POLITECNICO MILANO 1863

SCUOLA DI INGEGNERIA INDUSTRIALE E DELL'INFORMAZIONE

Executive Summary of the Thesis

Electrical Reserve Sizing: A Comparative Analysis of Methodological Approaches

Laurea Magistrale in Energy Engineering - Ingegneria Energetica

Author: Alessandra Colpani

Advisor: Prof. Marco Merlo

Co-advisors: Silvia Corigliano, Matteo Spiller

Academic year: 2025-2026

---

1. Introduction

Maintaining the instantaneous balance between generation and load is a fundamental requirement of power system operation. Any deviation manifests as a frequency excursion which, if not corrected within the timescales imposed by system dynamics, can cascade into large-scale supply interruptions. Real-time balance is hard to preserve because both demand and generation are subject to continuous uncertainty: load fluctuates, generating units trip without warning, and variable renewable output deviates from forecast. *Balancing reserves*, procured from generators, storage and flexible demand, are the primary instrument through which Transmission System Operators (TSOs) manage this risk.

Reserves are held as pre-contracted headroom across a hierarchy of activation timescales. This work adopts a cross-system conceptual classification into *primary* reserve (automatic governor response within seconds, arresting the frequency deviation), *secondary* reserve (activated automatically by Automatic Generation Control within minutes to restore nominal frequency), and *tertiary* reserve (activated manually over minutes to an hour to relieve secondary reserve and manage sustained imbalances). Different synchronous areas use different product names and activation boundaries; the primary/secondary/tertiary framing captures the same underlying logic consistently.

Reserve sizing is a central planning and operational decision for the TSO and an intrinsic risk-cost trade-off. Insufficient reserve leaves the system exposed to frequency excursions that available resources cannot contain; excess reserve withholds generation from the energy market and raises procurement costs. The reserve requirement depends on the statistical properties of the system: scale, interconnection, generation mix and cross-border sharing all shape the distribution of imbalances to be covered. The rapid growth of variable renewable generation has altered these properties, increasing forecast uncertainty and intra-interval variability while reducing synchronous inertia. In response, TSOs and researchers have progressively moved from deterministic sizing rules towards probabilistic and stochastic frameworks. This transition has not been uniform, producing a landscape of considerable methodological diversity.

This diversity raises a question the literature has not addressed directly. Each method has been developed and validated on a specific power system, with its own generation mix, scale and regulatory context. Differences in reported reserve volumes across studies are therefore ambiguous: they may reflect genuine methodological differences, or merely the characteristics of the systems studied. Isolating the methodological contribution from the system-specific one requires a controlled comparison, in which multiple methods are applied to the same system under identical conditions. To the best of the author's knowledge, no published study has done this systematically across a representative set of both TSO and academic methods. This thesis addresses that gap by developing a *Comparative Reserve Sizing Framework* and applying it to eight reserve sizing methodologies under identical input conditions. The summary first reviews how reserve sizing is performed across current practice and the academic literature, then introduces the comparative framework and the methodologies it integrates, and finally applies them to a common reference system to isolate the effect of the methodological choice on the resulting reserve volumes.

2. Methodological Landscape

Historically, reserve sizing relied on *deterministic* criteria: rule-based requirements derived from worst-case contingencies rather than from a statistical description of system uncertainty. Primary reserve has long followed the $N-1$ rule, holding a margin at least equal to the largest single infeed, a criterion still in force across most synchronous areas. Secondary reserve was sized through fixed percentages of load or empirical formulae, such as the UCTE expression $R = \sqrt{aL_{\max} + b^2} - b$, where $L_{\max}$ is the maximum load of the control area and $a = 10$ MW and $b = 150$ MW are empirical coefficients; the expression captures the sub-linear scaling of reserve with system size but reflects neither actual variability nor the renewable mix. As variable renewable penetration grew, increasing forecast uncertainty and reducing inertia, this limitation became consequential, and both TSOs and researchers progressively moved towards *probabilistic* and *stochastic* frameworks that characterise the imbalance distribution explicitly and set the reserve at a target confidence level.

