2 (3 NDs)			
GPI	OV LV BPL topology class		
	Rural case class	Suburban case class	Urban case A class
Inside the class (%)	95	100	100
Inside the box (%)	0	31	59
Scenario A.3 (2 NDs)			
GPI	OV LV BPL topology class		
	Rural case class	Suburban case class	Urban case A class
Inside the class (%)	92	100	100
Inside the box (%)	0	2	15

- In Scenario A.2, the NDs corresponding to low ND mean μ and varying ND standard deviation values of 0dB, 3dB and 7dB are combined, as analyzed in Figures 3(a), 3(c) and 3(e) of [1], respectively. The general trend of diagonal displacement in the ACA / SDCA plane is inherited to the resulting frequency-wise GMM model formed through the synthesis of these three NDs. Essentially, the generated frequency-wise GMM virtual OV LV BPL topology footprint represents a weighted average of the component topology footprints. Its centroid is comparable to that of Figure 3(c) of [1], while exhibiting a less compact spatial extent—a result that is also confirmed through comparison of Table 1 with Table 3 of [1]—. Therefore, not only can population be allocated to targeted regions, as already identified in Scenario A.1, but by incorporating multiple NDs into the frequency-wise GMM, it becomes possible to regulate the spatial extent of the resulting frequency-wise GMM virtual OV LV BPL topology footprint. This demonstrates that the number and characteristics of the contributing NDs offer an additional degree of control over both positioning and dispersion of the footprint. Importantly, a direct comparison for the same scenario between the vector-level GMM outcome (Figure 4(b) in [1]) and the frequency-wise GMM outcome (Figure 1(b) herein) highlights a population-mechanism effect: while both methodologies preserve the diagonal footprint orientation and yield comparable centroid tendencies dictated by the shared mixture definition, they differ in how they populate the class map. The vector-level GMM, due to its spectrum-wide latent consistency, tends to produce more coherently structured realizations that can manifest as more pronounced, globally aligned footprint elongation, whereas the frequency-wise GMM via independent per-frequency component selection yields a footprint with a modified dispersion pattern (typically appearing less strongly elongated and/or more “cloud-like” at the OV LV BPL topology class map level), thereby offering a distinct and more flexible handle on within-class diversity without necessarily altering the mixture-implied average placement.
- To further investigate the capability of adjusting both centroid position and footprint extent, Scenario A.3 employs two NDs that do not belong to the same family, in contrast to Scenarios A.1 and A.2. Specifically, Scenario A.3 uses two NDs: the first exhibits a high ND mean of +3dB with a low ND standard deviation of 0.5dB—see Figure 2(d) of [1]—and contributes with a weight of 0.5, while the second presents a low ND mean of 0.2dB combined with a high ND standard deviation of 5dB—see Figure 3(d) of [1]—, also contributing with weight 0.5. The objective is for the resulting frequency-wise GMM virtual OV LV BPL topology footprint to inherit favorable characteristics from both footprint families shown in Figure 1(a) and Figure 1(b). The results confirm that the frequency-wise GMM virtual OV LV BPL topology footprint can achieve population in an intermediate region, located between the horizontal displacement trend along the ACA axis and the diagonal trend associated with varying ND standard deviation, a behavior that is further verified by comparing the corresponding entries in Table 2 of [1], Table 3 of [1] and Table 1, where the GPI values of Scenario A.3 are effectively bounded by the respective values of its two ND components. Moreover, beyond the centroid shifting behavior, a noticeable reduction in the footprint extent is observed relative to the high-variance ND case, indicating that GMM synthesis enables not only centroid repositioning but also controlled footprint compactness. A same scenario comparison between the

vector-level GMM outcome (Figure 4(c) in [1]) and the frequency-wise GMM outcome (Figure 1(c) herein) reveals a clear distinction in the induced footprint population pattern, despite the fact that both methodologies employ the same two ND components and weights. In the vector-level formulation, the use of a shared latent component across the entire frequency range yields footprints that tend to be component-consistent per realization, which may manifest at the OV LV BPL topology class map level as multi-clustered populations reflecting the distinct “families” of the contributing NDs (i.e., realizations clustering around either the high- μ , low- σ behavior or the low- μ , high- σ behavior). In contrast, the frequency-wise formulation selects mixture components independently across frequencies, which effectively promotes within-realization blending of the two component behaviors; consequently, the resulting footprints appear more continuous and single-cloud-like, concentrating in an intermediate region rather than separating into distinct sub-clusters. Hence, for Scenario A.3, the key methodological takeaway is that the vector-level GMM emphasizes clustered, component-driven population, whereas the frequency-wise GMM favors smoother, more integrated population providing a different and more flexible lever over whether class-map population should be multi-modal (component-separable) or unimodal (interpolated) under the same scenario specification.

