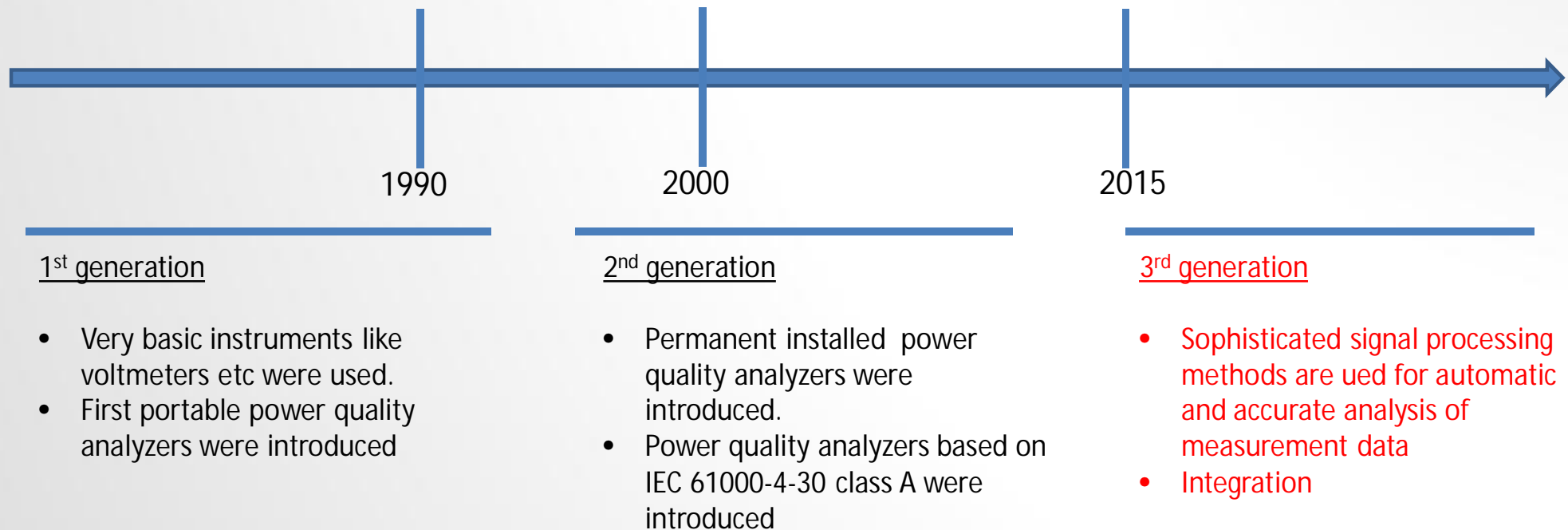


# " Using Machine Learning for Detection and Classification of PQ phenomenon"

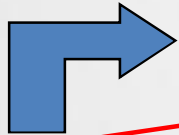
by  
Dr. Peter Axelberg  
By  
Dr. Peter Axelberg 2016

# Power Quality monitoring from past until today



# 3rd generation measurement system - objectives

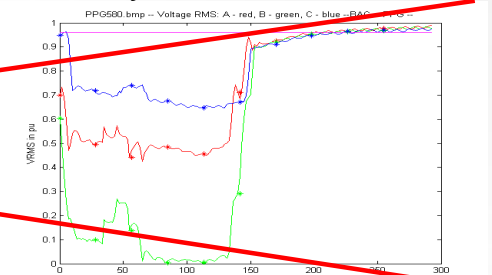
"Classical"



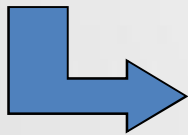
Manual Analysis of  
recorded data



Only characteristics



Something happen in  
the grid



" Preferred"



**3<sup>rd</sup> generation**



Tell what really happened



# Power Quality Monitoring – 3rd generation

- In the past: Evaluation of data was made by manual inspection
  - Time consuming (and tedious)
  - Quality of the result depends on the knowledge level and skills of the person doing the analysis
- 3rd generation: Take use of information (data) from previous measurements to automate the evaluation process
  - Automatic detection and classification of power quality phenomenon
  - Less time consuming evaluation process
  - Higher quality and more reliable results
  - Important information contained in the data - hidden for a manual inspection – can be detected – Trend analysis
  - Adaptive process – by continuously adding new data from previous measurements into the machine learning algorithm the PQ system will continuously learn and increase the precision and accuracy
  - Opens up to use the PQ system in new valuable applications like fault detection and preventive maintenance etc