This transition has not been uniform. As part of this thesis, an extensive review of current TSO practice was carried out across five synchronous areas, Continental Europe, Ireland and Northern Ireland, the Nordic area, Australia and North America, summarised in Table 1. It shows a wide spectrum of approaches coexisting today, from fully deterministic rules to dynamic probabilistic sizing recomputed for each scheduling interval. In parallel, the academic literature has developed methods that treat reserve sizing as a quantitative problem, making the individual uncertainty sources (forecast error, forced outages and intra-interval variability) explicit and combining them through Monte Carlo simulation or probabilistic convolution. The eight methods compared here are drawn deliberately from across this landscape, spanning the full range from deterministic to integrated stochastic, so

Table 1: Sizing approaches across the synchronous areas reviewed in the thesis. LC (Largest Contingency); ACEol (Area Control Error open loop); ATC (Available Transmission Capacity).

System	Primary sizing	Secondary sizing	Tertiary sizing
Continental Europe	Probabilistic (Monte Carlo)	Dynamic probabilistic (99th perc. of ACEol)	Deterministic (LC)
Ireland / N. Ireland	Deterministic (share of LC)	–	Deterministic (LC)
Nordic	Deterministic (LC)	Probabilistic (99th perc. of ATC-netted)	Deterministic (LC)
Australia (NEM)	Dynamic (inertia-dependent)	Co-optimised real-time	Co-optimised real-time
Australia (WEM)	Deterministic	Co-optimised real-time	Dynamic (inertia-dependent)
ERCOT	Performance-based	Statistical (95th perc. of net load)	Deterministic (fixed minimum)
Eastern / Western US	Varies by operator	Varies by operator	Varies by operator

that the comparison isolates the effect of the methodological philosophy rather than that of any single system.

3. The Comparative Reserve Sizing Framework

The Comparative Reserve Sizing Framework is designed to be system-agnostic: the same structure can be applied to any power system for which the required input data are available. All methodologies share the same system inputs, namely the generation fleet parameters and the time series of load, solar and wind production, so that any difference in the resulting reserve volumes reflects methodological choices rather than differences in the underlying data. The overall structure is shown in Figure 1.

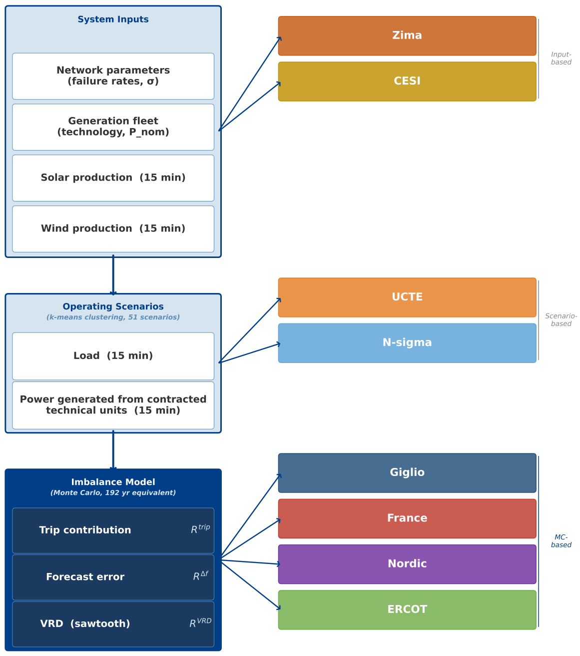

Figure 1: Computational structure of the Comparative Reserve Sizing Framework.

The procedure is organized around a set of representative operating scenarios, each paired with a dedicated Monte Carlo imbalance simulation. This two-stage structure follows the approach of Giglio et al. [2]. The present framework extends it in two respects, which together constitute its original contribution. First, the operating scenarios are derived from real operational data rather than constructed synthetically. Second, the framework applies eight different methodologies to the same scenarios and imbalance signal, under identical conditions, so that their results can be compared directly.

Processing each quarter-hourly interval independently would require one simulation per interval, at prohibitive computational cost. Since reserve requirements vary smoothly with system state, the operating year is instead summarized into a compact set of representative scenarios. The 35040 quarter-hour intervals of the reference year are clustered with k-means applied to the joint distribution of load, renewable generation and online generation capacity, with the number of clusters fixed by the elbow criterion on the within-cluster sum of squares. Each centroid defines one scenario, characterised by load level, the capacity factors of offshore wind, onshore wind and solar, and the number of units online per dispatchable technology.