Across Scenarios A.1–A.3, the GPIs corroborate the visual evidence that frequency-wise GMM tends to improve class-consistent population while simultaneously producing less box-concentrated (i.e., more dispersed) footprints compared with the vector-level GMM. In Scenario A.1, frequency-wise GMM increases the “inside-the-class” GPI rates from 57% to 84% (rural) and 55% to 93% (suburban) while maintaining 100% (urban), yet the “inside-the-box” GPI rates collapse from 57% / 55% / 49% (rural / suburban / urban) under vector-level GMM to 0% / 0% / 0% under frequency-wise GMM, indicating that although more realizations remain within their intended topology-class regions, they are spread beyond the tighter box footprint. A similar pattern appears in Scenario A.2: “inside-the-class” GPI improves from 78% to 95% (rural) and 95% to 100% (suburban) (urban remains 100% in both), whereas “inside-the-box” GPI decreases from 25% to 0% (rural), 57% to 31% (suburban) and 69% to 59% (urban), reflecting a shift toward broader within-class variability under frequency-wise component selection. In Scenario A.3, where both methodologies already achieve near-saturated “inside-the-class” GPI performance (from 91% to 92% rural; 100% suburban; 100% urban), the main difference remains the “inside-the-box” GPI concentration, which is consistently higher for vector-level (0% vs 0% rural; 7% vs 2% suburban; 26% vs 15% urban). Overall, the joint GPI trends quantitatively confirm the methodological trade-off highlighted by the OV LV BPL topology class map footprints: vector-level GMM preferentially yields more compact, box-centered population (higher “inside-the-box” GPI due to the applied ND components), whereas frequency-wise GMM yields more expansive, diversity-enhancing population within the same topology classes (higher or comparable “inside-the-class” GPI but systematically lower “inside-the-box” GPI), enabling a controllable shift between concentrated versus dispersed footprint population for a fixed scenario definition.

In this subsection, the ND components participating in Scenarios A.1–A.3 were assigned equal weights, allowing the impact of mixture composition to be examined under a controlled and comparable setting. It is observed that increasing the number of NDs within the GMM affects both the centroid location and the spatial extent of the resulting GMM virtual OV LV BPL topology footprints, thereby enabling population in

additional regions of the ACA/SDCA plane. Consistent with the vector-level GMM findings reported in [1], Scenario A.3 emerges as the most versatile configuration, since it combines ND components belonging to different footprint-behavior families under equal weighting and hence supports an “intermediate” population regime between distinct displacement trends. However, the comparative analysis further indicates that, for the same scenario definitions, the frequency-wise and vector-level GMM methodologies may yield systematically different population patterns (e.g., differences in footprint compactness and concentration within the predefined box regions), reflecting the distinct cross-frequency component-selection mechanisms of the two frameworks. Motivated by this versatility and by the observed sensitivity of the footprint population to the mixture synthesis mechanism, the next subsection focuses on Scenario A.3 and investigates the extent to which non-uniform weight allocation can be used as an additional control knob for targeted footprint displacement and dispersion regulation, beyond what is achieved under equal weighting.

