HiPerDNO

High Performance Computing Technologies for Smart Distribution Network Operation

FP7 - 248135

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Positioning of sensors in the network for estimation accuracy and cost effectiveness. Deliverable D.2.1.4

Executive Summary

The purpose of the HiPerDNO project is to develop scalable HPC solutions for smart distribution network operation. The smart operation of the MV network is based on the results of a state estimation function, which must be able to treat large zones of MV networks. This document is focused on the positioning of sensors in the network for state estimation accuracy and cost effectiveness.

To do so, a first analysis of the impact of each type of sensor on estimated variables has been run. This analysis has shown that estimated voltage amplitudes can be improved with voltage amplitude or voltage phase sensors. Regarding active and reactive loads of MV/LV substations, only PQ sensors measuring the load can improve estimated powers. Current and PQ flow sensors improve PQ loads estimations only if they measure a line supplying only one load.

Once the impact of each single sensor is analysed, it has been decided to investigate the impact of adding sensors sequentially on estimated variables. To do so, PQV sensors (to improve estimated voltage amplitudes as well as active and reactive powers) have been added sequentially into a French semi-urban network and a network provided by Elecktro Gorenjska (EG). Case studies have been run with different sensors' accuracy (0.5%, 1% and 2%) to determine the number of additional sensors required depending on their accuracy. These results are summarized in tables allowing to determine the number of additional sensors required to achieve a mean or a maximum error for voltage amplitudes.

Finally a cost analysis has been run to determine the cost of instrumentation required by a DSE function. This analysis takes into account instrumentation costs. Regarding instrumentation costs, it depends on the number of additional sensors to be installed. The number of sensors is directly related to the accuracy required by automation functions that use DSE results as input data.

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Abstract	This document focuses on the positioning of sensors in the network for state estimation accuracy and cost effectiveness. The impact of isolated sensors on estimated variables has been analysed to determine the type of sensors to use to obtain the best results in the state estimation of voltage amplitudes. In a second part, the document shows the impact of adding sensors sequentially. Finally, a cost analysis of a DSE function has been run taken into account instrumentation cost.			
Keywords	Distribution State Estimation, Sensor's impact, Cost analysis			

Contents

I. Introduction

The purpose of the HiPerDNO project is to develop a new generation of distribution network management systems using near to real time High Performance Computing (HPC) solutions. Figure 1 describes the architecture of these new DMS tools. Network information (measurements and topology changes) is gathered in real-time by the SCADA. These data, as well as static data (network data and load models) are used by the DSE to provide the state of the network in real time. DSE results are then transmitted to automation and asset management functions. The automation functions will then send set points to different equipment on the network (switches, capacitors, tap changers) and to the Disperser Energy Resources (DER). Depending on the automation functions, different levels of accuracy will be expected from the DSE results (for different state variables).

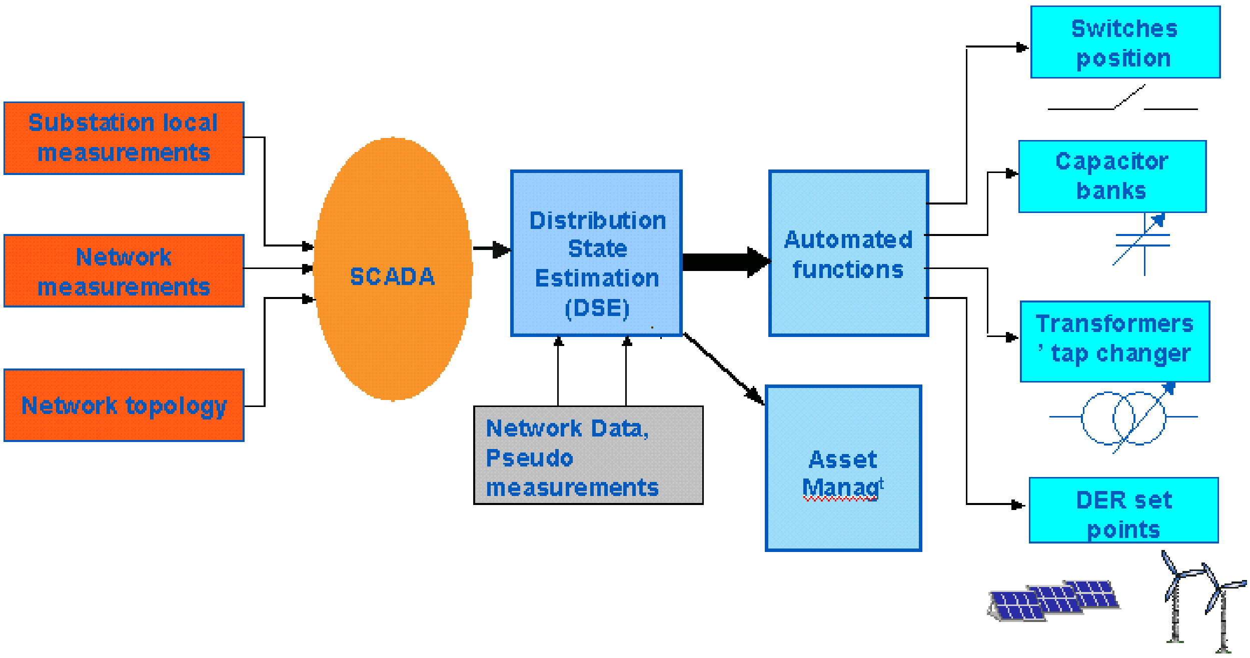


Figure 1 : Architecture of new DMS

First of all, the impact of each type of sensor on DSE results is analysed. This analysis provides the type of the sensors to be installed to obtain suitable accuracy for different state variables.

With this information, and depending on the chosen state variable, sensors will be added sequentially. Accuracy obtained with different configurations of sensors is then compared to the accuracy required by automation functions.

This analysis leads to the assessment of the instrumentation required by automation functions. The number of sensors will determine the cost of implementing the instrumentation for the DSE function. This analysis takes also into account the accuracy of the sensors to determine the cost of the corresponding instrumentation.

II. Sensors

Current and voltage transformers are the most common sensors currently used in distribution networks. They convert measurements at high primary potential to levels acceptable to intelligent electronic devices (IEDs). They have been mainly used for protection devices for which the non saturation of magnetic cores is more relevant than the actual accuracy of the sensors (protection relays usually only require to know whether the current / voltage is above or below a pre-defined threshold). Although instrument transformers with magnetic cores have traditionally been accepted as standard, new smaller and less costly sensing devices without the saturation characteristics of iron are being introduced as an alternative.

The following sections present different technologies (existing and emerging) for current and voltage sensors in 3-phase MV distribution networks and the use of these technologies for DSE. It is important to notice that the accuracy of the measurement received by a SCADA system is the global accuracy of the full measurement chain (sensor + transducer + signal conditioning unit + RTU + telecom to SCADA + messaging layer).

1. Voltage sensors

1.1 Voltage transformers (VTs)

A voltage transformer is an instrument transformer in which the secondary voltage, in normal conditions of use, is substantially proportional to the primary voltage and differs in phase from it by an angle which is approximately zero for the appropriate direction of the connections. Voltage transformers are defined according to the IEC 60044.

In distribution networks, most VTs are inductive. VTs, apart from providing voltage measurement, might be useable as a power supply to the IED cabinet.

1.2 Resistive voltage dividers

Resistive voltage dividers are used for voltage measurements in MV switchgear providing a small lightweight device that does not contribute to nor is affected by ferroresonnace. The construction of resistive voltage dividers must be able to withstand all normal and abnormal (fault) voltages. These conditions place very heavy demands on the divider, requiring the resistance of the divider to be very high.

Sensor accuracy is dependent on the accuracy of the resistors (the division ratio must not change). The main sources of inaccuracy come from the resistor’s temperature coefficient, drift of resistors (voltage, temperature dependent), stray capacitance and effects from adjacent phases.

Normally, an accuracy of ±0.5% can be achieved through temperature compensation, choice of resistive material (critical for long term accuracy) and minimization of stray capacitance.

EMC effects on the operation of voltage dividers must be considered in the design and testing of the installation environment, because 50Hz signals in the order of a few millivolts per ampere can affect the low signal level from the divider in difficult EMC environments.

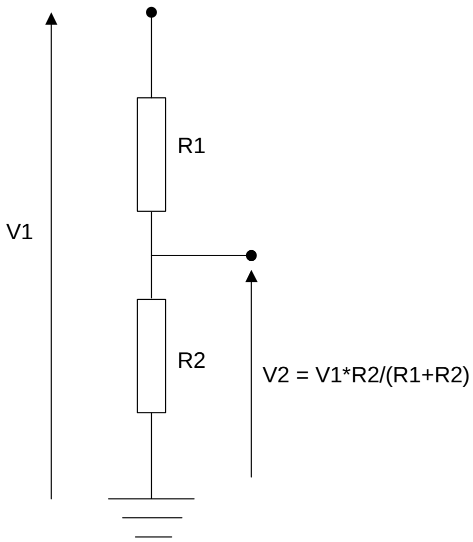


Figure 2 : Resistive voltage dividers

1.3 Capacitor dividers

The principle is similar to the one used in resistive dividers: resistances are replaced by capacitors.