For each scenario, a Monte Carlo imbalance signal is generated minute by minute over a long synthetic horizon: at each time step, independent realisations of three contributions are drawn and summed, and repeating this over the equivalent of 192 years builds the imbalance distribution from which the reserve percentiles are read. The three contributions are:

$$R_{\bar{t}}^{\text{imb}}(\mathbf{x}) = R_{\bar{t}}^{\text{trip}}(\mathbf{x}) + R_{\bar{t}}^{\Delta f}(\mathbf{x}) + R_{\bar{t}}^{\text{VRD}}(\mathbf{x}) \quad (1)$$

where $\bar{t}$ is the simulation time step and $\mathbf{x}$ the system state vector. The Monte Carlo domain is equivalent to 192 years of 1-minute operation, consistent with ENTSO-E guidelines [1], providing a sufficiently large sample for reliable estimation of rare events within a fixed operating scenario.

The *tripping* contribution $R_{\bar{t}}^{\text{trip}}$ models the sudden loss of a generating unit or storage converter: for each asset a trip occurs when a uniform random variable exceeds the trip probability $\mu_a^{\text{trip}} = 1 - e^{-\lambda_a}$ derived from the annual failure rate λ_a, and persists for 30 min. The *forecasting uncertainty* contribution $R_{\bar{t}}^{\Delta f}$ is sampled from a Gaussian. Its total standard deviation is obtained as the quadrature sum of the independent contributions of load and of each renewable technology [3, 4]:

$$\sigma_{\Delta f}(\mathbf{x}) = \sqrt{(\sigma_l L_l)^2 + \sum_{r \in \Omega_R} (\sigma_r P_r CF_r)^2} \quad (2)$$

where σ_l and σ_r are the normalised forecast error standard deviations of load and renewable technology r. The *variation of residual demand* (VRD) contribution R_t^{VRD} captures the intra-interval ramp not seen by the interval-average dispatch signal, modelled as a sawtooth wave over the 15-minute market interval.

4. The Eight Methodologies

The eight methods span the full spectrum from deterministic to integrated stochastic. Four are drawn from TSO practice (France RTE, Nordic, ERCOT and UCTE), three from the academic literature (Giglio et al. 2025, n-sigma and Zima et al. 2008), and one is a proprietary method developed at CESI SpA. They attach to the modelling in three ways: four (Giglio, France, Nordic, ERCOT) read their requirements from the percentiles of the common Monte Carlo imbalance signal, two (UCTE, n-sigma) apply analytical expressions to the parameters of each scenario, and two (Zima, CESI) operate on their own dedicated inputs. Table 2 summarises the eight methods.

Table 2: The eight reserve sizing methodologies compared, grouped by how they attach to the modelling framework.

Method	Sizing approach
Monte Carlo based	
Giglio et al. (2025)	Percentiles of the imbalance distribution
France (RTE)	Deterministic Primary, percentiles of imbalance for Secondary and Tertiary
Nordic	Deterministic Primary, percentiles of imbalance for Secondary and Tertiary
ERCOT	Six products, mixed deterministic/statistical
Operating scenario based	
UCTE	Fully deterministic
n-sigma	Parametric (combined forecast-error σ)
System input based	
Zima et al. (2008)	Probabilistic convolution of load and outages
CESI	Proprietary (numerical results only)

What separates the methods is not only this input structure but how they size each reserve layer. For the *primary* reserve, most methods retain a deterministic logic anchored to the *dimensioning incident* (DI), the loss of the largest unit online: France, UCTE, ERCOT and the Nordic FCR-D component set it equal to the DI regardless of operating conditions, guaranteeing coverage of the largest credible contingency at all times. Only the Giglio FCR and the Nordic FCR-N component size the primary reserve statistically, at the 99th percentile of the imbalance distribution, which captures the tripping contribution without forcing full DI coverage in every scenario.

For the *secondary and tertiary* reserves the methods diverge more widely, but the percentile-based ones share a common logic: they size the slower products on the fast imbalance that remains after subtracting its 15-minute running mean, isolating the within-interval variability that secondary reserve must follow. The n-sigma and Zima methods instead derive their requirements analytically, from the combined forecast-error standard deviation and from a probabilistic convolution of load variability with the generation outage distribution respectively; neither defines a primary reserve. CESI, being proprietary, is included on the basis of its numerical results only.