ND Weighting and their Impact on GMM Virtual Topology Footprints and GPIs

Building upon the findings of Scenarios A.1–A.3 in the previous subsection, this subsection exploits Scenario B of [1], where the ND components no longer contribute with equal weighting. Instead, a set of selected (non-uniform) weight distributions is applied to the same two ND components employed in Scenario A.3, with the objective of quantifying how weight reallocation influences the positioning and dispersion of the resulting frequency-wise GMM virtual OV LV BPL topology footprints on the ACA / SDCA class maps. In the context of this short paper, the analysis is conducted primarily for the frequency-wise GMM, so that the effect of the ND weighting is first made explicit through the corresponding OV LV BPL topology footprint projections and GPI outcomes; this establishes a clear baseline on how non-uniform weighting acts as a practical control knob for footprint population under frequency-wise component selection. Afterwards, the obtained trends are interpreted comparatively with respect to the vector-level GMM results reported in [1], thereby highlighting which observed footprint shifts and concentration / dispersion changes stem from weighting itself and which are attributable to the underlying population mechanism (shared latent component versus frequency-independent selections). Similar to the previous subsection, the GMM configurations are organized in the form of scenarios, as detailed in [1] and below.

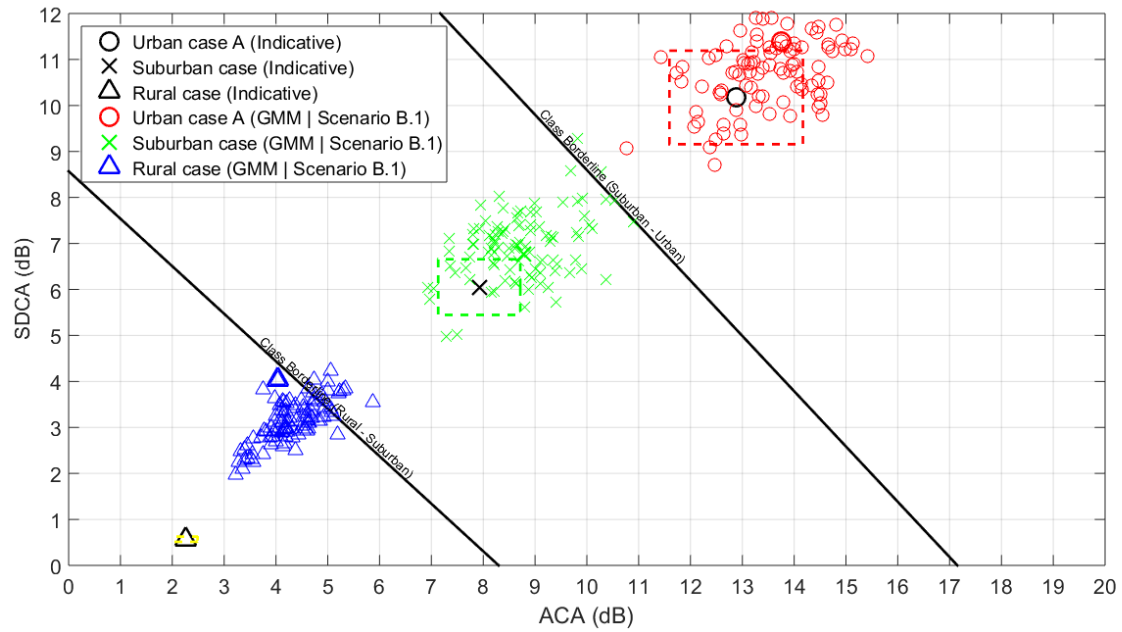
- *Scenario B.1:* This GMM consists of 2 ND components. The first ND of this scenario is characterized by its mean $\mu_{B.1.1}$ and standard deviation $\sigma_{B.1.1}$ that are equal to 3dB and 0.5dB, respectively, with weight $w_{B.1.1} = 0$. The second ND of this scenario is characterized by its mean $\mu_{B.1.2}$ and standard deviation $\sigma_{B.1.2}$ that are equal to 0.2dB and 5dB, respectively, with weight $w_{B.1.2} = 1$. Practically, the Scenario B.1 consists of the same NDs (i.e., identical ND mean and ND standard deviation values) as those used in Scenario A.3, but with different weight assignments. Specifically, selecting $w_{B.1.2} = 1$ implies that only the second ND is considered, leading the GMM virtual OV LV BPL topology footprint to degenerate into the analysis of a similar footprint to one shown in Figure 3(d) of [1].
- *Scenario B.2:* This scenario is based on Scenario B.1, with the only difference being that it applies weights $w_{B.2.1} = 0.25$ and $w_{B.2.2} = 0.75$ for the same NDs of Scenario B.1. This weight configuration is introduced in order to examine the

effect of varying the ND weights within the GMM, while keeping the ND components fixed.

