ROBUST AND SCALABLE OPTIMIZATION MODELING: THE ENABLER FOR RELIABLE OPERATION OF DECARBONIZED POWER SYSTEMS

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Knowledge Extraction from Massive Data

- Optimal power systems operation requires intensive computations
- Field sensors analysis could provide the necessary information aimed at better understanding and reducing the impact of perturbations.
- This process requires massive data processing and complex and NP-hard problem solutions, whereas computation times should be fast enough for the information to be useful.

Knowledge Extraction from Massive Data

- In solving this challenging issue, the development of computing paradigms aimed at supporting rapid power systems analysis in a data rich, but information limited environment are necessary
- These paradigms should quickly convert the field data into actionable information by allowing the power system operator to have a full understanding of the context and the confidence degree of the information

A Knowledge-based Framework for Optimal Power Flow Analysis

- ❑ Optimal Power Flow analysis could sensibly benefit from the conversion of data into information
- ❑ It is one of the most heavily used tools for solving many complex power system operation problems
- ❑ It has attracted a large amount of research efforts aimed at defining effective paradigms for reducing the complexities of the solution algorithm

EXAMPLE OF REACTIVE POWER FLOW

$$f_1(x) = \sum |V_i - Vn|^2$$

$$f_2(x) = \max |V_i - Vn|$$

$$f_3(x) = \sum \left(Ploss_i - Ploss_j\right)$$

$$f_4(x) = C_{gen} Q_{gen} + C_{cap} Q_{cap} + C_{slack} Q_{slack}$$

$$\begin{aligned} &\min_{x \in R^n} \quad f(x) \\ &\quad g(x) \le 0 \\ &\quad h(x) = 0 \\ &\quad m \le x \le M \end{aligned}$$

$$\begin{cases} P_i = V_i \sum_{j \varepsilon i} V_j [G_{ij} \cos(\theta_i - \theta_j) + B_{ij} \sin(\theta_i - \theta_j)] & i = 1, 2, \cdots, N \\ Q_j = V_j \sum_{k \varepsilon j} V_k [G_{jk} \sin(\theta_j - \theta_k) + B_{jk} \cos(\theta_j - \theta_k)] & j = 1, 2, \cdots, N_c \end{cases}$$

$$x = \left[Q_{dg,1}, \cdots, Q_{dg,Ng}, \cdots, Q_{cap,1}, \cdots, Q_{cap,Nc}, V_{DFTS,1}, \cdots V_{DFTS,Nf}, m \right]$$

A Knowledge-based Framework for Optimal Power Flow Analysis

To deal with the intrinsic complexities of optimal power flow analysis the following paradigms have been explored in the literature:

- ❑ alternative formalization of the **power flow equations**
- ❑ soft-computing based solution techniques
- ❑ distributed processing architectures

A Knowledge-based Framework for Solving the Power Flow Equations

- To exploit the potential actionable information that could be extracted from historical operation data-sets
- These are expected to sensibly grow over time due to the pervasive deployment of wide area measurement systems
- This is a new possible approach to speed up the power flow solution process

A Knowledge-based Framework for Solving the Power Flow Equations

- Formal methods are proposed here for knowledge discovery from large quantity of data as an enabling methodology for reducing the complexity of power flow analysis.
- Thus, a knowledge-based paradigm for power flow analysis is used to extract hidden relationships and useful hypotheses potentially describing regularities in the power flow problem

A Knowledge-based Framework for Solving the Power Flow Equations

- This is realized by designing a knowledge-extraction process based on Principal Components Analysis (PCA)
- The structural knowledge extracted by this process is then used to project the power flow equations into a new domain in which these equations can be solved more effectively.

A Knowledge-based Framework for Solving the Power Flow Equations

- In this new domain, the cardinality of the power flow problem is sensibly reduced and, consequently, a more efficient algorithm can be used to obtain power flow solutions.

Problem Formulation

$$P_i^{SP} = V_i \sum_{j=1}^{N} V_j Y_{ij} \cos(\delta_i - \delta_j - \theta_{ij}) \quad \forall i \in nP$$

$$Q_j^{SP} = V_j \sum_{k=1}^{N} V_k Y_{jk} \sin(\delta_j - \delta_k - \theta_{jk}) \quad \forall j \in nQ$$

We advocates the role of knowledge-discovery paradigms in effectively solving this problem.

Solving the Power Flow problem in the Principal Components domain

- Knowledge extraction from power flow data relies on the availability of observations of statistically correlated variables which is typically referred to as a knowledge base as follows:

$$x(k) = \left[\delta_{nP_1}(k),\ldots,\delta_{nP_{NP}}(k),V_{nQ_1}(k),\ldots,V_{nQ_{NQ}}(k)\right] \quad \forall k \in [0,T]$$

- The knowledge extraction problem consists then in discovering the relationships among these variables, and in reducing the amount of data needed to define these relationships.

Solving the Power Flow problem in the Principal Components domain

- This can be accomplished by identifying a suitable domain transformation such that the elements of the knowledge base can be accurately represented by an inverse model of the form:

$$x(k) = f^{-1}(z(k)) + r(k) \quad \forall k \in [0,T]$$

- PCA aims at solving the aforementioned transformation by approximating the state vector observations by a linear combination of a proper number of orthogonal and uncorrelated principal components with decreasing variance

Solving the Power Flow problem in the Principal Components domain

$$x(k) = \Omega\ s(k) + x_{med} \quad \forall k \in [0,T]$$

$$x_{med} = \frac{1}{T}\sum_{k=1}^{T} x(k)$$

Where the principal component vector can be computed as follows:

$$s(k) = \Gamma\left(x(k) - x_{med}\right) \quad \forall k \in [0,T]$$

$$\Gamma_i = \sigma_i(X\ X^T) \qquad\qquad X = \left[x(k)\right] \quad k \in [0,T]$$

Solving the Power Flow problem in the Principal Components domain

This domain transformation mainly consists in translating and rotating the original coordinate axes, in such a way that:

- the first principal component is characterized by the largest variance
- each following component by the highest variance under the constraint that it should be orthogonal and uncorrelated with the previous components

Solving the Power Flow problem in the Principal Components domain

- Each principal component carries different and uncorrelated information to other components, and only a limited number of them are necessary to accurately approximate the historical observations for highly correlated datasets
- Thanks to this feature, the historical power flow data can be approximated by storing and processing a limited number of variables
- This represents the data compression capability of the PCA based knowledge extraction process

Solving the Power Flow problem in the Principal Components domain

The data compression capability, for a large number of observations, tends to the following value:

$$CR^{\infty} = \lim_{T \to \infty} CR(T) = \lim_{T \to \infty} \frac{n_n T}{n_{pc} T + n_n n_{pc} + n_x} = \frac{n_x}{n_{PC}}$$