# Machine learning (ML)

- q Herbert Simon:  
"Learning is any process by which a system (computer, robot etc) improves performance from experience".
- q Machine Learning is concerned with computer programs that automatically improve their performance through experience



**Herbert Simon**  
Turing Award 1975  
Nobel Prize in Economics 1978

# Pattern recognition

Pattern recognition:

A machine learning algorithm that is trained to recognize a particular pattern in a large data stream

# Pattern recognition – a general technique used in many applications

- Text analysis: Search engines
- Image analysis: Face recognition
- Financial analysis: Stock price forecasts
- *Power system analysis:*
  - Detection and lassification of voltage disturbances*
  - fault detection and classifications*
  - preventive maintenance*
  - trend analysis, forecasting*

# Pattern recognition methods

Many pattern recognition methods are available (different techniques with the same goal – to identify a particular pattern in a data stream)

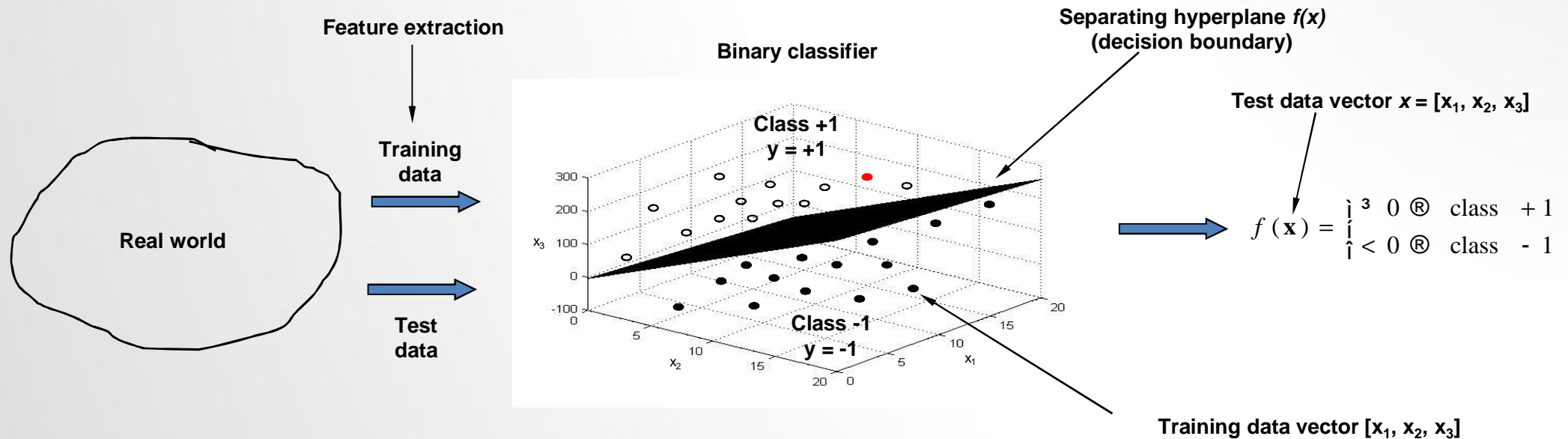
- k Nearest Neighbor (kNN)
- Neural Networks
- AdaBoost
- *Support Vector machines*



# A premium method: The Support Vector Machine (SVM)

- q Uses large number of pre-classified training data.
- q Features are extracted from the training data and placed in an n-dimensional data space.
- q The classifier decides type of disturbance (class) by using an optimal separating hyperplane.