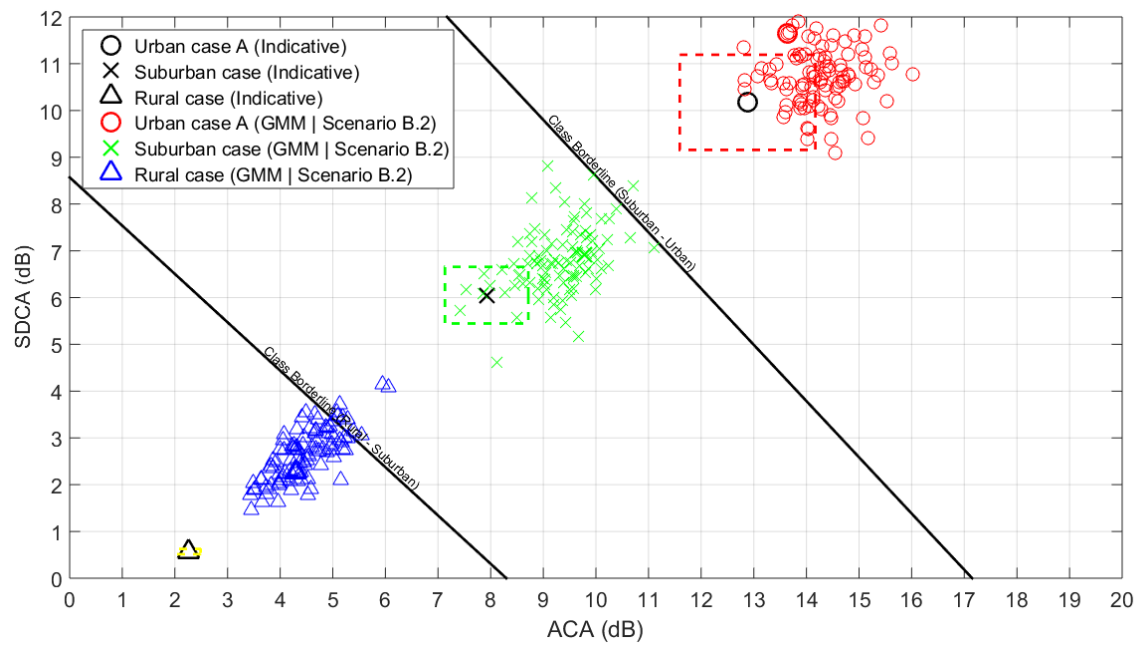
- *Scenario B.3:* Following the rationale of Scenarios B.1 and B.2, Scenario B.3 employs weights $w_{B.3.1} = 0.50$ and $w_{B.3.2} = 0.50$ for the same NDs of Scenarios B.1 and B.2 in order to investigate the effect of varying the ND weights within the GMM, consistent with the analysis conducted in Scenario B.2. In fact, this particular weight combination corresponds to the case illustrated in Figure 1(c).
- *Scenario B.4:* Same with Scenario B.1 but with applied weights $w_{B.4.1} = 0.75$ and $w_{B.4.2} = 0.25$ for the same NDs of Scenario B.1.
- *Scenario B.5:* This scenario is structurally identical to Scenario B.1; however, it represents its counterpart in terms of weight allocation. Specifically, in Scenario B.5, the weights are assigned as $w_{B.5.1} = 1$ and $w_{B.5.2} = 0$. This configuration implies that only the first ND is effectively considered in the analysis. Consequently, the resulting GMM virtual OV LV BPL topology footprint degenerates into a case analogous to that examined in Figure 2(d) of [1].

As the impact of the ND weights is concerned in the operation of frequency-wise GMM, in Figure 2(a), the OV LV BPL topology class map with the frequency-wise GMM virtual topology footprints of the rural case, suburban case and urban case A is presented when the GMM default operation settings are applied and frequency-wise GMM consists of the NDs of the Scenario B.1. Each frequency-wise GMM virtual OV LV BPL topology footprint of Figure 2(a) comprises 100 GMM virtual topologies per indicative OV LV BPL topology. In Figures 2(b)-2(e), similar plots to Figure 2(a) are given, but for the case of Scenarios B.2-B.5, respectively. The same GPIs of Table 1 are applied to the frequency-wise GMM virtual OV LV BPL topologies of the three OV LV BPL topology classes of Figures 2(a)-2(e) and are reported in Table 2.