1.4 Fiber optic voltage sensor

The concept of such sensors is based on the following physical law: when a steady electric field is applied to certain optically birefringent materials, their refractive indices change, roughly in proportion to the strength of the applied field. This property, known as the Pockels effect, is widely used in the fiber optic telecommunications field, specifically in electrotoptic modulators and other devices. The Pockels effect occurs only in certain optical crystals, such as lithium niobate or gallium arsenide. In sensor systems that exploit the Pockels effect, a sensor assembly is placed into an electric field. When polarized light is projected through the Pockels cell that is in this voltage field, the state of polarization of the light travelling in the crystal is rotated. From this knowledge, the voltage across the crystal can be determined.

2. Current sensors

2.1 Current transformers

A current transformer is an instrument transformer in which the secondary current, in normal conditions of use, is substantially proportional to the primary current and differs in phase from it by an angle which is approximately zero for the appropriate direction of the connections. CTs can be subdivided into the protective CT, which is intended to supply protective relays, and the measuring CT, which is intended to supply indicating instruments (meters and similar apparatus).

Measurement CTs must be as accurate as required by the user in the range of rated primary current, but outside this range of load currents, its accuracy is of less importance. On the other hand, protection CTs are required to operated with the fault currents that may be found on the particular system in the region of many thousand of amps. As long as the protection CT can detect the fault and cause protection to operate, it does not need to be as accurate as a measurement CT. Therefore, two different classes of CTs are defined in the international standards:

- Class M for measurement CTs
- Class P for protection CTs

The non linearity of magnetic cores in CTs sets constraints on the measurement range and accuracy.

The introduction of alternative sensing technologies such as Rogowski coil provides a large measurement range with high accuracy and integrated measurement and protection from one sensor.

2.2 Rogowski coil (RC)

The Rogowski coil is a uniformly wound coil that has a non magnetic core, the simplest shape being a toroidal air-cored coil. This coil has to be wound very precisely to achieve the desired accuracy band stability. The current going through the coil induces a voltage e given by the following approximate formula:

$$e=\mu_0 * N * A * dI/dt = H\, dI/dt$$

where:

μ_0 = permeability of free space / N= turn density (turns/m) / A=single turn area (m2) and H=coil sensitivity (Vs/A)

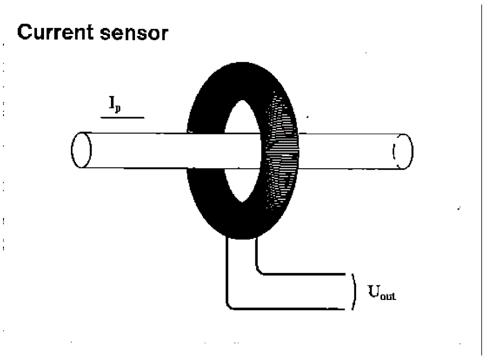


Figure 3 : Rogowski coil

The output signal of a Rogowski coil is therefore not a current, but a voltage.

The design of the RC without a magnetic core eliminates the non linear effects of saturation and permits isolated current measurement with a megahertz bandwidth. In most respects, the RC approach is the ideal sensor for applications where measurement of DC current is not necessary. The major disadvantage is that the output is proportional to the time derivative of the current output and must be integrated. This must be dealt with in the digital integrators.

The overall accuracy of the RC approaches 0.5% provided care is taken to minimize the major sources of inaccuracy from temperature changes, assembly tolerances and the effect of other phases. Temperature dependency can be lowered by use of special materials and by compensation methods.

EMC effects on the operation of RC sensors must be considered in the design and testing of the installation environment, because 50Hz signals in the order of a few millivolts per ampere can affect the low signal level from the RC in difficult EMC environments.

2.3 Overhead mountable optical current sensor

When linearly polarized light travels through flint glass that is exposed to a magnetic field, its plane of polarization rotates. This property, known as Faraday effect, is widely used in the fiber optic telecommunications field. In sensor systems that exploit the Faraday effect, a sensor assembly is placed into a magnetic field. By monitoring the rotation of the incident polarization state, a direct measurement of the magnetic field intensity or current can be inferred.

3. Signal conditioning unit and RTU

The signal conditioning unit accepts input signals from the analog sensors and gives a conditioned output of 0-5V DC corresponding to the entire range of each parameter. Such output meets the requirements of the next stage for further processing (calculation of power from current and voltage sensors for example).

The RTU (Remote Terminal Unit) is the device that allows communication of the local process to a master or central system. The RTU applied at the distribution level must be of the lowest possible cost. The fundamental role of an RTU is as follows:

- The acquisition of various types of data from the power process
- The accumulation, packaging, and conversion of data in a form that can be communicated back to the master
- The interpretation of commands received from the master
- The performance of local filtering, calculation and processes to allow specific functions to be performed locally.
-

4. Sensors for DSE

The technologies presented in previous paragraphs will be installed in Distribution Networks to make available different measures to DSE. These sensors will be connected to a signal conditioning unit and this one to a RTU to send the information to the SCADA system. In some cases a transducer is needed because the magnitude is not directly measured by the sensor so a calculation is required (taken into account several sensors' information).

In our case five different measures have been considered :

- Voltage amplitude : this measure is directly provided by a voltage sensor,
- PQ load : a transducer is needed to process the information coming out of a voltage sensors and a current sensor (measuring the current of the load),
- Current amplitude : this measure is directly provided by a current sensor,

- PQ flow : a transducer is needed to process the information coming out of a voltage sensor and a current sensor (measuring the current flowing the line),
- Voltage Phase : a PMU equipment has to be placed at the reference node and at the nodes to be measured, and a GPS synchronised transducer is needed to obtain the measure used by DSE.

In the next paragraphs, a detailed diagram of each type of configuration is presented.

III. Impact of isolated sensors on DSE results

This chapter investigates the impact of each type of sensor on the accuracy of DSE results. This analysis will make possible the determination of the optimal placement of sensors in order to achieve a predefined accuracy of state variables. Five different types of sensors have been analysed:

- Voltage amplitude (nodes),
- PQ load (nodes),
- Current amplitude (lines),
- PQ flow (lines),
- Voltage Phase (nodes).

For each type of sensors, and with the initial sensor's configuration, all available positions have been tested.

Type of sensor	Initial configuration	Tested positions	Sensors configurations
Voltage amplitude	PQV sensor at the beginning of the MV feeder+ PQV sensor at DG connection node + pseudo-measurements at loads	All nodes in the network	PQV at MV busbar + pseudo-measurements for loads + V sensor at node *i*
PQ load		All loads in the network	PQV at MV busbar + pseudo-measurements for loads except load *j* + PQ load sensor at load *j*
Current amplitude		All lines in the network	PQV at MV busbar + pseudo-measurements for loads + I flow sensor at line *i*
PQ flow		All lines in the network	PQV at MV busbar + pseudo-measurements for loads + PQ flow sensor at line *i*
Voltage Phase		All nodes in the network	PQV at MV busbar + pseudo-measurements for loads + Voltage Phase sensor at node *i*

Table 1 : Sensors configurations

For each sensor configuration and for all types of sensors, the accuracy of three estimated[1] variables has been analysed:

- Voltage amplitude
- PQ load
- Copper losses

The impact of pseudo-measurements has also been analysed in order to determine if an improvement of load models can contribute to improve DSE results.

[1] PQ loads and Copper losses have been calculated from estimated voltages and the model of the network.

1. Network's description

For the tests, a French semi-urban network has been chosen. Its topology is described in Figure 4 and the characteristics of MV feeders used for tests are summarized in Table 2.