# A premium method: The Support Vector Machine (SVM)



# Calculating the separating hyperplane

$$f(\mathbf{x}) = (\mathbf{w} \cdot \mathbf{x}) + b$$

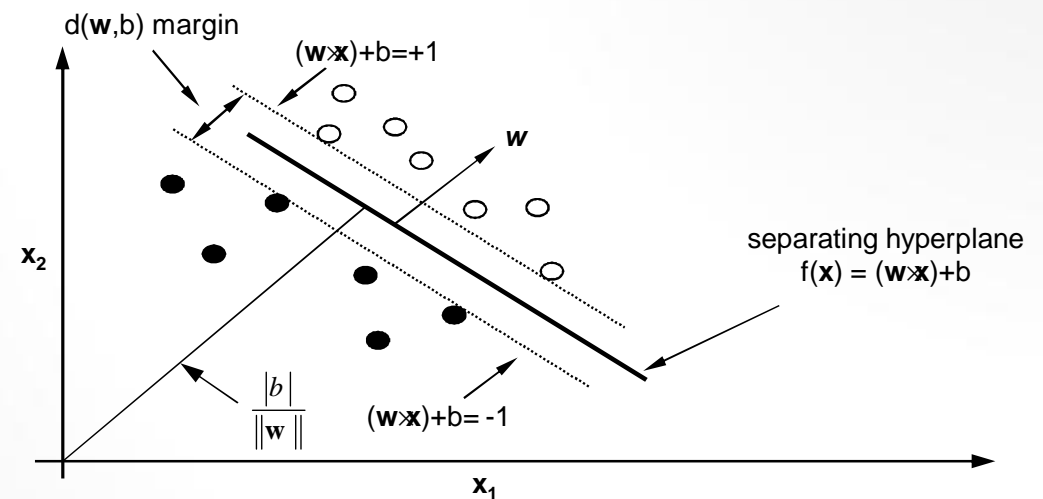
$$(\mathbf{w} \cdot \mathbf{x}_i) + b \geq 1 \quad \text{for } y_i = +1$$

$$(\mathbf{w} \cdot \mathbf{x}_i) + b \leq -1 \quad \text{for } y_i = -1$$

$$y_i \times ((\mathbf{w} \cdot \mathbf{x}_i) + b) \geq 1 \quad i = 1, \dots, n$$

The margin

$$d(\mathbf{w}, b) = \frac{|(\mathbf{w} \cdot \mathbf{x}_1) + b|}{\|\mathbf{w}\|} + \frac{|(\mathbf{w} \cdot \mathbf{x}_2) + b|}{\|\mathbf{w}\|} = \frac{2}{\|\mathbf{w}\|}$$



Maximum margin is achieved for

$$\min_{\mathbf{w}} \frac{1}{2} \|\mathbf{w}\|^2$$

$$y_i \times ((\mathbf{w} \cdot \mathbf{x}_i) + b) \geq 1 \quad i = 1, \dots, n$$

← Quadratic Optimization problem (QP-problem)

# Calculating the separating hyperplane

$$\min_{\mathbf{w}} \frac{1}{2} \|\mathbf{w}\|^2$$

$$y_i \times ((\mathbf{w} \times \mathbf{x}_i) + b) \geq 1 \quad i = 1, \dots, n$$

Introduce the Lagrangian functional and re-formulate the QP-problem:

$$L(\mathbf{w}, b, \mathbf{a}) = \frac{1}{2} \|\mathbf{w}\|^2 - \sum_{i=1}^n a_i [y_i \times ((\mathbf{w} \times \mathbf{x}_i) + b) - 1] = \frac{1}{2} \|\mathbf{w}\|^2 - \sum_{i=1}^n a_i \times y_i \times (\mathbf{w} \times \mathbf{x}_i) - b \sum_{i=1}^n a_i y_i + \sum_{i=1}^n a_i$$

Optimal solution is given by the saddle point of the Lagrangian functional

$$\max_{\mathbf{a}} \min_{\mathbf{w}, b} L(\mathbf{w}, b, \mathbf{a}) \xrightarrow{\frac{\partial}{\partial \mathbf{w}, b}}$$

$$\frac{dL(\mathbf{w}, b, \mathbf{a})}{db} = - \sum_{i=1}^n a_i y_i = 0 \quad \text{p} \quad \sum_{i=1}^n a_i y_i = 0$$

$$\frac{dL(\mathbf{w}, b, \mathbf{a})}{d\mathbf{w}} = \mathbf{w} - \sum_{i=1}^n a_i y_i \mathbf{x}_i = 0 \quad \text{p} \quad \mathbf{w} = \sum_{i=1}^n a_i y_i \mathbf{x}_i$$

$$\max_{\mathbf{a}} L(\mathbf{w}, b, \mathbf{a}) = \max_{\mathbf{a}} \left[ \sum_{i=1}^n a_i - \frac{1}{2} \sum_{i,j=1}^n a_i a_j y_i y_j (\mathbf{x}_i \times \mathbf{x}_j) \right]$$

subject to the constraints

$$\sum_{i=1}^n a_i y_i = 0 \quad \text{and} \quad a_i \geq 0 \quad i = 1, \dots, n$$