Solving the Power Flow problem in the Principal Components domain

A further, and certainly more attractive, mathematical result:

$$x(k) = \left(\Omega \; \tilde{s}(k) + x_{med}(k) \right) \quad \forall k > T$$

Which allows to solve the power flow problem, by identifying the unknown principal components such that:

$$P_i^{SP}(k) = P_i(x(k)) = P_i\left(\Omega \; \tilde{s}(k) + x_{med}(k) \right) \quad i \in nP$$

$$Q_j^{SP}(k) = Q_j(x(k)) = Q_i\left(\Omega \; \tilde{s}(k) + x_{med}(k) \right) \quad j \in nQ$$

Solving the Power Flow problem in the Principal Components domain

- Benefits of this new formulation:
  - Drastic reduction of the problem cardinality
  - Better convergence proprieties of the solution algorithm
  - Lower complexity and computational burdens.
- These claims may be justified by observing that the complexity reduction could be noticeable, especially in the presence of statistically dependent load/generation patterns

Solving the Power Flow problem in the Principal Components domain

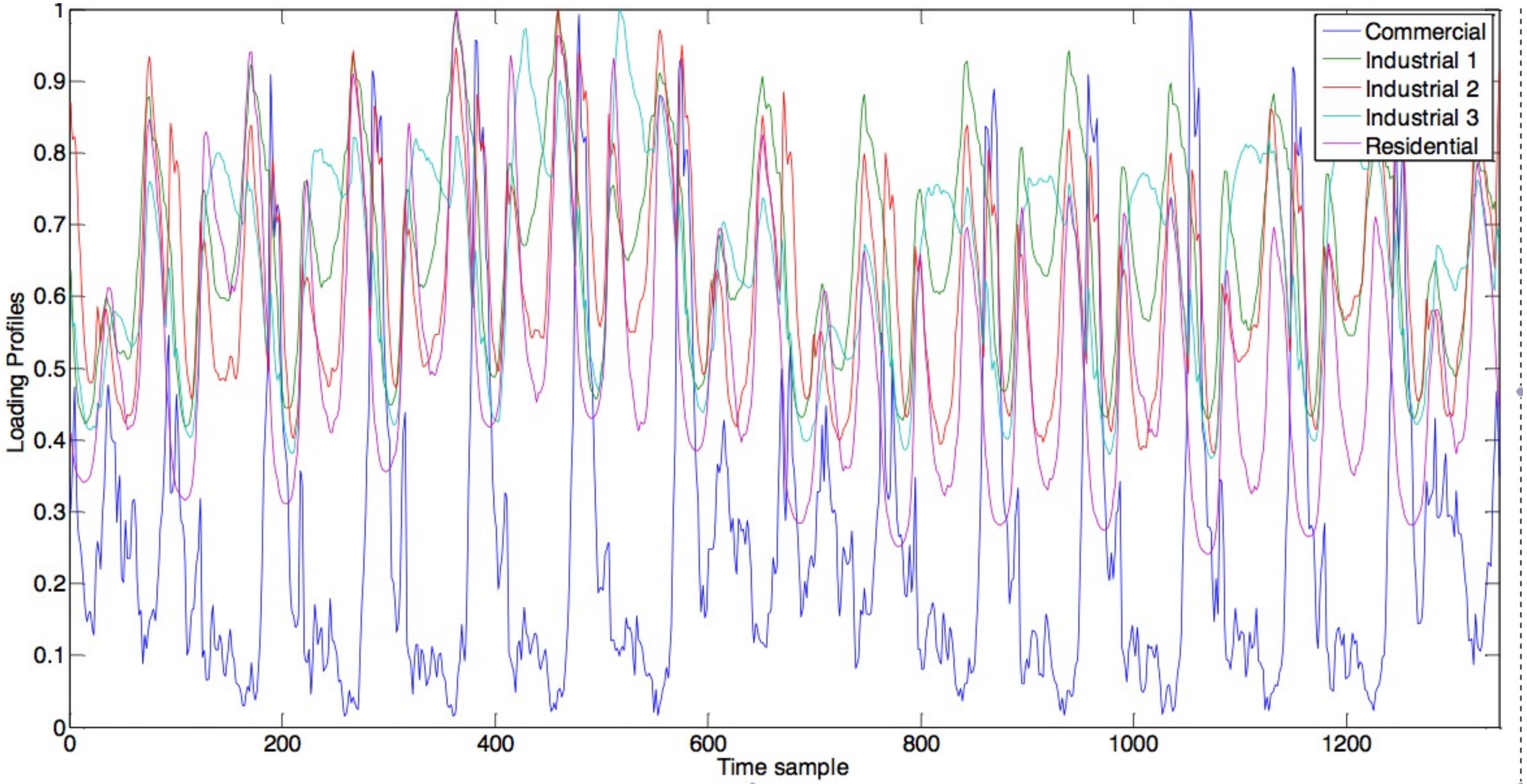
The integration of the proposed solution paradigm on existing power systems analysis toolbox is straightforward:

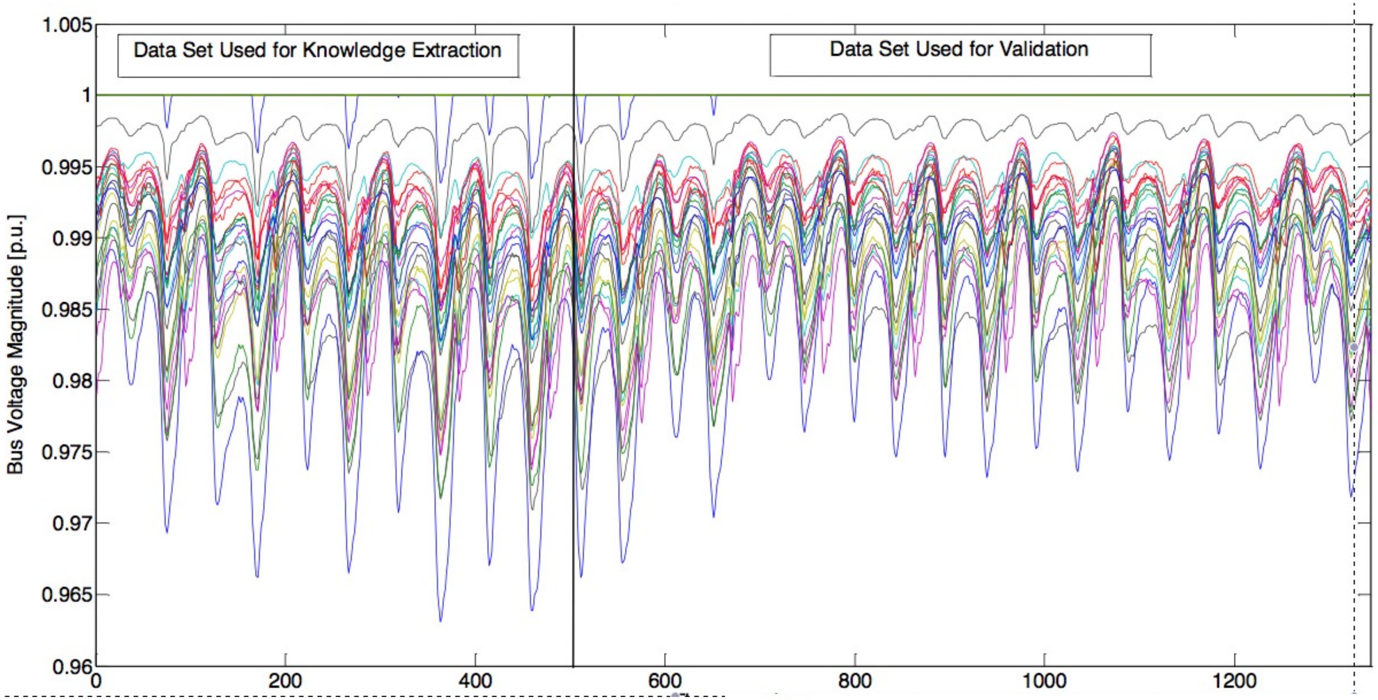
$$J_{pc} = \frac{\partial F}{\partial \tilde{s}} = \frac{\partial F}{\partial x}\frac{\partial x}{\partial \tilde{s}} = J\Omega$$

The traditional paradigms adopted for managing the reactive power generation limits can be integrated in the proposed framework by properly partitioning the matrix Ω