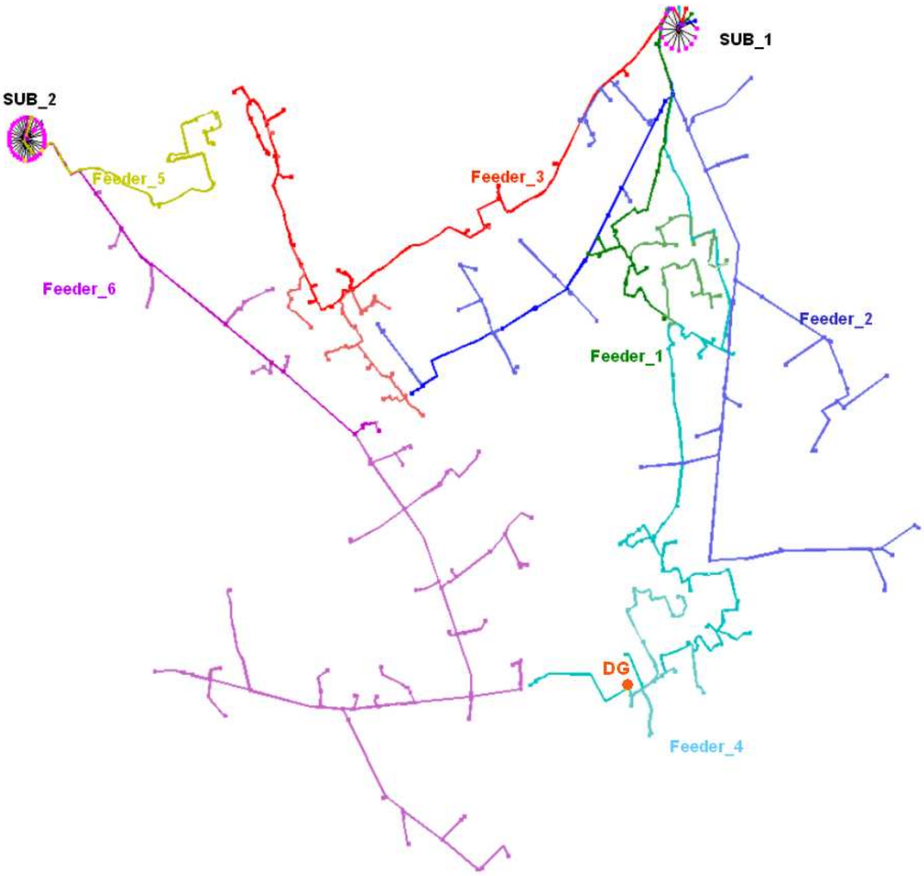


Figure 4 : Network topology

MV feeder	HV/MV substation	HV/MV transformer	Maximal Transit (kVA)	Length (km)	Overhead length (km)	Number of LV clients	Maximal voltage drop (%)
Feeder_1	Sub_1	T311	4020.6	12.543	0	1924	1.04%
Feeder_2	Sub_1	T311	965	27.256	24.324	204	0.32%
Feeder_3	Sub_1	T312	5906.5	19.176	0	1635	2.09%
Feeder_4	Sub_1	T312	5833.2	23.072	0	1694	3.94%
Feeder_5	Sub_2	T001	3400.2	6.147	0	54	0.60%
Feeder_6	Sub_2	T002	1712.5	27.790	24.393	343	1.65%

Table 2 : Network characteristics

A Distributed Generator is connected to feeder 4. For all tests, it is assumed that this generator is monitored with a PQV sensor.

To define the real state of the network, a network simulator developed in Matlab is used. One can simulate the network steady state behaviour at different times using several load profiles for customers and producers. The simulation includes the modelling of existing voltage and var control regulations at the HV/MV substation. The result of the power flow obtained with the network simulator is considered as the real state of the network. Measurements are modeled using the real value calculated by the power flow simulation to which a gaussian error is applied. This gaussian error depends on the accuracy of the simulated sensor. For the tests, we assumed that the sensors have a 1% error. In a similar way, pseudo-measurements are centered on the mean value[2] of the load and have a gaussian error of 50%.

For each DSE case study, 100 estimations have been run with the same state of the network (only the random error of pseudo-measurements and real measurements are different from one estimation to another).

To analyse the accuracy of DSE results when a new sensor is installed in the network, two errors have been calculated:

- Mean error for variable "i" : it is the mean value of relative errors of all nodes (lines) and all estimations (case studies take into account 100 estimations).
- Maximum error for variable "i" : it is the maximum relative error of all nodes (lines) and all estimations (case studies take into account 100 estimations).

2. Impact of PQ sensors

This sensor measures the active and reactive power of loads (PQ load in Figure 5). For each MV feeder of the network a sensitivity analysis has been run. This analysis tries to determine the impact of each PQ sensor (all available positions are tested) on the accuracy of state variables. The initial configuration of sensors consists of a PQV sensor of 1% of accuracy at the beginning of the MV feeder as well as a PQV sensor for each Distributed Generation connected to the feeder. For all simulations in this paragraph PQ sensors are considered to have an accuracy of 1%.

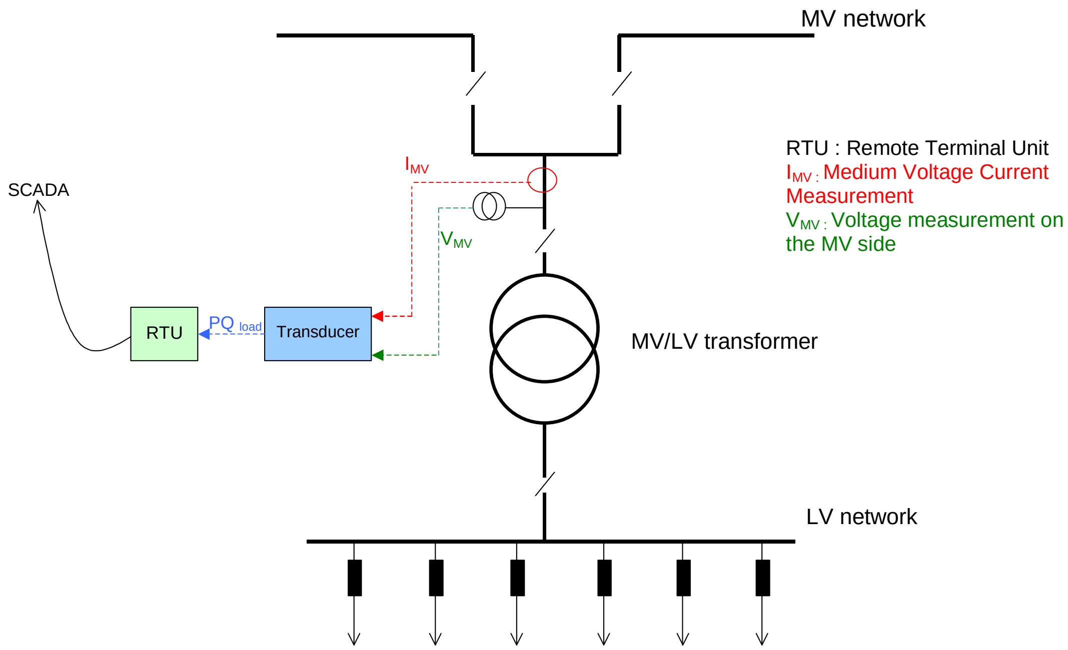


Figure 5 : Measure of active and reactive power of one load

Table 3, Figure 6 and Figure 7 summarize the results obtained for MV feeder 5.

[2] To determine the mean value, it is supposed that the load is at the maximum value during h hours and at 0 the rest of the time, so the mean value is: max. load * h/8760 (h depends of the type of the network)

These figures depict how PQ sensors have no impact on the estimation of voltage amplitudes. The results on voltage amplitude estimation obtained with an additional PQ sensor (at different MV/LV substations) are the same as those obtained with the initial configuration.

Regarding estimated PQ loads, the PQ sensor has a local impact : only the estimation of the measured load is improved with the sensor. This local impact explains the small variations of the mean and the maximum error for active and reactive power when only a PQ sensor is added (the estimation of the other loads is not improved).

Sensors configuration \ Estimated variable	Voltage amplitude		P load		Q load		Copper losses	
	Mean error	Max error	Mean error	Max error	Mean error	Max error	Mean error	Max error
Initial	0.271%	1.228%	37.30%	137.5%	36.96%	131.9%	1.15%	3.91%
Init + PQ_1	0.270%	1.198%	31.76%	120.1%	31.33%	145.9%	1.52%	4.26%
Init + PQ_2	0.272%	1.224%	35.64%	139.1%	35.31%	155.6%	1.23%	4.30%
Init + PQ_3	0.271%	1.240%	28.82%	144.9%	28.99%	143.0%	1.08%	3.63%
Init + PQ_4	0.271%	1.220%	35.17%	135.0%	34.81%	145.8%	1.15%	3.92%
Init + PQ_5	0.271%	1.238%	30.42%	141.4%	29.58%	151.0%	1.09%	3.65%
Init + PQ_6	0.272%	1.238%	30.61%	138.3%	30.50%	145.9%	2.07%	4.99%
Init + PQ_7	0.271%	1.224%	34.84%	136.6%	34.67%	148.0%	1.43%	3.84%
Init + PQ_8	0.271%	1.229%	31.89%	138.2%	31.38%	147.7%	1.15%	3.89%
Init + PQ_9	0.271%	1.228%	34.87%	137.3%	34.73%	131.9%	1.12%	3.67%