# Support Vector Machine

For the binary classifier

$$f(\mathbf{x}) = \text{sign} \left( \sum_{i=1}^n a_i y_i (\mathbf{x} \cdot \mathbf{x}_i) + b \right)$$

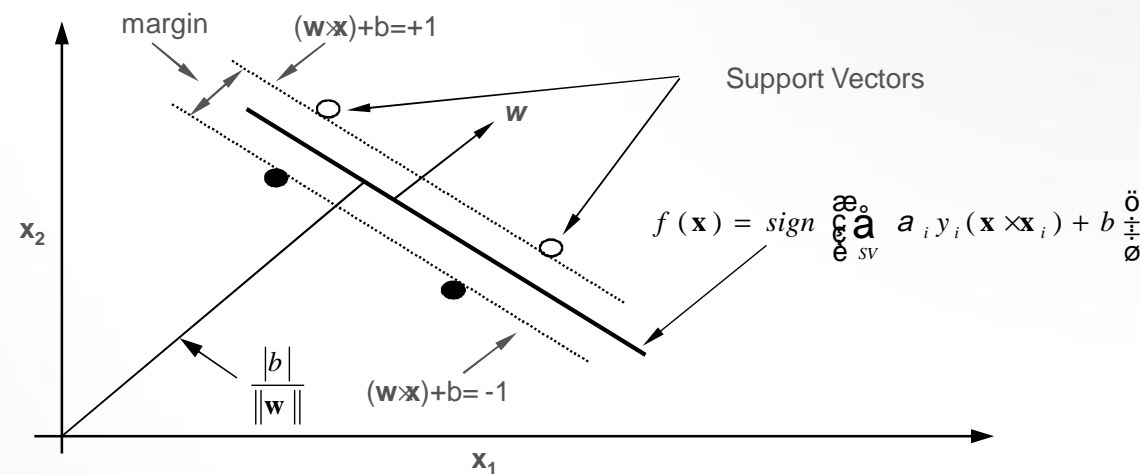
Karush-Kuhn-Tucker conditions states

$$a_i (y_i ((\mathbf{w} \cdot \mathbf{x}_i) + b) - 1) = 0 \quad \text{for } i = 1, \dots, n$$

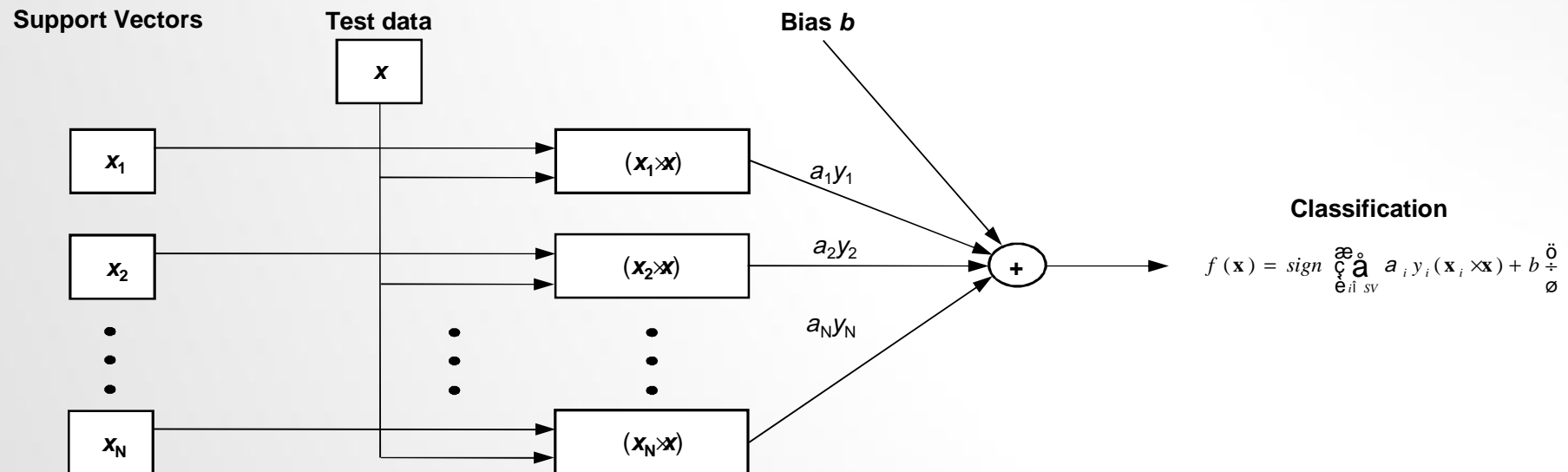
Only those training samples corresponding to non-zero Lagrange multipliers are needed!