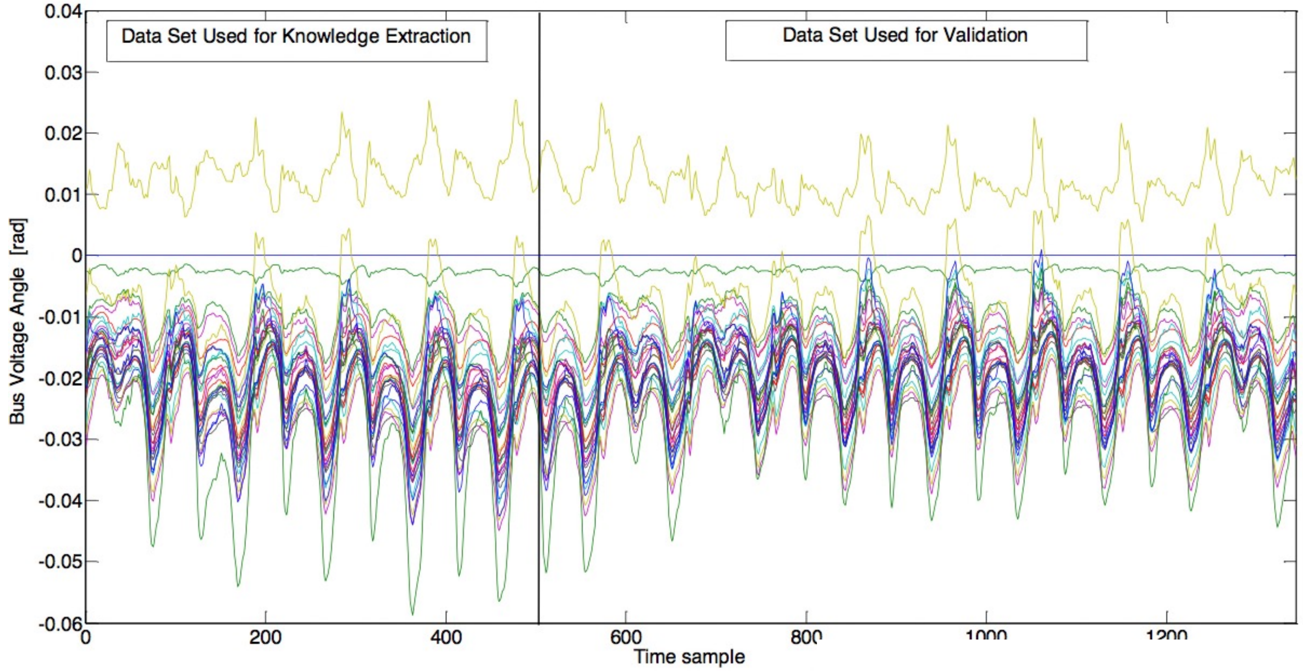
Case studies

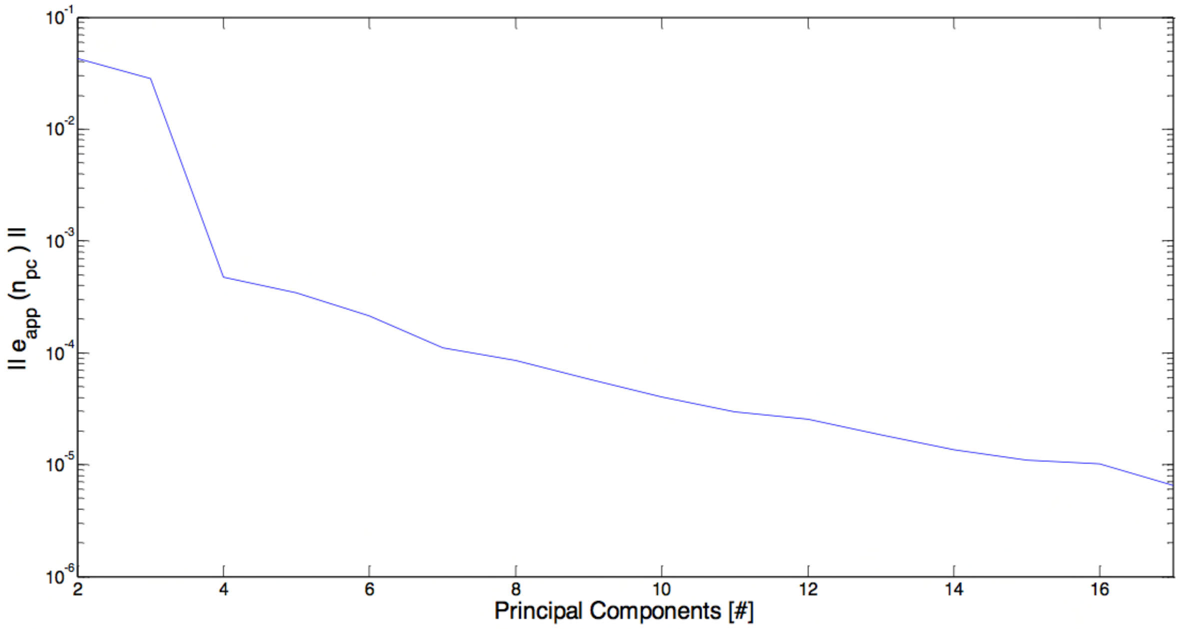
IEEE 30-bus Test System



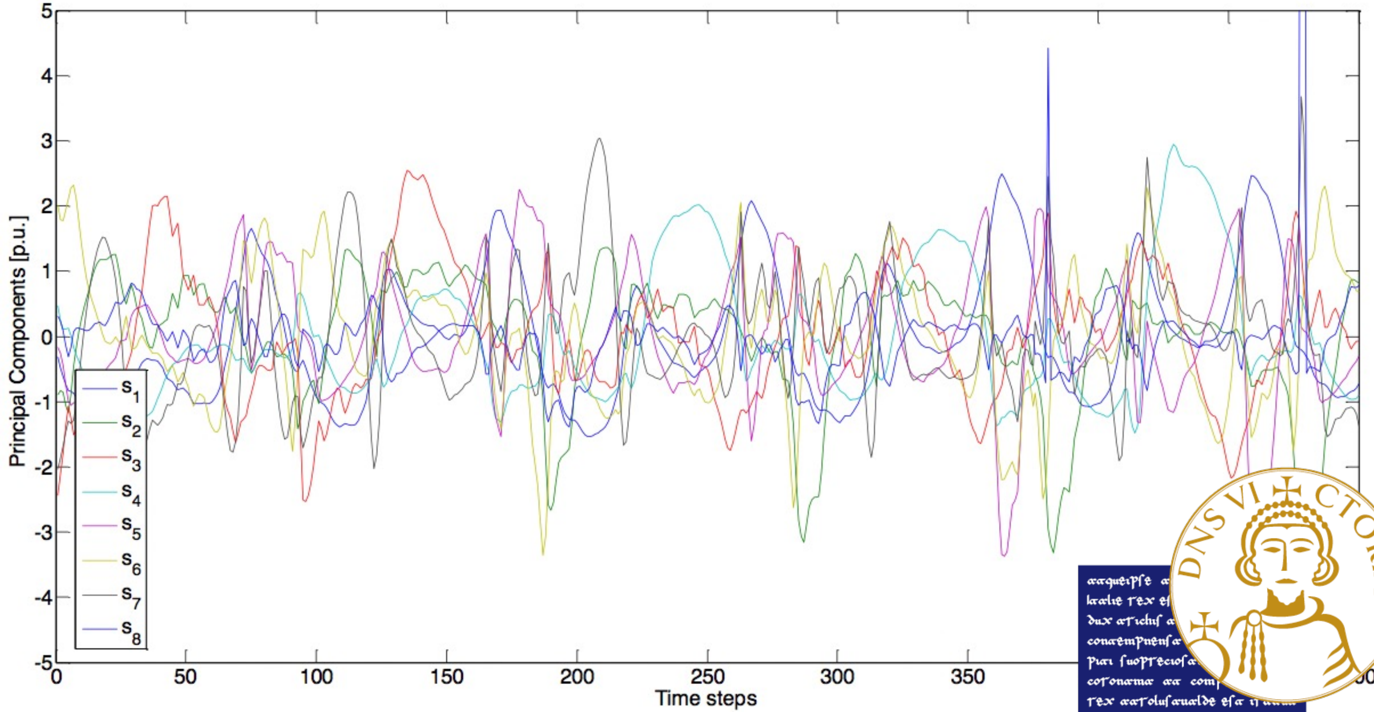


Power System Data

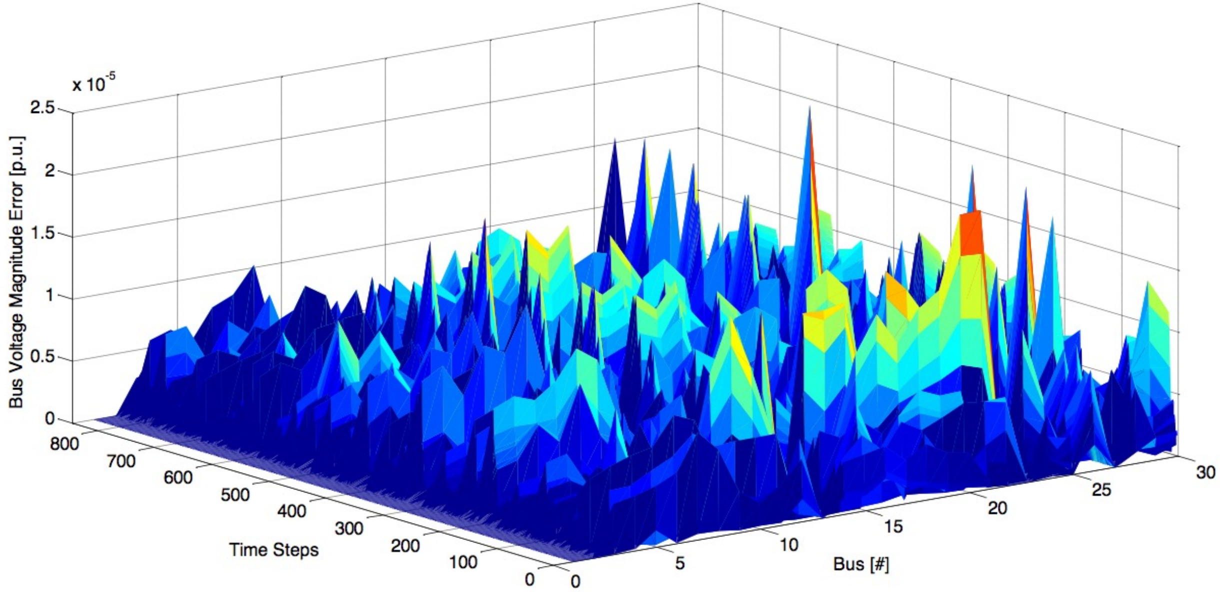


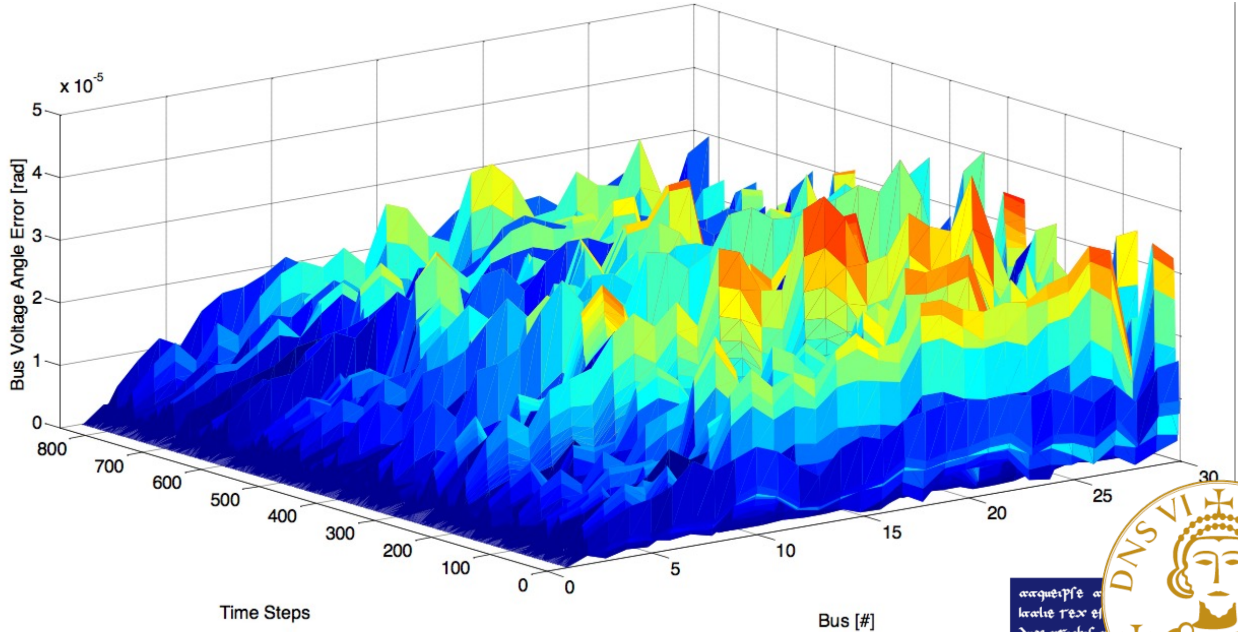


Knowledge Extraction Process

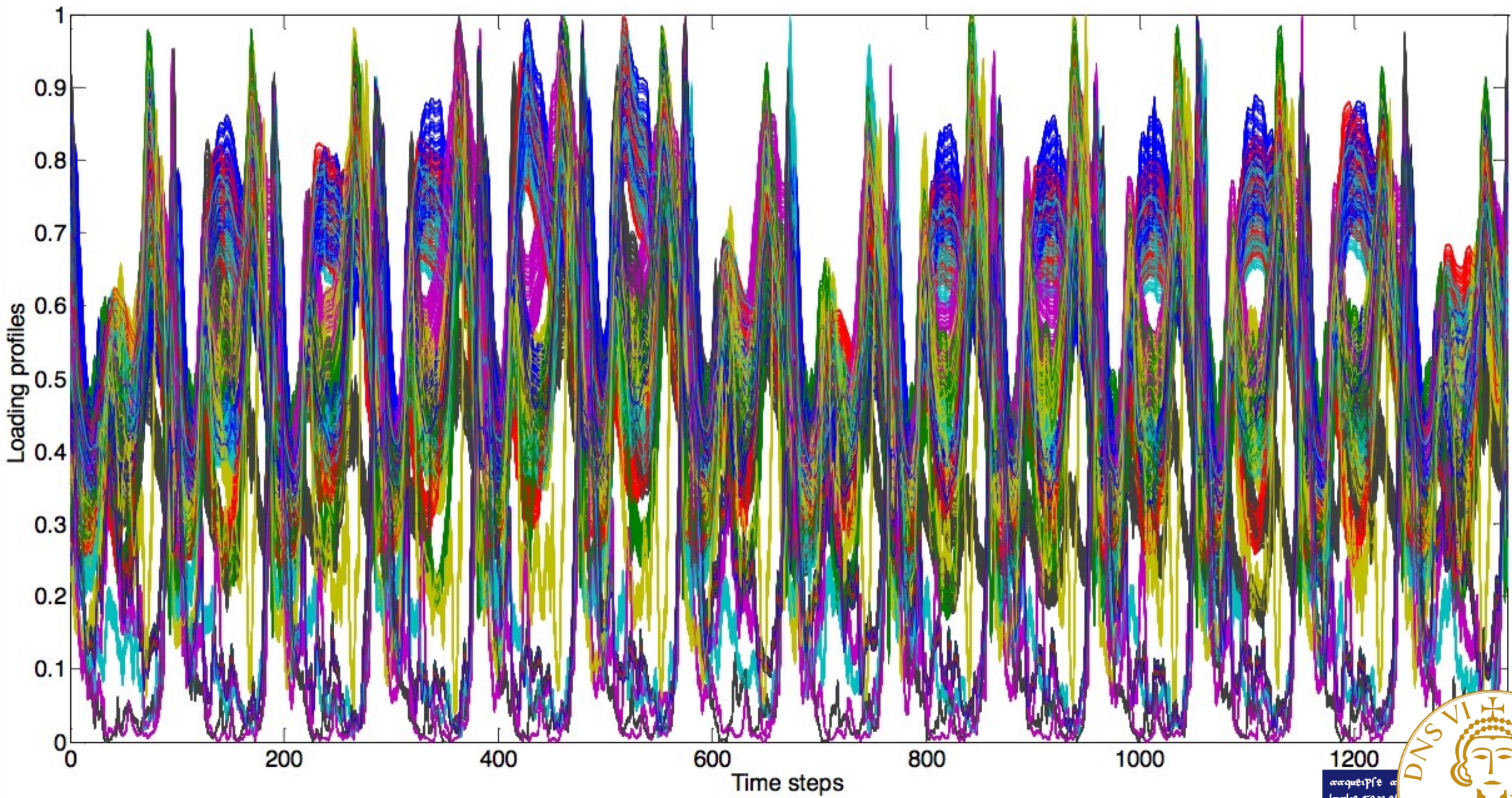


Validation Phase

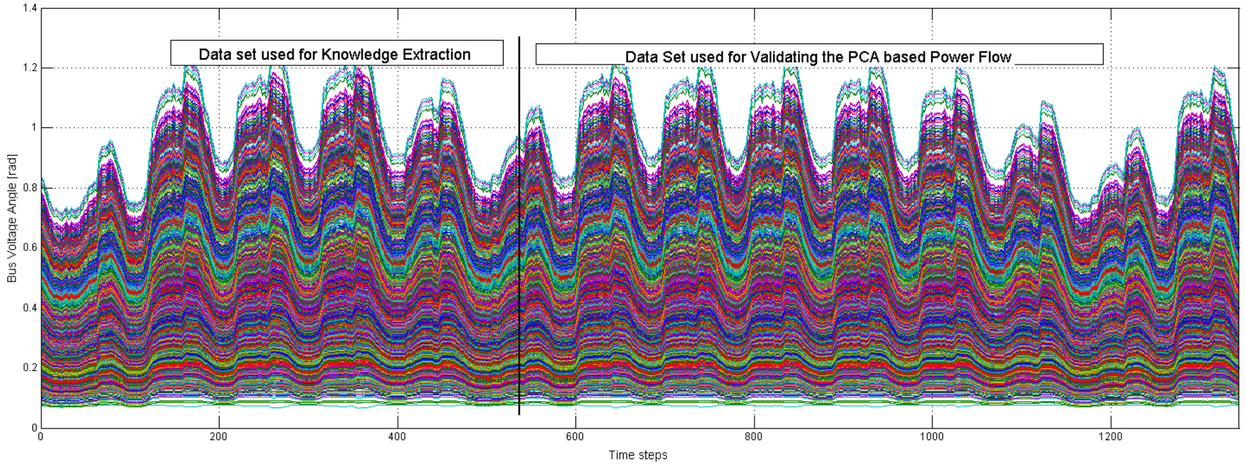