Table 3 : Impact of PQ sensors on estimated variables in MV feeder 5

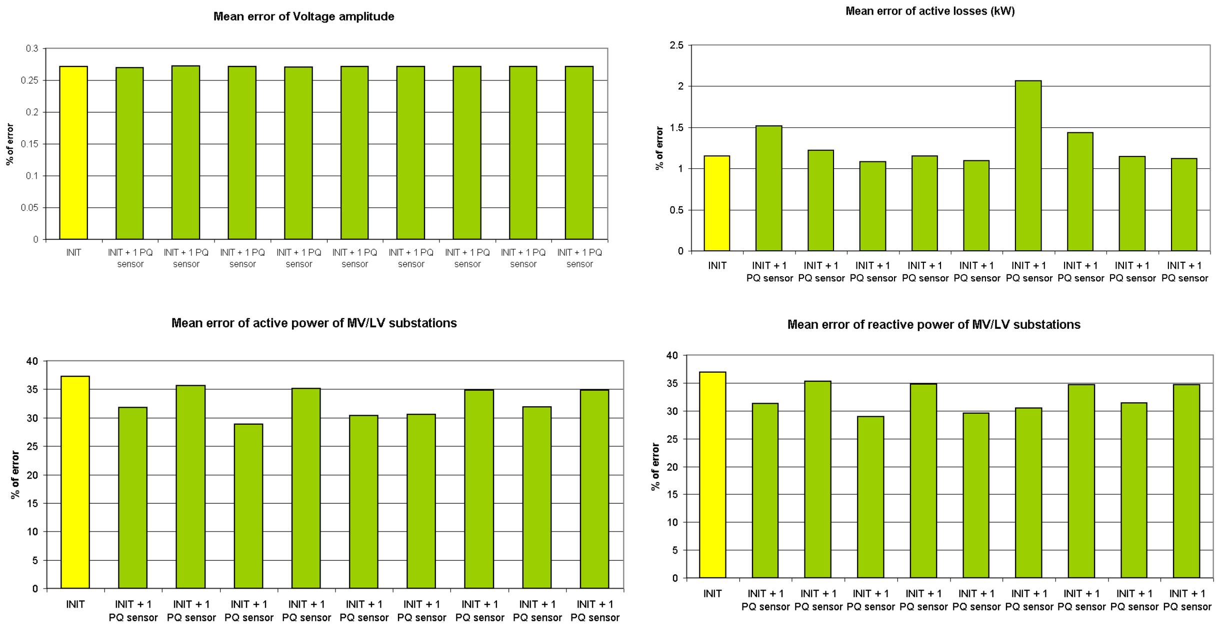


Figure 6 : Impact of PQ sensors on mean error of estimated variables in MV feeder 5

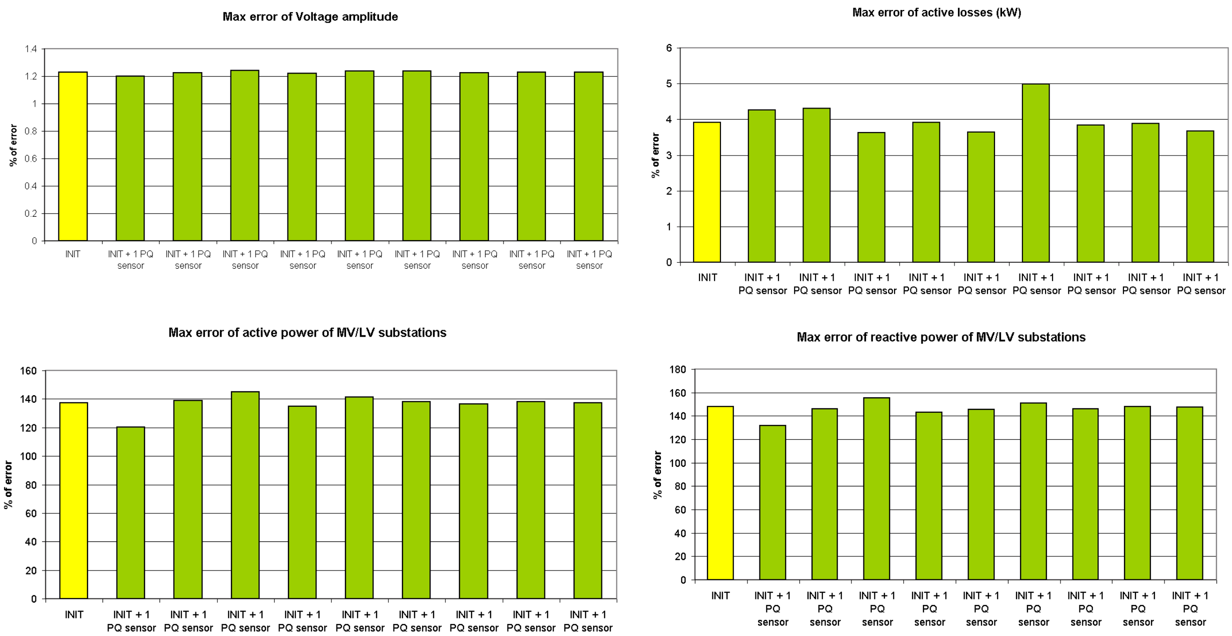
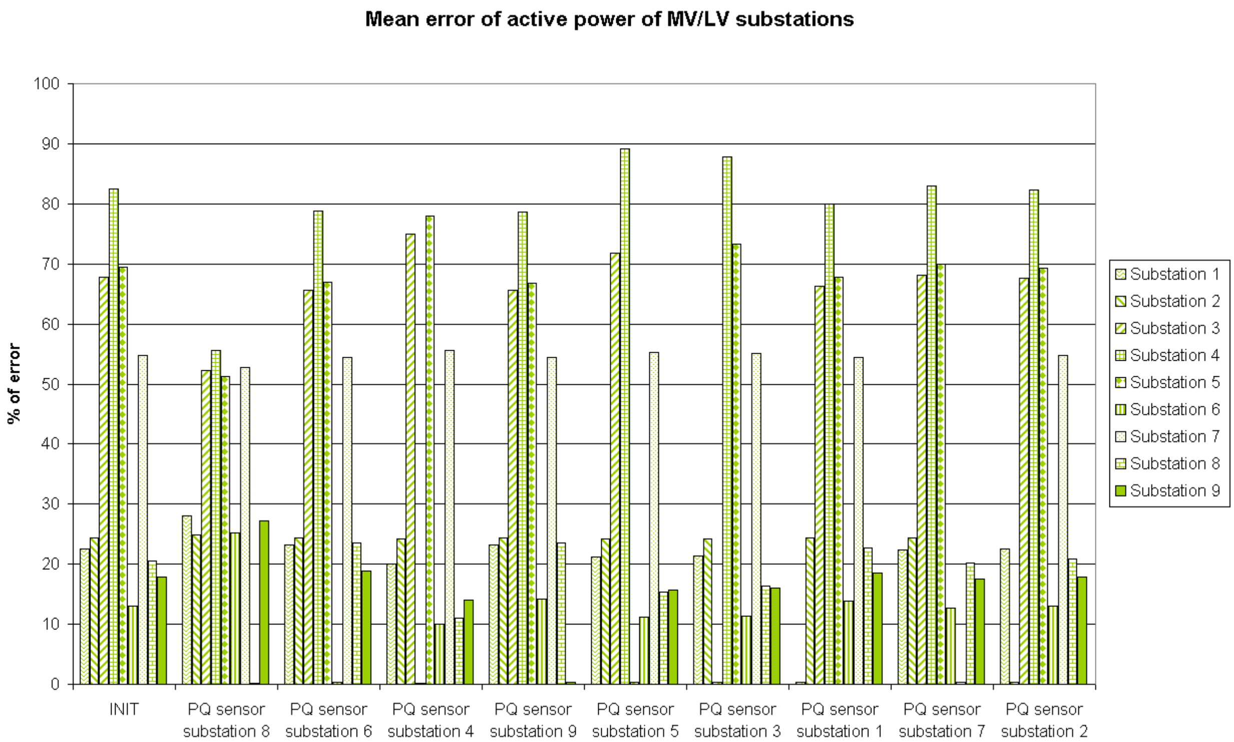


Figure 7 : Impact of PQ sensors on the maximum error of estimated variables in MV feeder 5

Figure 8 and Figure 9 detail the impact of PQ sensors in the estimated power of all MV/LV substation of MV feeder 5. It is possible to see how the estimated powers are only improved when a PQ sensor is placed in the considered MV/LV substation.