These are placed on the margins and called Support Vectors

$$f(\mathbf{x}) = \text{sign} \left( \sum_{i \in SV} a_i y_i (\mathbf{x} \cdot \mathbf{x}_i) + b \right)$$



# Blockdiagram of the Support Vector Machine



# Conducted experiments

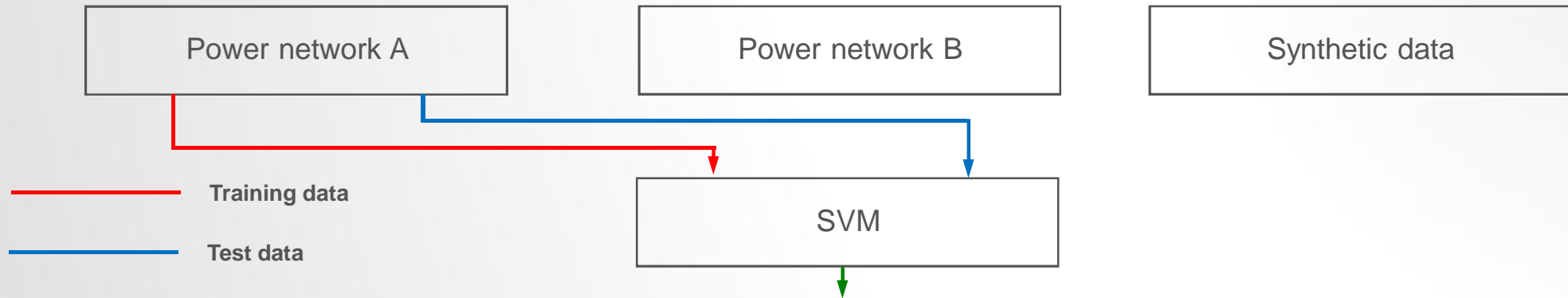


# Types of voltage disturbances

Type	Fault types	# of disturbances originated from Power network A	# of disturbances Originated from Power network B	# of disturbances originated from synthetic generated data
D1	Single phase-to-ground fault	141	475	225
D2	Phase-to-phase fault	181	125	225
D3	Three-phase fault	251	196	223
D4	Double phase fault with one phase more affected	127	67	250
D5	Transformer energizing	214	0	250