5. Reference System

The case study is built on data from the Belgian power system for 2024, published by Elia through its open data portal and selected for the breadth and quality of its publicly available operational data. The 35040 quarter-hourly intervals are clustered into $k = 51$ representative operating scenarios spanning loads from approximately 3200 MW to 10500 MW and renewable shares from roughly 2% to 36%.

Two scalar parameters are applied uniformly across all methods: the dimensioning incident, set to $DI = 1013$ MW, corresponding to the largest nuclear unit, and the variation of residual demand, set to $VRD = 580$ MW, the 99.7th percentile of the absolute quarter-hourly changes in residual demand over 2024. The reference system is deliberately treated as electrically isolated to hold conditions constant across methods. The results consequently *do not represent the actual reserve requirements of the Belgian system,* which participates in cross-border sharing arrangements (IGCC, PICASSO, MARI) that reduce the volumes Elia holds domestically.

6. Results

Figure 2 gives an overview of the results across all methods and reserve categories, reporting for each the minimum, the weighted mean and the maximum across the 51 scenarios, where each scenario is weighted by the number of hours per year it represents; the detailed comparison by reserve product follows.

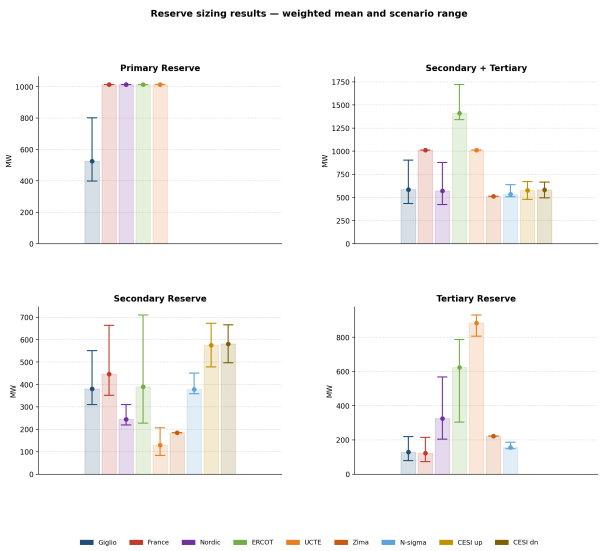

Figure 2: Overview of reserve sizing results. Circle: weighted mean; T-bar: scenario range.

6.1. Imbalance Decomposition

For the four Monte Carlo methods, the imbalance signal combines the tripping, forecast-error and VRD contributions. Figure 3 shows their relative magnitude across the 51 scenarios. The forecast-error component dominates in all scenarios, the VRD ramp is constant by construction, and the tripping contribution increases with system load as more large units come online. The PC_{99} of the total signal sits systematically below the sum of the three analytical components taken separately, the tripping, forecast-error and VRD standard deviations, because the three sources partially compensate each other minute by minute rather than adding linearly.

6.2. Primary Reserve

The primary reserve results expose the contingency-versus-statistical divide directly. France, ERCOT, UCTE and the Nordic FCR-D fix the primary reserve at $DI = 1013$ MW under all conditions. The Giglio FCR and the Nordic FCR-N instead range from 398.1 MW to 801.8 MW across scenarios, with a weighted mean of 525.7 MW, substantially below the deterministic threshold. Two methods can therefore share the same probabilistic infrastructure and confidence level yet differ by a factor of two, depending solely on whether the DI is treated as a binding floor.

6.3. Secondary and Tertiary Reserve

The combined secondary and tertiary reserve results reveal three groupings. Giglio and Nordic produce the lowest estimates, with weighted means of 585.7 MW and 569.8 MW and substantial scenario variability. France and UCTE are fixed at 1013 MW by construction, since their tertiary formula forces the combined requirement to equal the DI. ERCOT produces the highest total, approximately 1410 MW, because it stacks six independently sized products. The