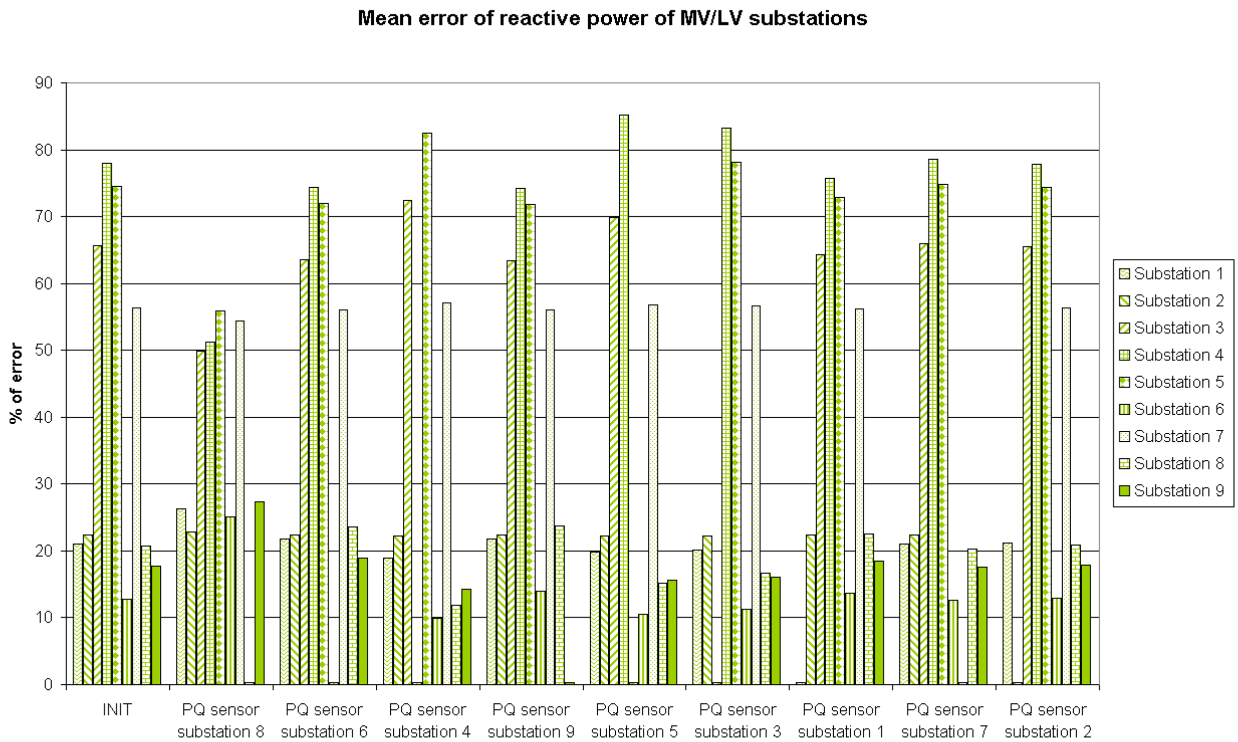
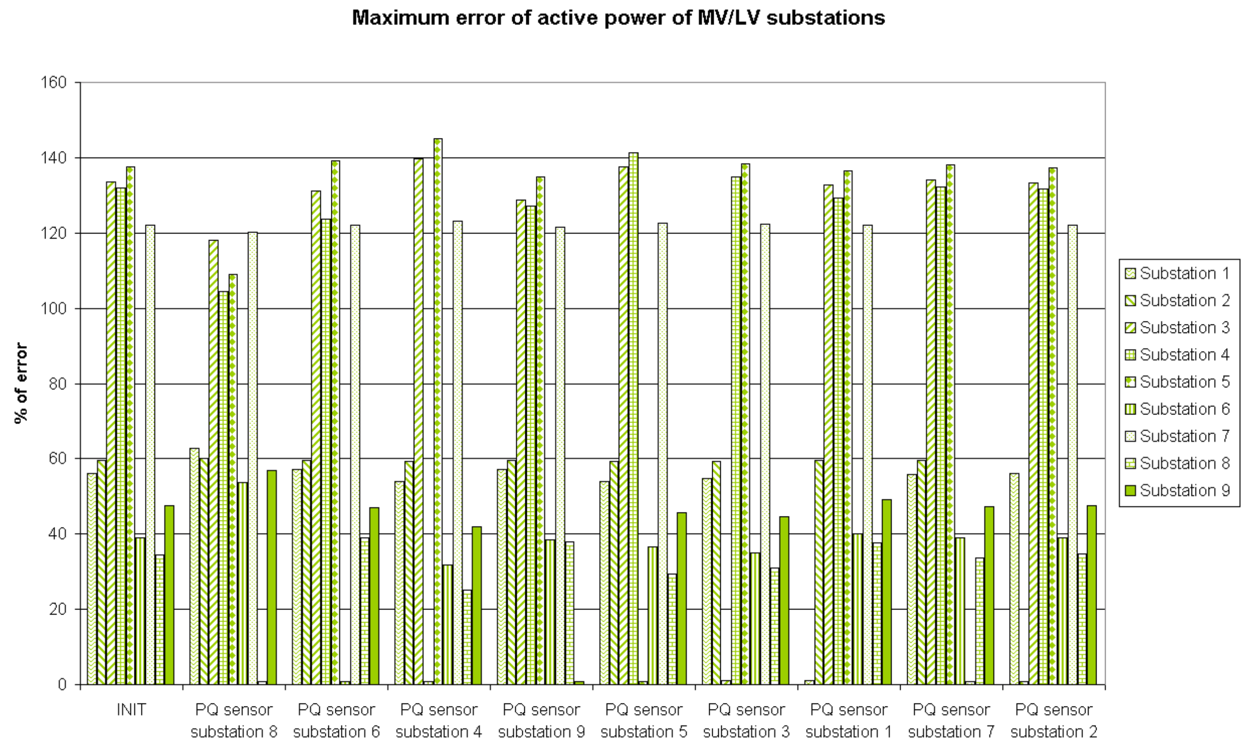


Figure 8 : Impact of PQ sensors on the mean error of estimated power of MV/LV substations in MV feeder 5



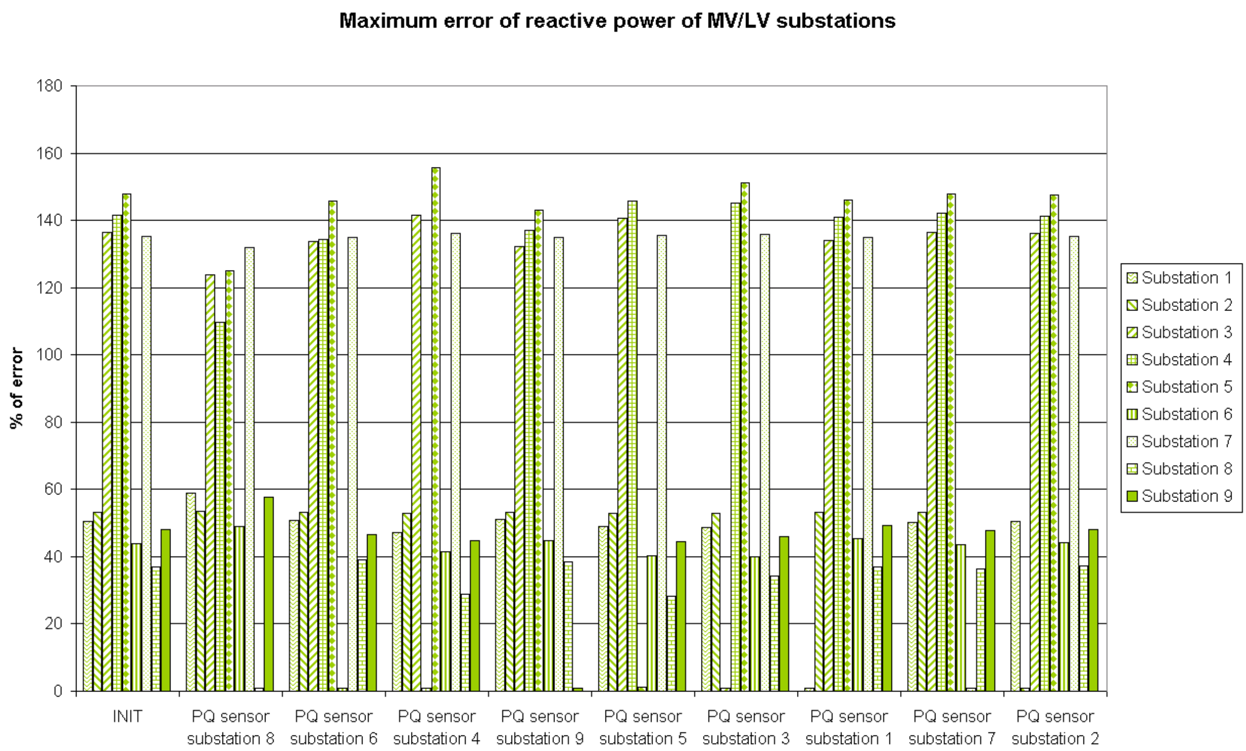


Figure 9 : Impact of PQ sensors on the maximum error of estimated power of MV/LV substations in MV feeder 5

Tests run for the other feeders lead to the same conclusions (for example, results for MV feeder 1 are in Appendix 1).