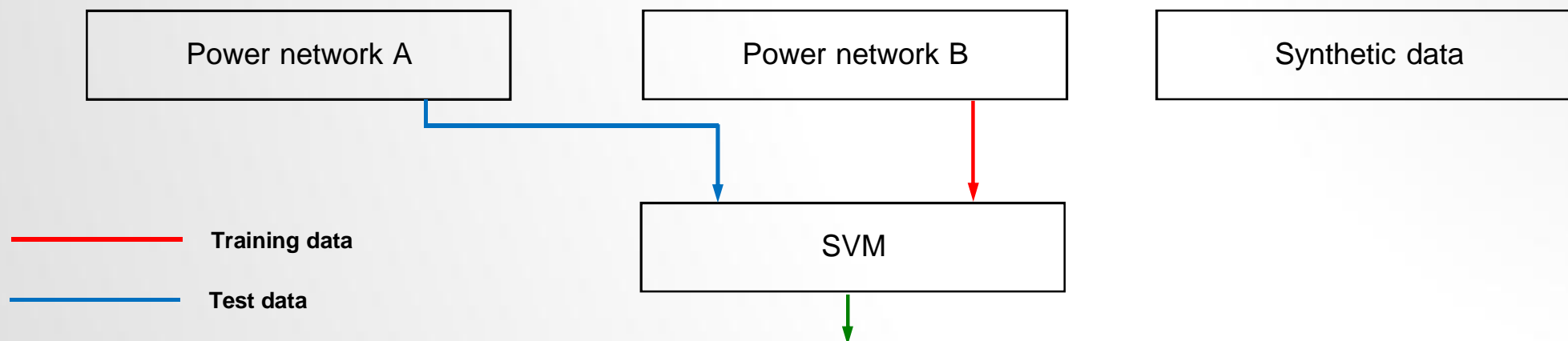


# Experiment #1



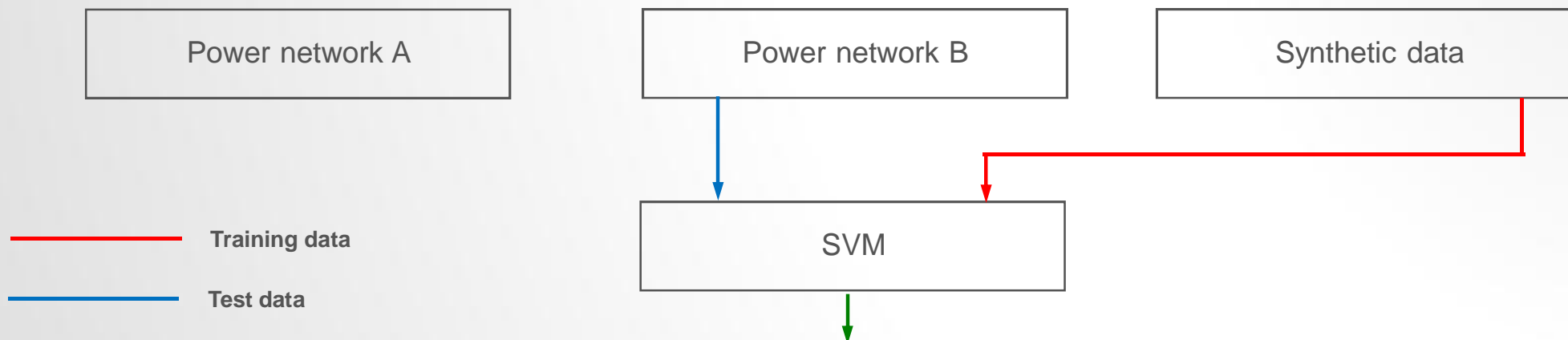
	D1	D2	D3	D4	D5	NC	Detection rate
Single phase-to-ground fault (D1)	<b>63</b>	0	1	3	0	4	<b>88.7 %</b>
Phase-to-phase fault (D2)	0	<b>84</b>	4	0	0	3	<b>92.3 %</b>
Three-Phase Fault (D3)	5	3	<b>113</b>	0	0	5	<b>89.7 %</b>
Double phase fault with one phase more affected (D4)	0	0	0	<b>63</b>	1	0	<b>98.4 %</b>
Transformer energizing (D5)	0	0	0	0	<b>103</b>	4	<b>96.3 %</b>
Overall detection rate: <b>93.1 %</b>							

## Experiment #2



	D1	D2	D3	D4	D5	NC	Detection rate
Single phase-to-ground fault (D1)	<b>137</b>	0	2	1	0	1	<b>97.2 %</b>
Phase-to-phase fault (D2)	0	<b>154</b>	16	0	0	11	<b>85.1 %</b>
Three-Phase Fault (D3)	10	1	<b>232</b>	0	0	8	<b>92.4 %</b>
Double phase fault with one phase more affected (D4)	4	1	1	<b>121</b>	1	0	<b>95.2 %</b>
Overall detection rate: <b>92.5 %</b>							