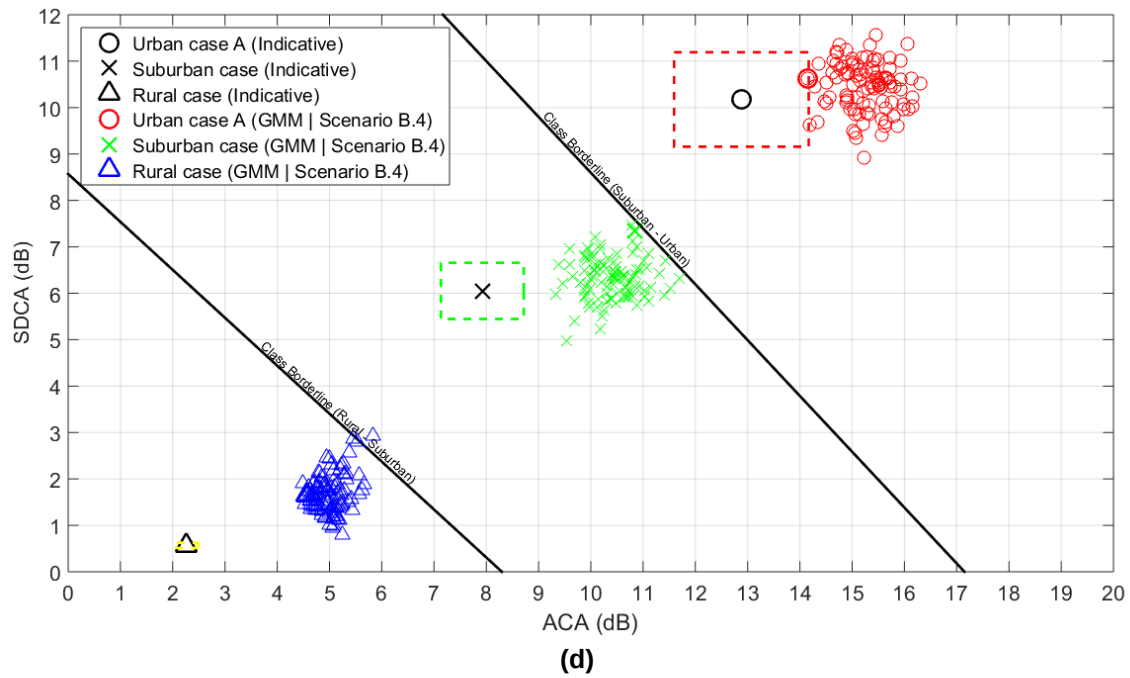
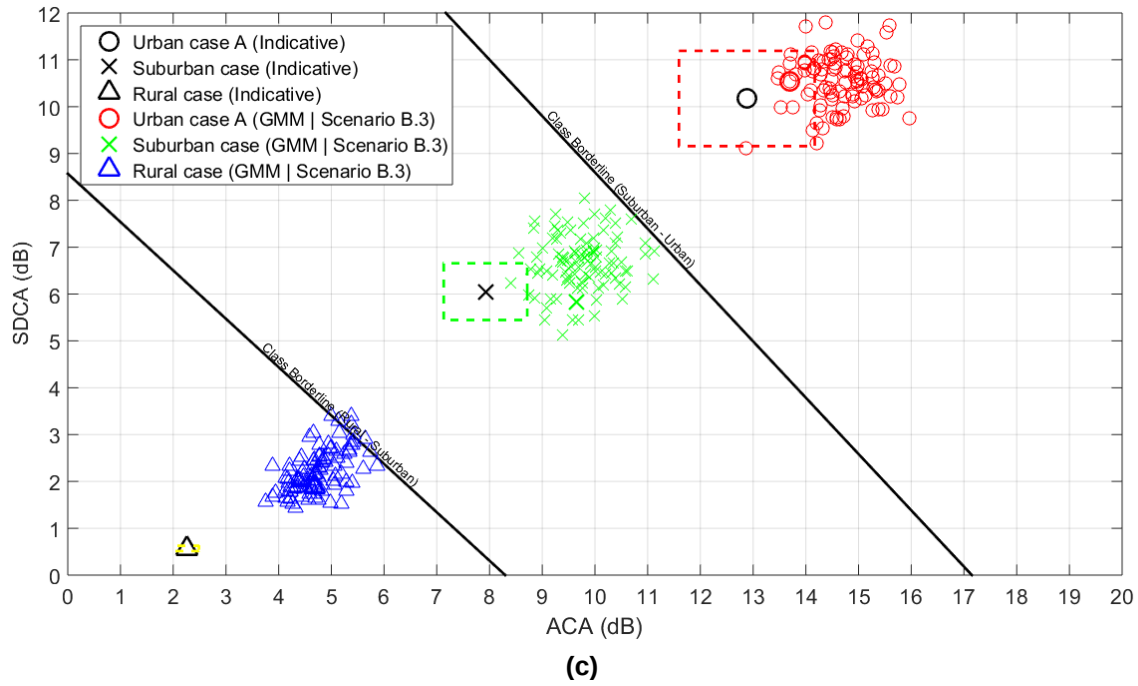
From Figures 2(a)-2(e), the influence of ND weighting on both the centroid and the spread of the frequency-wise GMM virtual OV LV BPL topology footprints is evident. Starting from the family of footprints derived from NDs with high ND standard deviation and low ND mean, whose focal point lies along the diagonal with a broad extent like Figure 3(d) of [1], a gradual shift of the footprint centroid and a reduction in its spread can be observed, ultimately reaching the family of footprints generated by NDs with high ND mean and low ND standard deviation, which align along a line parallel to the horizontal ACA axis like Figure 2(d) of [1]. Through an appropriate selection of ND