The impact of PQ sensors in state variables can be summarized as follows:

- **Voltage amplitude : no impact of additional PQ sensors on the accuracy of the voltage amplitude (the results are the same as for the initial configuration).**
- **PQ loads : PQ sensors have an impact only on the accuracy of the load that they measure. This local impact explains why mean error and maximum error changes but it is not highly decreased with only one sensor.**
- **Copper losses: PQ sensors have no impact on the estimation of Copper losses.**

These results imply that if good accuracy is required for active and reactive power of a given load, it is necessary to place a sensor at this node.

3. Impact of V sensors

These sensors measure voltage amplitude at the node where they are installed. For each node where a sensor is placed, a simulation has been run to determine the accuracy of DSE results with this new voltage sensor. All sensors have been considered to have an accuracy of 1%.

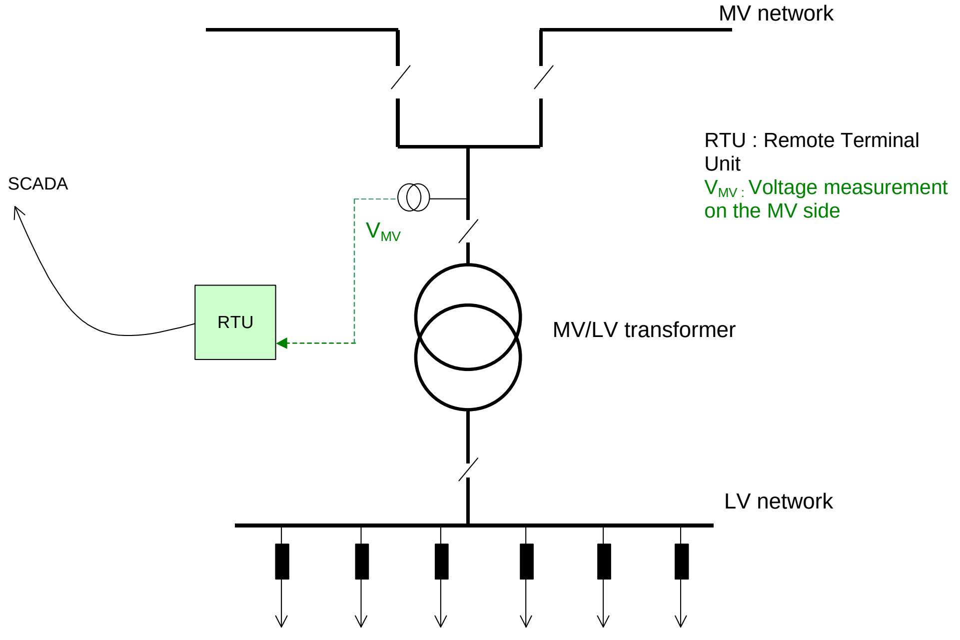


Figure 10 : Measure of voltage amplitude at one node

Results obtained for feeder 5 are summarized in Table 4, Figure 11 and Figure 12.

It is possible to observe that voltage sensors have neither impact on active and reactive power of loads nor on copper losses.

However, voltage sensors have a global impact on the results of voltage amplitude estimation (estimated voltage amplitudes are improved in all nodes when a voltage sensor is placed in the network).

Estimated variable / Sensors configuration	Voltage amplitude		P load		Q load		Copper losses	
	Mean error	Max error	Mean error	Max error	Mean error	Max error	Mean error	Max error
Initial	0.271%	1.228%	37.3%	137.5%	36.96%	147.8%	1.15%	3.91%
Init + V_1	0.175%	0.683%	37.3%	137.5%	36.96%	148.1%	1.10%	3.77%
Init + V_2	0.205%	0.722%	37.3%	137.5%	36.96%	147.9%	1.07%	3.59%
Init + V_3	0.202%	0.858%	37.3%	137.5%	36.96%	147.7%	1.14%	3.50%
Init + V_4	0.193%	0.706%	37.3%	137.5%	36.96%	147.7%	1.14%	3.67%
Init + V_5	0.177%	0.626%	37.3%	137.5%	36.96%	148.0%	1.09%	3.63%
Init + V_6	0.188%	0.605%	37.3%	137.5%	36.96%	147.8%	1.17%	3.99%
Init + V_7	0.182%	0.665%	37.3%	137.5%	36.96%	147.9%	1.08%	3.58%
Init + V_8	0.182%	0.607%	37.3%	137.5%	36.96%	147.9%	1.10%	3.04%
Init + V_9	0.191%	0.564%	37.3%	137.5%	36.96%	147.8%	1.04%	3.47%

Table 4 : Impact of V sensors on estimated variables in MV feeder 5

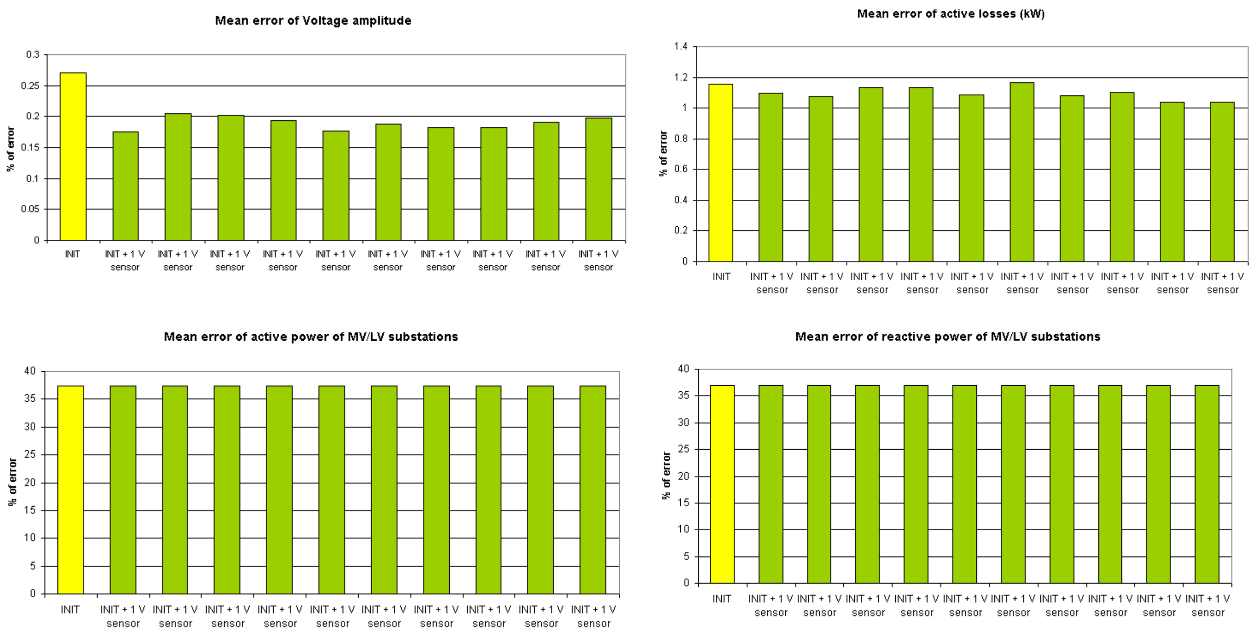


Figure 11 : Impact of V sensors on mean error of estimated variables in MV feeder 5

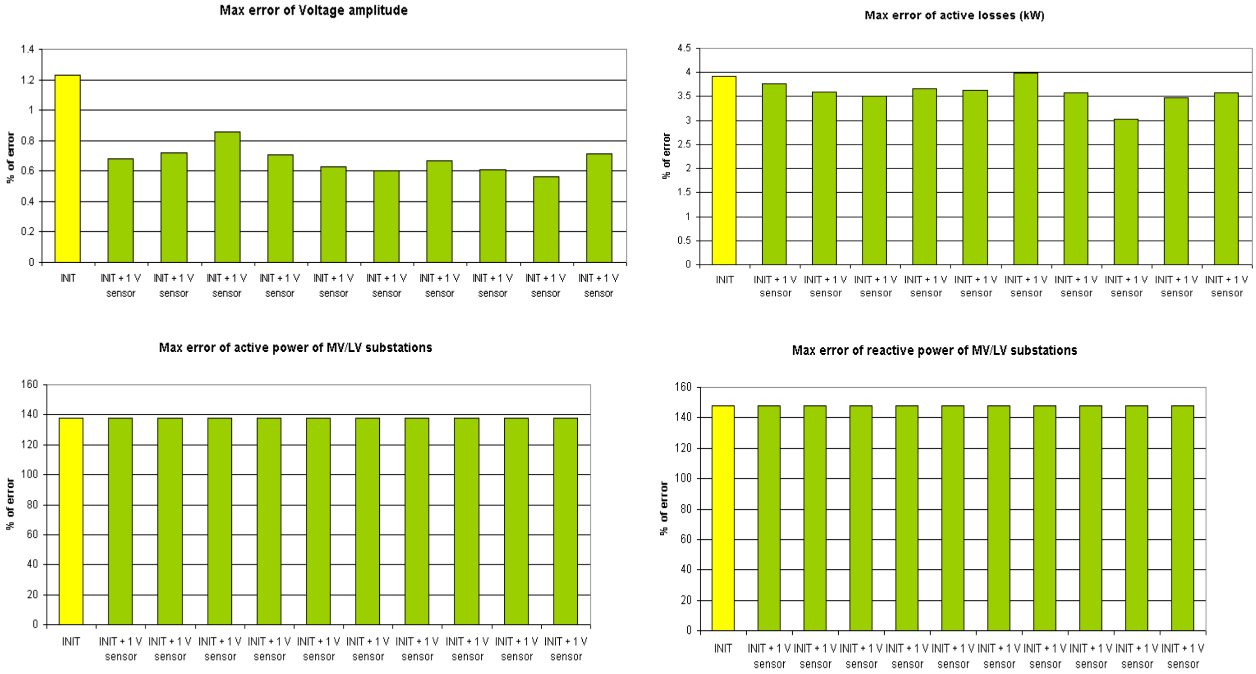


Figure 12 : Impact of V sensors on maximum error of estimated variables in MV feeder 5

The results obtained for feeder 5 are confirmed with the results obtained for the other feeders (for example, results for MV feeder 1 are in Appendix 1).