# Experiment #3

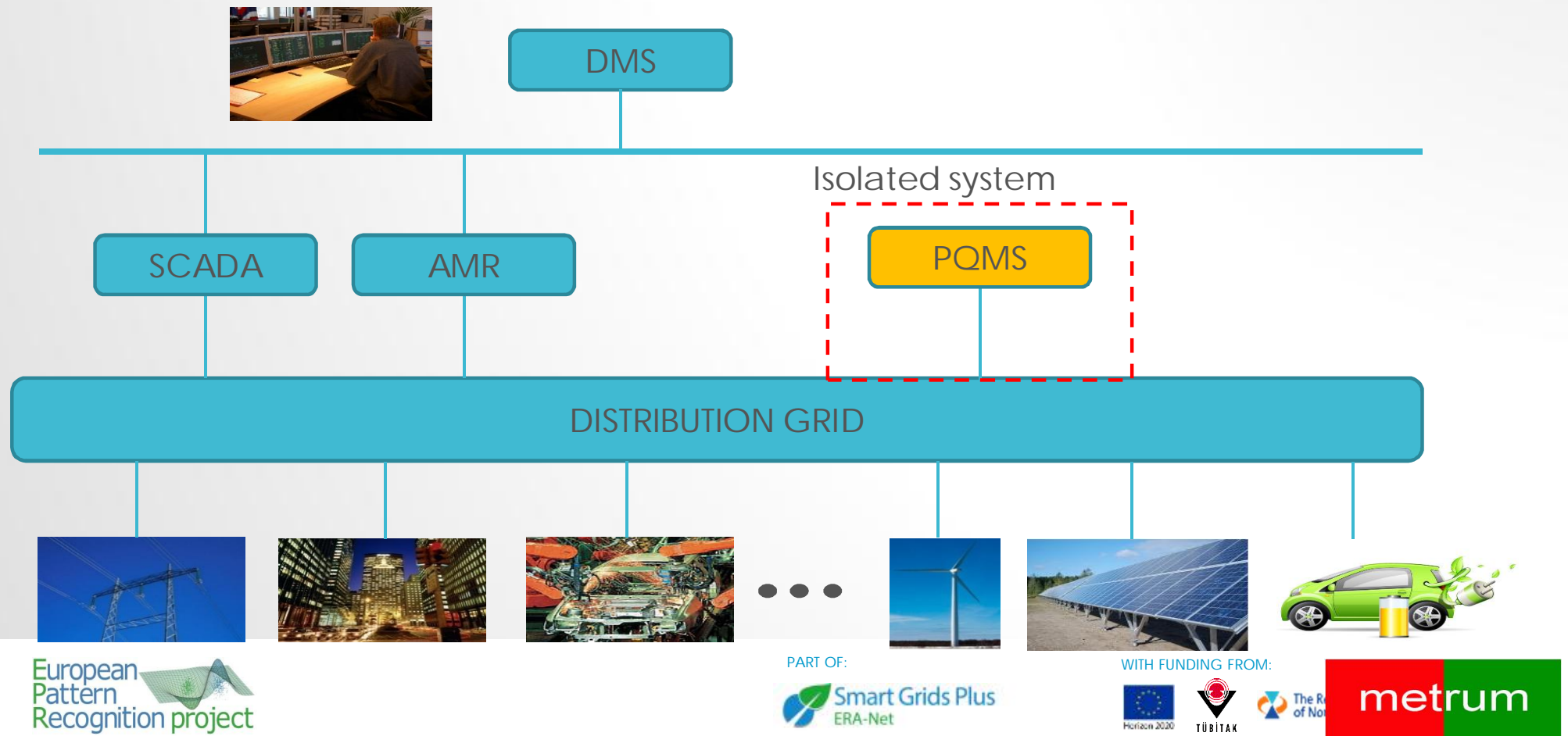


	D1	D2	D3	NC	Detection rate (%)
Single phase-to-ground fault (D1)	<b>393</b>	0	2	23	<b>94.0%</b>
Phase-to-phase fault (D2)	3	<b>80</b>	0	9	<b>87.0%</b>
Three-Phase Fault (D3)	2	0	<b>126</b>	14	<b>88.7%</b>
Overall detection rate: <b>91.9%</b>					