(a)



(b)



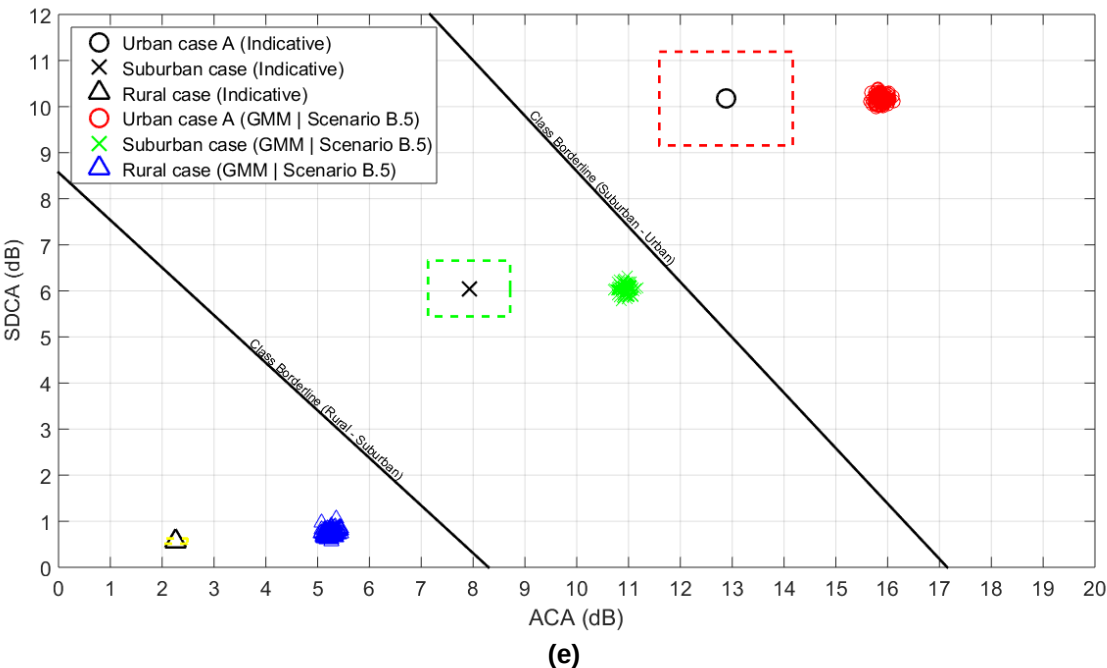


Fig. 2. OV LV BPL topology class map with frequency-wise GMM virtual topology footprints of the three indicative OV LV BPL topologies for various ND weights. **(a)** Scenario B.1: $-w_{B.1.1} = 0$ and $w_{B.1.2} = 1$, like Figure 3(d) of [1]-. **(b)** Scenario B.2 ($w_{B.2.1} = 0.25$ and $w_{B.2.2} = 0.75$). **(c)** Scenario B.3 $-w_{B.3.1} = 0.5$ and $w_{B.3.2} = 0.5$, like Figure 1(c)-. **(d)** Scenario B.4 ($w_{B.4.1} = 0.75$ and $w_{B.4.2} = 0.25$). **(e)** Scenario B.5 $-w_{B.5.1} = 1$ and $w_{B.5.2} = 0$, like Figure 2(d) of [1]-.

Table 2. GPIs of the frequency-wise GMM OV LV BPL topologies of the three OV LV BPL topology classes for different scenarios of ND weights (GMM default operation settings are applied).

Scenario B.1			
GPI	OV LV BPL topology class		
	Rural case class	Suburban case class	Urban case A class
Inside the class (%)	85	98	100
Inside the box (%)	0	13	50

Scenario B.2			
GPI	OV LV BPL topology class		
	Rural case class	Suburban case class	Urban case A class
Inside the class (%)	91	99	100
Inside the box (%)	0	12	36

Scenario B.3			
GPI	OV LV BPL topology class		
	Rural case class	Suburban case class	Urban case A class
Inside the class (%)	94	100	100
Inside the box (%)	0	1	19

Scenario B.4			
GPI	OV LV BPL topology class		
	Rural case class	Suburban case class	Urban case A class
Inside the class (%)	99	100	100
Inside the box (%)	0	0	0

Scenario B.5			
GPI	OV LV BPL topology class		
	Rural case class	Suburban case class	Urban case A class
Inside the class (%)	100	100	100
Inside the box (%)	0	0	0

weights within the GMM, the frequency-wise GMM virtual OV LV BPL topology footprint can be positioned at various locations along the trajectory formed between the two ND components. Furthermore, the choice of suitable ND components provides additional degrees of freedom to the population of the OV LV BPL topology class map.