The impact of V sensors on estimated variables can be summarized as follows:

- **Voltage amplitude : a voltage amplitude sensor has a global impact on estimated voltage amplitudes and the impact is mostly the same for all positions.**
- **PQ loads : there is no influence of a voltage sensor on active and reactive power estimations.**
- **Copper losses: there is no impact of voltage amplitude sensors on estimated copper losses in the network.**

These results imply that if a better accuracy is needed for estimated voltages, a voltage sensor has to be placed at any node of the network.

4. Impact of current sensors

These sensors measure the amplitude of the current transiting in an MV line (Figure 13). All lines have been tested (one by one) to determine the impact of a current sensor on the estimated results and check if one placement leads to more accurate estimated results than another. For all tests, sensors are considered to have an accuracy of 1%.

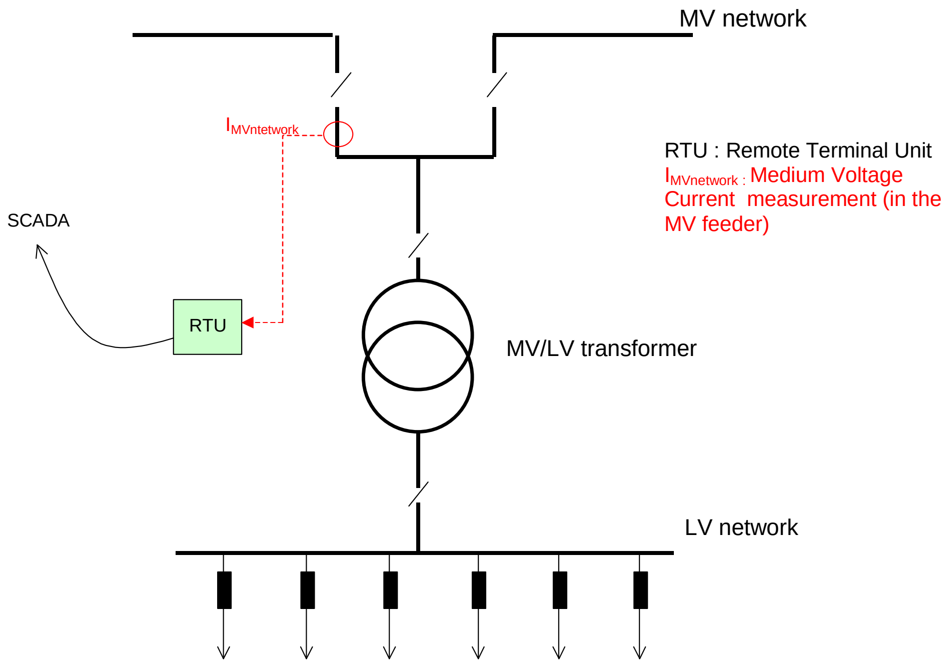


Figure 13 : Measure of current transiting in an MV line

Table 5, Figure 15 and Figure 16 summarize the results obtained for the sensitivity analysis of the current sensors impact for feeder 5.

These figures show that current sensors have no impact on estimated voltage amplitudes (the results with a current sensor are the same as for the initial sensors' configuration).

Most current sensors have no impact on estimated active and reactive power of loads. The only current sensor that has an impact on power loads' estimation is when the current sensor measures directly the current of the load (Figure 14). In this particular case, a local impact appears (improvement of estimation of load 1).

The impact of one current sensor on Copper losses is not important, as it only improves the estimation of the current of the line (local impact).

The results of the other MV feeders have the same behaviour as MV feeder 5 (for example, results for MV feeder 1 are in Appendix 1).

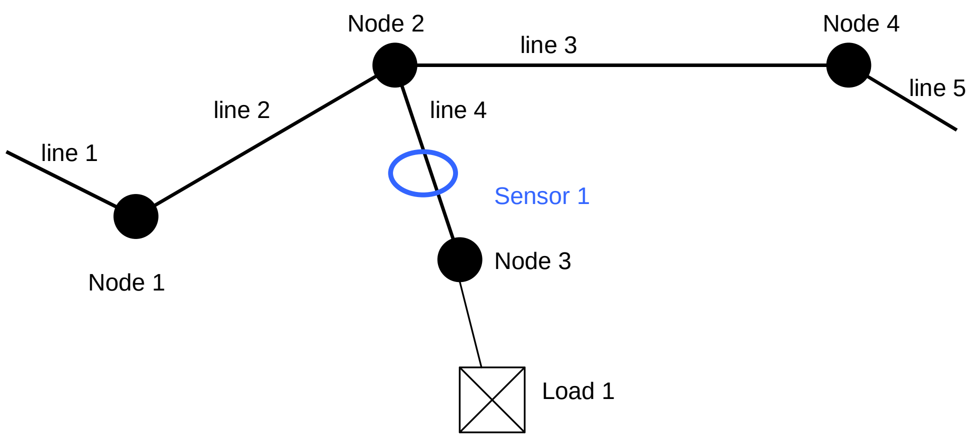


Figure 14 : Current sensor with an impact on estimated active and reactive power of a load

Estimated variable / Sensors configuration	Voltage amplitude		P load		Q load		Copper losses	
	Mean error	Max error	Mean error	Max error	Mean error	Max error	Mean error	Max error
Initial	0.271%	1.228%	37.3%	137.5%	36.96%	147.8%	1.153%	3.911%
Init + I_1	0.239%	0.765%	37.3%	137.5%	36.96%	147.7%	1.007%	2.956%
Init + I_2	0.287%	1.035%	35.6%	136.8%	36.75%	147.8%	1.368%	3.166%
Init + I_3	0.290%	1.078%	35.3%	136.3%	36.69%	147.7%	1.596%	3.115%
Init + I_4	0.286%	1.305%	36.1%	137.5%	36.78%	147.8%	1.801%	3.593%
Init + I_5	0.271%	1.210%	37.2%	134.7%	36.95%	147.0%	0.890%	3.015%
Init + I_6	0.272%	1.208%	36.8%	136.2%	36.85%	142.7%	1.087%	3.924%
Init + I_7	0.276%	1.291%	31.6%	119.7%	36.12%	144.5%	1.646%	4.466%
Init + I_8	0.273%	1.236%	36.0%	139.8%	36.84%	148.0%	1.221%	4.307%
Init + I_9	0.271%	1.216%	32.5%	138.1%	37.22%	147.8%	1.145%	3.880%