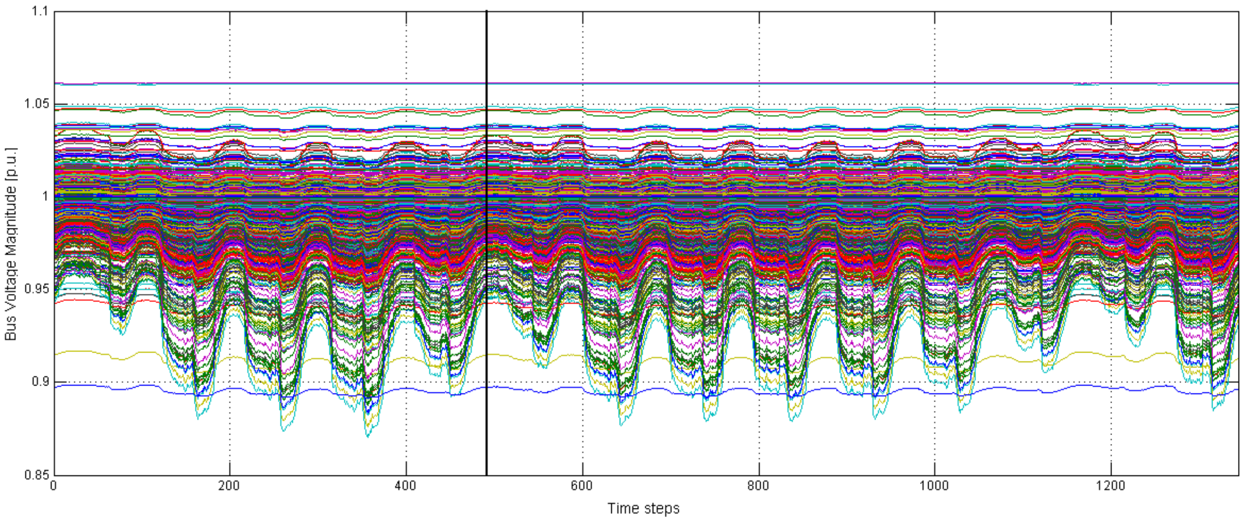


2383-bus Polish Power System

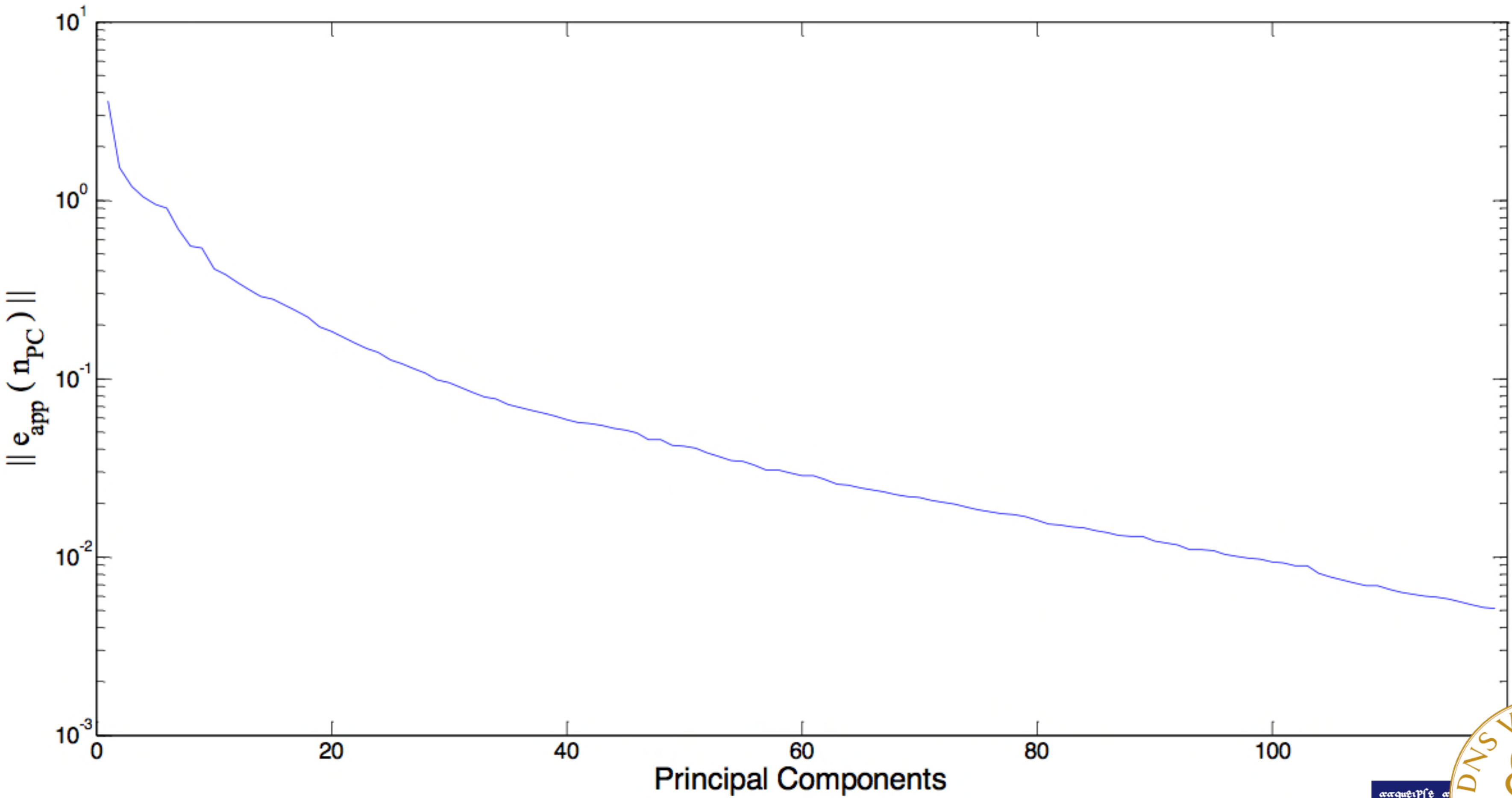


Knowledge Extraction Process

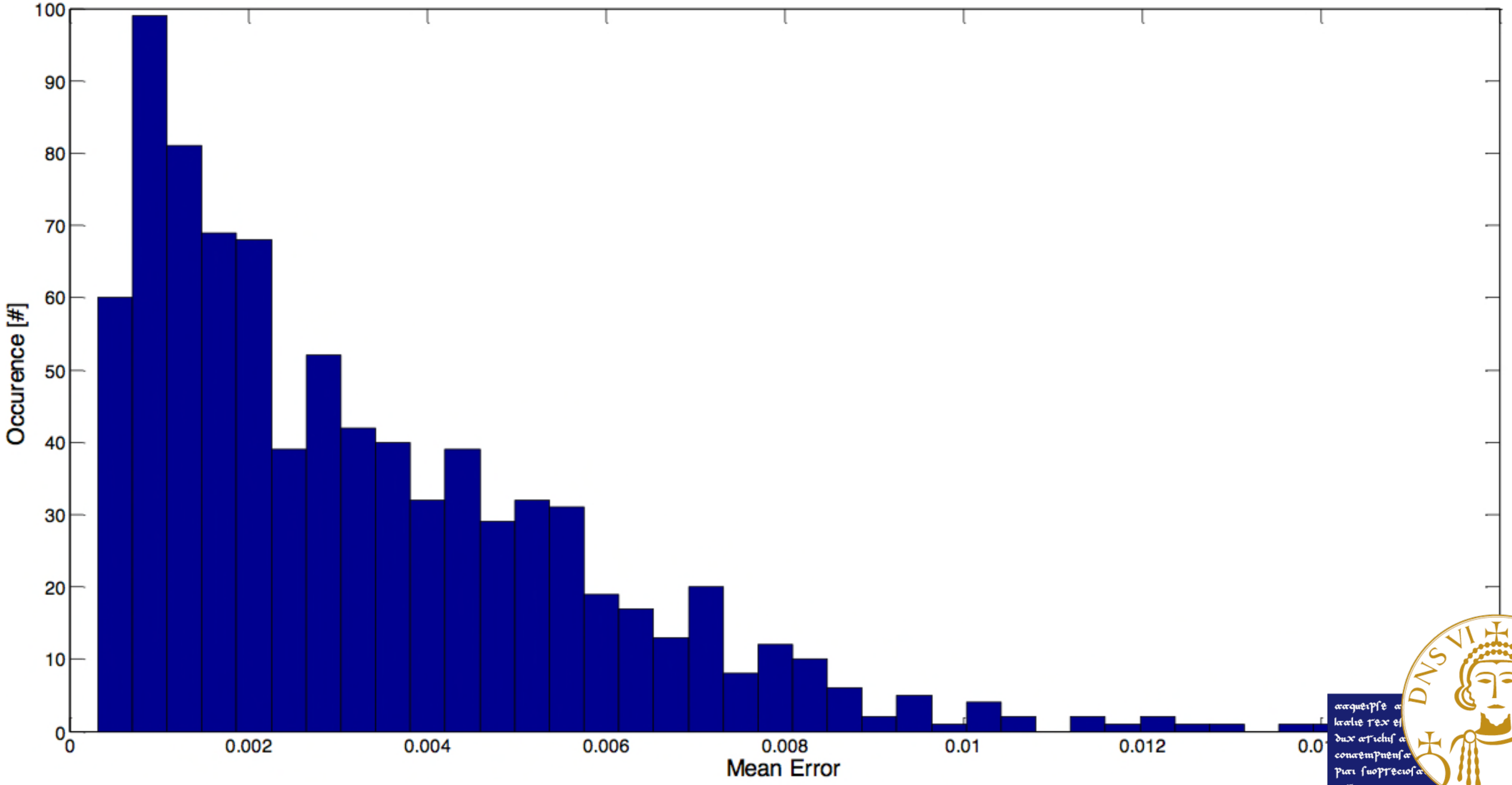




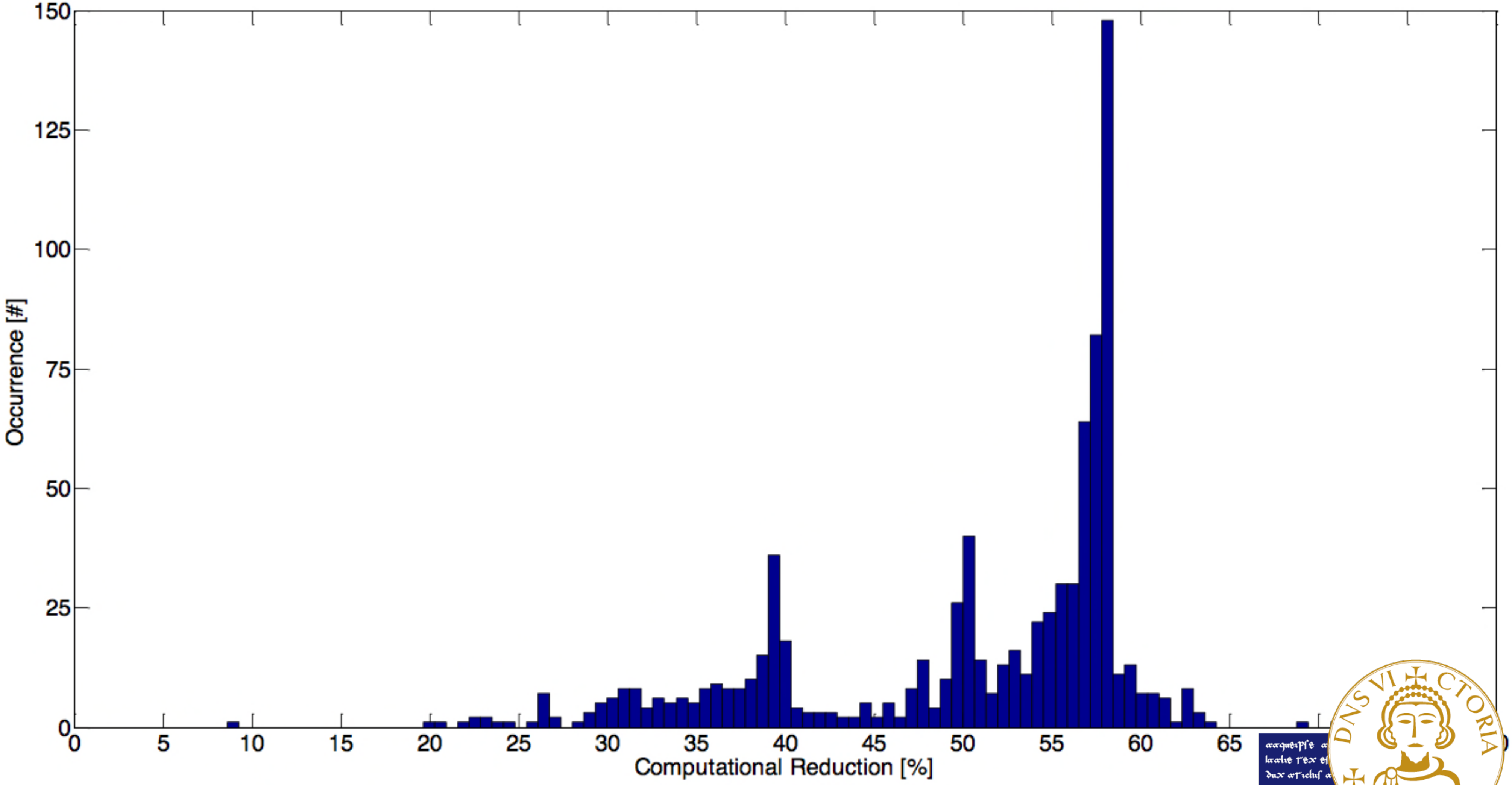
Knowledge Extraction Process



Validation Phase: Approximation Error Norm

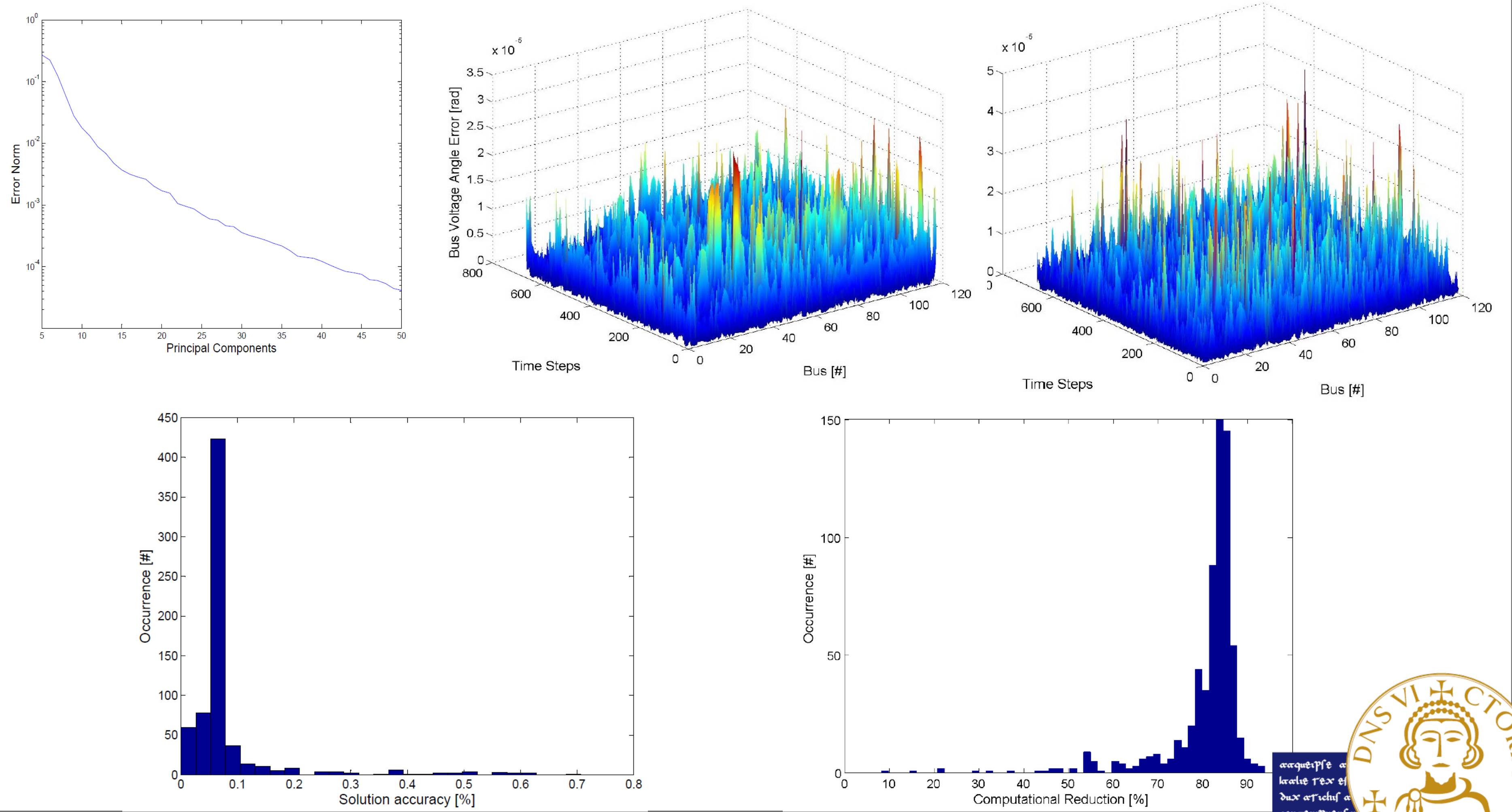


Validation Phase: Computational Reduction Factor



SIMULATION STUDIES: PCA-BASED OPF

IEEE 118-bus system:



Conclusive Remarks

- A novel framework aimed at identifying potentially regularities of the power flow solutions has been proposed
- Based on structural knowledge, a mathematical method projecting the power flow equations to a new domain has been defined, thus reducing the complexity and computational burden of the power flow problem.
- The numerical results obtained for small and large scale power system under realistic operating scenario demonstrated that the overall complexity of the power flow problem in the transformed domain could be sensibly reduced, especially in the presence of correlated variables.

Conclusive Remarks

- The approximation accuracy and the computational burdens observed during the experiments were strictly influenced by the number of principal components selected to decompose the power system state variables
- Therefore, formal methods aimed at defining a proper tradeoff between the solutions accuracy and the algorithm complexity would be necessary for a comprehensive deployment of the proposed framework
- This topic is currently under investigation