The movement of the frequency-wise GMM virtual OV LV BPL topology footprints along the trajectory formed between the two ND components through the appropriate selection of ND weights is indirectly confirmed by the GPI values presented in Table 2. Specifically, starting from the family of footprints derived from NDs with high ND standard deviation and low ND mean, which is located near the boundaries of the indicative OV LV BPL topology class to which they correspond in this paper (rural case and suburban case), a gradual shift of the footprint centroid and a reduction in its spread can be observed, moving toward the interior of the class. This progression ultimately leads to the family of footprints generated by NDs with high ND mean and low ND standard deviation, where all GMM virtual OV LV BPL topologies lie entirely within the class, as validated by the “inside the class” GPIs. The opposite trend is observed for the “inside the box” GPI: initially, the footprints of the suburban case and urban case A remain relatively close to the indicative OV LV BPL topology due to their dispersion. As the process evolves, the footprints not only rotate but also exhibit reduced dispersion, ultimately resulting in zero values for the “inside the box” GPIs for the footprints of the suburban case and urban case A. It is evident that, through an appropriate selection of ND weights within the GMM, GPIs for the frequency-wise GMM virtual OV LV BPL topology footprints can be determined at values approaching the limits defined by the ND components of the GMM.

In the case where more than two NDs are considered for constructing the frequency-wise GMM, the resulting outcome—both in terms of class maps and GPI values—will follow a pattern analogous to that observed for the two-ND scenarios presented in Figures 2(a)-2(e) and Table 2. However, for a frequency-wise GMM comprising two or more ND components, the results will emerge as weighted combinations determined by the selection of ND weights, with footprints positioned within regions defined by the ND components in the Figures and GPI values lying within ranges established by those ND components.