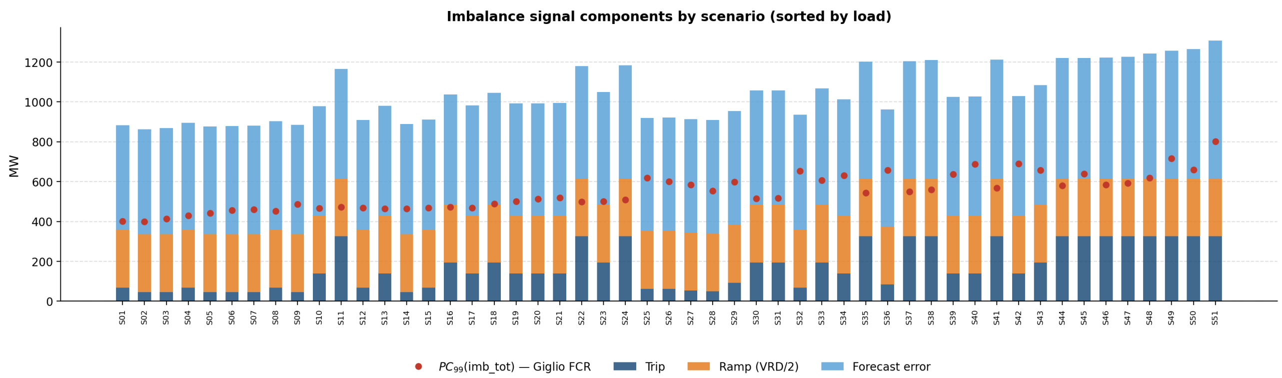

Figure 3: Decomposition of the Monte Carlo imbalance signal

Zima and n-sigma academic methods occupy an intermediate position (roughly 508 to 637 MW), as does CESI (478 to 673 MW upward, 497 to 666 MW downward), though the asymmetric and seasonal structure of CESI makes direct comparison difficult.

6.4. Dependence on Operating Conditions

A key distinction between methods is how they respond to changing operating conditions. The effect of renewable penetration is most visible on the secondary reserve, on which the thesis concentrates its analysis. Figure 4 shows the aFRR against system load, with point colour encoding the renewable share, so both dependencies can be read at once. All methods trend upward with load, and for Giglio, France and Nordic the high-renewable points (green) sit above the trend at a given load level, confirming that renewable share adds a positive effect on top of the load dependence. The UCTE aFRR follows its square-root relationship with load almost exactly.

The primary reserve behaves differently. France, ERCOT, UCTE and the Nordic FCR-D component fix it at $DI = 1013$ MW under all conditions, while the Giglio FCR and the Nordic FCR-N component rise strongly with load, from approximately 398 MW to 802 MW, as more large units online increase the aggregate tripping contribution.

The same structure governs the restoration reserves. The France and UCTE combined reserve is flat with both load and renewable share, since their tertiary formula offsets any change in aFRR with an opposite change in mFRR. The Giglio and Nordic combined reserve instead grows with load, by roughly 466 MW and 452 MW respectively across the full range, driven by the growth of the tripping contribution.

Across the 51 scenarios, load level is the dominant driver of variability for all probabilistic methods, while renewable penetration provides a secondary positive effect on the secondary and tertiary reserves, reflecting the additional forecast uncertainty introduced by variable generation. The Giglio FCR shows a weak negative trend with renewable share, because in the reference system high-renewable scenarios coincide with a smaller online conventional fleet and hence a lower aggregate trip risk. The contingency-based methods are insensitive to operating conditions only for the primary reserve, whose requirement is anchored to the dimensioning incident; their secondary and tertiary reserves still vary across scenarios as a function of the imbalance signal. The UCTE secondary reserve is similarly load-dependent here, because it is applied to each scenario rather than to a single annual peak load as in its original usage. This partial insensitivity of the primary reserve has a direct procurement implication: contingency-anchored methods tend to over-procure FCR in low-load conditions and may under-procure relative to the stochastic risk in high-load, high-renewable conditions.