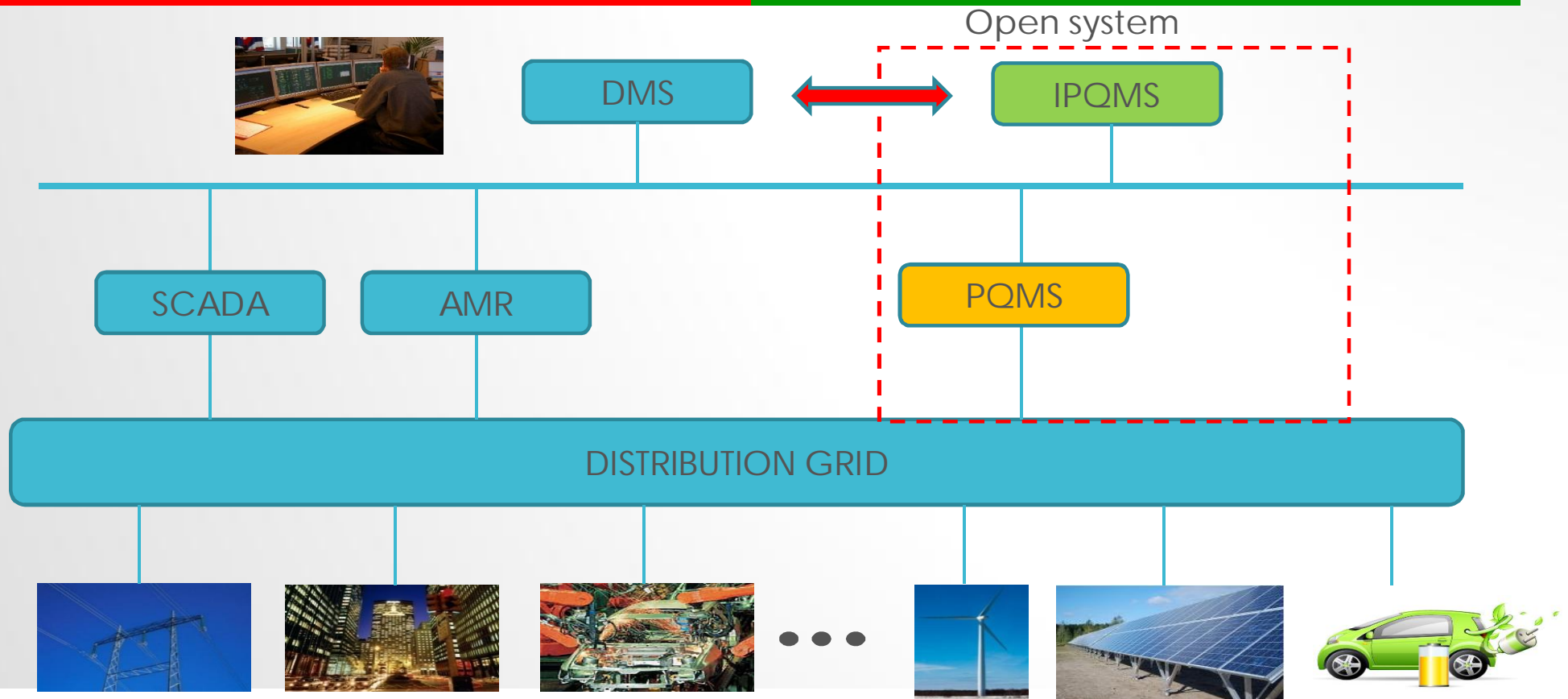
# System Integration



# System Integration – situation until today



# Integration – situation tomorrow



IPQMS = Integrated Power Quality Monitoring System

European  
Patent  
Recognition project

PART OF:

WITH FUNDING FROM:



# Conclusions

- q The 3<sup>rd</sup> generation system will be based on powerful pattern recognition techniques to perform traditional PQ analysis in a more efficient way
  - from manual toward automatic analysis of PQ data
  - trend analysis used for preventive maintenance
  - automatic detection and classification of faults
  - forecasting
- q The 3<sup>rd</sup> generation system will be an open system ready to interchange data with other systems