A direct comparison between the frequency-wise footprints of Figs. 2(a)-2(e) (and Table 2) and the vector-level counterparts of Figs. 5(a)-5(e) in [1] (and Table 5) highlights that the same weighting scenarios B.1-B.5 induce qualitatively different

population mechanisms in the OV LV BPL topology class map. In the vector-level GMM, the two component “poles” are largely preserved as distinct modes and non-uniform weighting mainly performs a rebalancing of probability mass between a diffuse diagonal mode and a compact right-shifted mode. By contrast, in the frequency-wise GMM, the independent per-frequency component selection promotes within-realization blending of the two components; consequently, the OV LV BPL topology footprint tends to behave more like a single cloud whose centroid and orientation evolve with the weights, giving the impression of continuous translation and rotation along the trajectory between the two ND families rather than a mere change in the relative prominence of two stable clusters.

This distinction is also reflected by the GPIs. In terms of class adherence, both methodologies remain robust across all weightings; however, the frequency-wise GMM shows a more monotone “interior-seeking” progression in the rural class (“inside-the-class” GPI: from 85% to 91% to 94% to 99% to 100% from B.1 to B.5), whereas the vector-level starts higher and varies more mildly (from 93% to 91% to 96% to 97% to 100%). More importantly, the “inside-the-box” GPI reveals different dynamics under intermediate weights: in the urban class, vector-level retains higher box concentration at B.2-B.3 (41%–43%) than frequency-wise (36% at B.2 and 19% at B.3), with a similar contrast in the suburban class (10–11% versus 12% then 1%). These trends are consistent with the underlying mechanisms: vector-level weighting primarily reallocates probability mass between persistent modes, preserving a near-indicative contribution at moderate weights, whereas frequency-wise weighting induces blended footprint steering (migration / rotation of a single cloud) that departs more decisively from the indicative box even around balanced mixtures (e.g., B.3).

Overall, Scenario B demonstrates that non-uniform weighting provides controllability in both frameworks, but the type of controllability differs: the vector-level GMM is better suited when the desired OV LV BPL topology class map population should preserve mode separability (i.e., maintain distinct clusters and tune their relative prevalence), whereas the frequency-wise GMM is preferable when the objective is to realize smooth, continuous footprint steering (centroid displacement and dispersion / orientation shaping) to populate intermediate regions more progressively. This methodological trade-off complements the Scenario A findings and clarifies how the selection mechanism (shared latent component versus frequency-independent selections) can be exploited to achieve different population behaviors on OV LV BPL topology-class maps.

Conclusions

In this short paper, the frequency-wise GMM methodology has been introduced and evaluated for populating OV LV BPL topology classes with statistically consistent virtual OV LV BPL topologies, using the established ACA / SDCA class maps and GPIs to quantify footprint placement, dispersion and concentration. Building on the operating assumptions of the vector-level GMM in [1], a focus has been given on those GMM parameters that directly affect population under frequency-wise component selection, namely the mixture composition (Scenarios A.1–A.3) and the non-uniform weight allocation (Scenario B) since the effects of the ND mean μ and standard deviation σ are methodologically identical to those already characterized in [1] under frequency-invariant component settings. The results show that combining multiple ND components enables

controlled population of new regions in the ACA / SDCA plane by jointly shaping footprint centroid and extent, while weight reallocation provides a practical knob for steering the footprint between component-defined regions. Importantly, the comparative analysis against the vector-level baseline in [1] reveals a fundamental trade-off between the two modeling strategies: vector-level GMM imposes global cross-frequency structure and tends to preserve clustered, mode-consistent populations via a shared latent component, whereas frequency-wise GMM increases flexibility by modeling marginal distributions independently per frequency, leading to smoother blended footprint steering (migration / reshaping) as weights vary. Consequently, the frequency-wise GMM methodology complements vector-level GMM by enabling population strategies that prioritize either progressive intermediate-region coverage and within-class diversity (frequency-wise) or mode-preserving clustering and compactness (vector-level), while remaining fully compatible with the same class-map / GPI evaluation pipeline.

CONFLICTS OF INTEREST

The author declares that there is no conflict of interest regarding the publication of this paper.

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