7. Conclusions

The comparative application of eight reserve sizing methodologies to a common system dataset produces a clear result: the choice of method

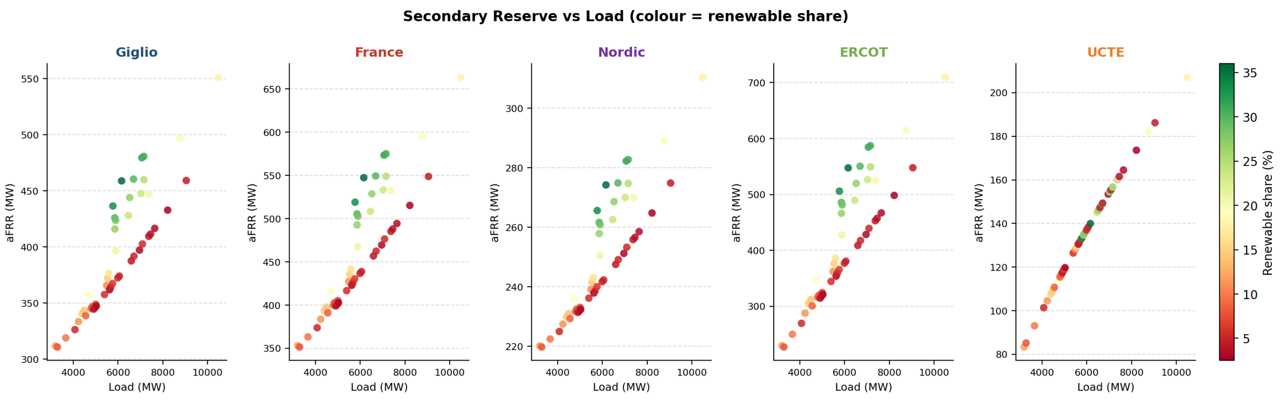

Figure 4: Secondary reserve versus system load across the 51 scenarios; point colour encodes renewable share. For ERCOT, Regulation Up is shown.

matters. The spread between the lowest and highest estimates is not marginal. For primary reserve, the gap between the probabilistic estimate and the deterministic threshold spans a factor of two under average conditions; for the combined secondary and tertiary reserve, the range runs from approximately 424 MW to over 1700 MW. These are not artefacts of parametrisation but reflect genuine disagreement between methodological philosophies about what reserves are for and which risks they must cover. The most fundamental divide is between methods that anchor the requirement to the dimensioning incident and those that derive it from the full imbalance distribution. While the direction of travel in both research and practice is clearly towards probabilistic frameworks, the transition is not uniform: several probabilistic methods retain the DI as a binding floor, while others derive the requirement purely from the aggregate distribution. The practical consequence is that two methods can share the same probabilistic infrastructure and confidence level yet produce requirements that differ by a factor of two or more. The magnitude of this divide depends on the size of the DI relative to the system; in the reference system, the large nuclear units make the DI dominant and amplify the gap.

The decomposition of the imbalance signal shows that forecast error is the dominant source of imbalance across all 51 scenarios, while the tripping contribution grows strongly with load and drives the positive relationship between load and probabilistic FCR.

Several directions extend this work. A systematic sensitivity analysis of the parametric choices, a scenario-dependent formulation of the VRD parameter, and the application of the framework to systems with different generation mixes would separate genuinely methodological findings from system-specific ones. Coupling the methods to a capacity-expansion model, moving to dynamic day-ahead sizing, and introducing reserve-sharing mechanisms would bring the comparison closer to the operational reality of the most advanced TSOs.

References

[1] ENTSO-E. SAFA annex 1 — policy on load-frequency control and reserves. Continental Europe synchronous area framework agreement. Technical report, ENTSO-E, 2019. In force 14 April 2019, as subsequently amended.

[2] Enrico Giglio, Davide Fioriti, Munyaradzi Justice Chihota, Davide Poli, Bernard Bekker, and Giuliana Mattiazzo. Integrated stochastic reserve estimation and MILP energy planning for high renewable penetration: Application to 2050 South African energy system. *Sustainable Energy, Grids and Networks*, 42:101650, 2025.

[3] Hannele Holttinen, Michael Milligan, Erik Ela, Nickie Menemenlis, Jan Dobschinski, Barry Rawn, Ricardo J. Bessa, Damian Flynn, Emilio Gomez-Lazaro, and Nina K. Detlefsen. Methodologies to determine operating reserves due to increased wind power. *IEEE Transactions on Sustainable Energy*, 3(4):713–723, 2012.

[4] Miguel A. Ortega-Vazquez and Daniel S. Kirschen. Estimating the spinning reserve requirements in systems with significant wind power generation penetration. *IEEE Transactions on Power Systems*, 24(1):114–124, 2009.