Table 5 : Impact of current sensors on estimated variables in MV feeder 5

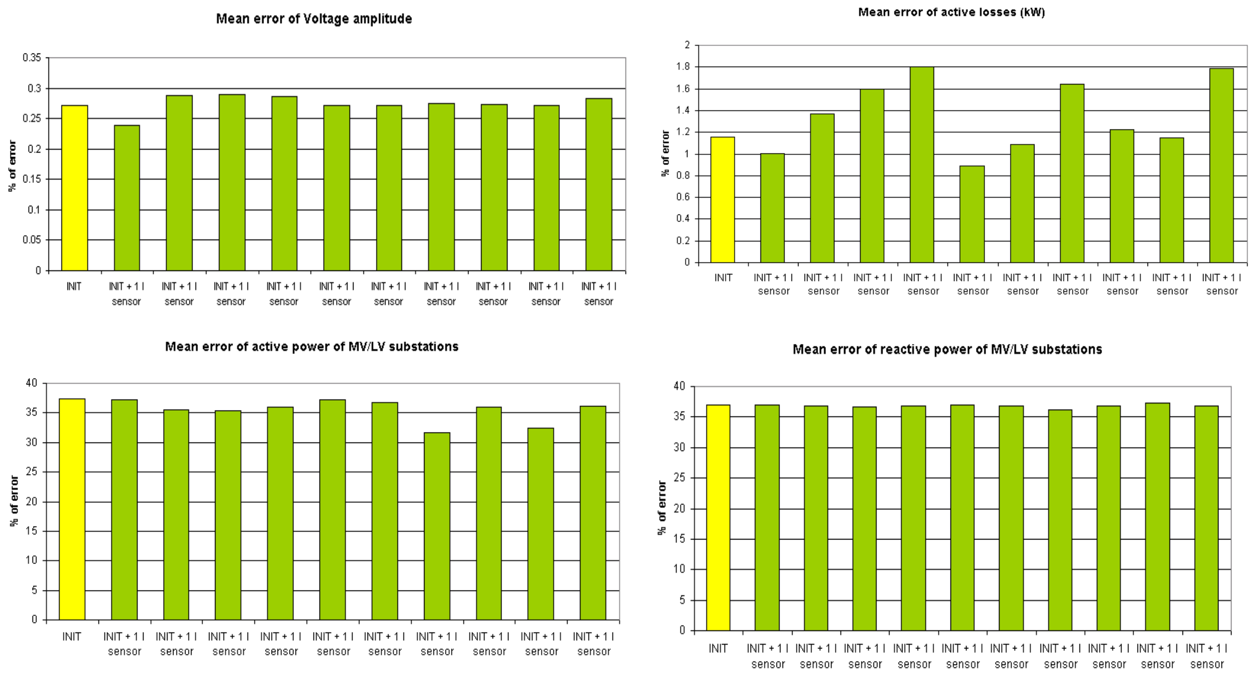


Figure 15 : Impact of current sensors on mean error of estimated variables in MV feeder 5

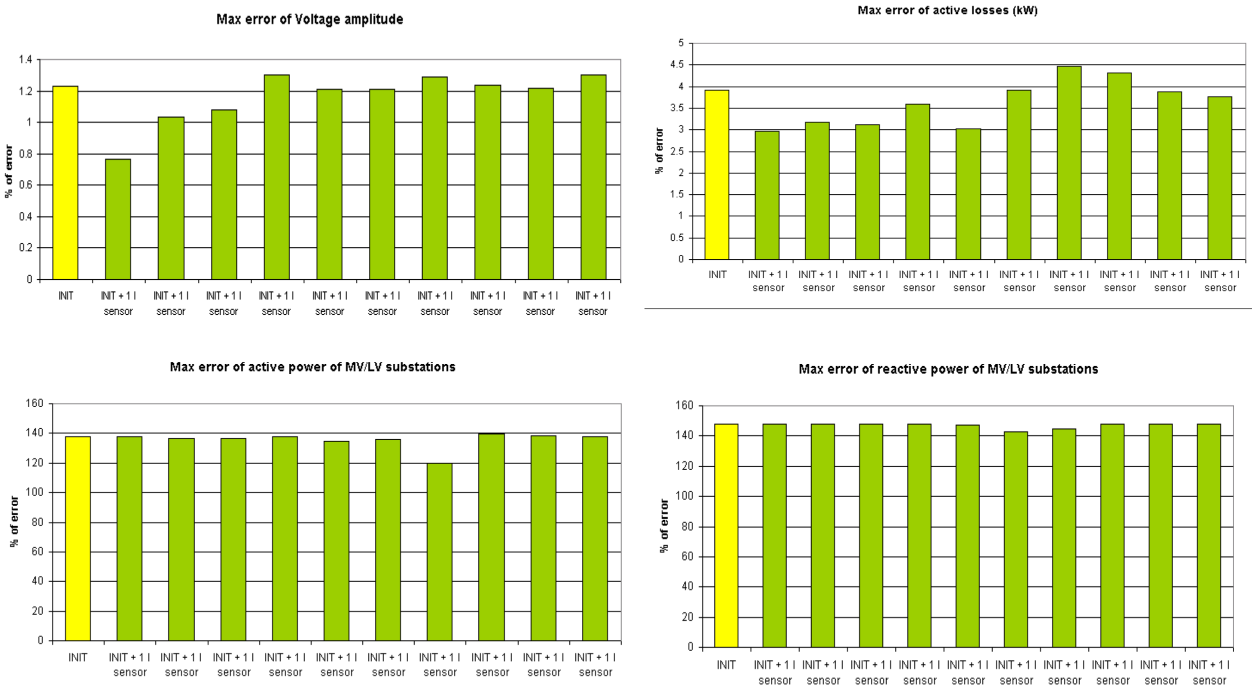


Figure 16 : Impact of current sensors on maximum error of estimated variables in MV feeder 5

The impact of current sensors on estimated magnitudes can be summarized as follows:

- **Voltage amplitude : there is no impact of a current sensor on estimated voltage amplitudes.**
- **PQ loads : in general, there is no improvement of estimated active and reactive power of loads when a current sensor is placed in the network. The only situation where a current sensor improves PQ load estimation, is when the current sensor measures directly the current absorbed by the load.**
- **Copper losses: one current sensor has not an important impact on copper losses as it only improves the estimation of the current of the line in which it is placed. If a current sensor is placed in each line, the estimation of copper losses will be improved.**

5. Impact of PQ flow sensors

These sensors measure the active and reactive power flow transiting in an MV line (PQ flow in Figure 17). For each MV feeder, a PQ flow sensor has been simulated in each line (tested one by one) to determine the impact of the sensor on the accuracy of DSE results.

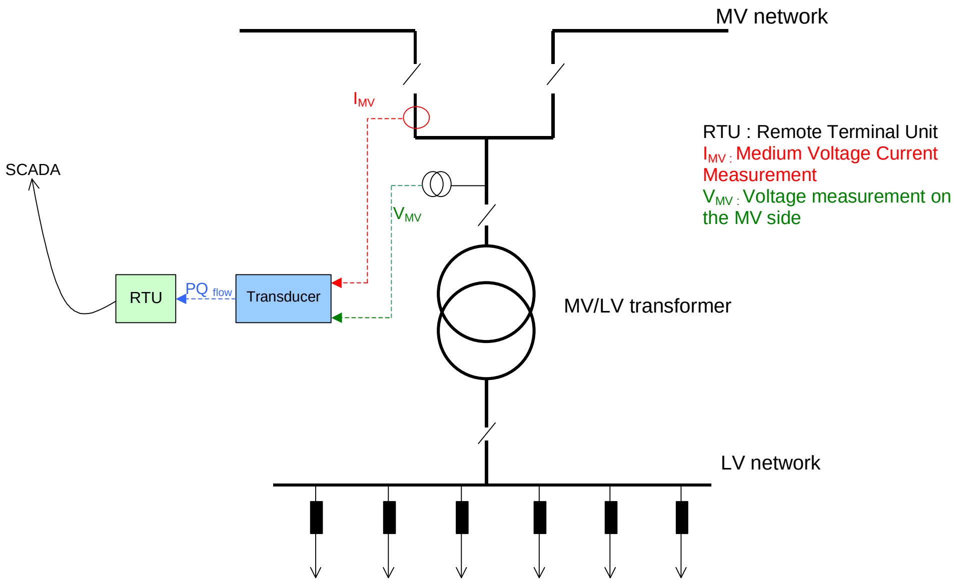


Figure 17 : Measure of active and reactive power flow in an MV line

Table 6, Figure 18 and Figure 19 summarize results for feeder 5.

The impact of this type of sensors is similar to the impact of current sensors. There is no impact of the PQ flow sensors on the estimated voltages (the mean and the maximum errors are the same as the ones obtained with the initial configuration).

Regarding estimated active and reactive power of loads, most PQ flow sensors have no impact. The only situation for which a PQ flow sensor improves the estimated power of the load is when the line with the sensor supplies only one load.

The impact on Copper losses is not important when only one PQ flow sensor is available, as it only improves the estimation of PQ flow in the measured line.

Estimated variable / Sensors configuration	Voltage amplitude		P load		Q load		Copper losses	
	Mean error	Max error	Mean error	Max error	Mean error	Max error	Mean error	Max error
Initial	0.271%	1.228%	37.298	137.498	36.955	147.797	1.153%	3.911%
Init + PQ flow$_1$	0.271%	1.228%	37.293	137.222	36.951	147.665	1.130%	3.784%
Init + PQ flow$_2$	0.277%	1.285%	35.469	136.795	35.056	145.811	1.274%	3.866%
Init + PQ flow$_3$	0.279%	1.281%	35.200	136.236	34.901	146.316	1.342%	3.933%
Init + PQ flow$_4$	0.268%	1.184%	36.128	136.469	35.692	148.883	1.677%	3.891%
Init + PQ flow$_5$	0.273%	1.235%	37.173	134.634	36.842	143.762	0.950%	3.057%
Init + PQ flow$_6$	0.272%	1.232%	36.832	135.941	36.427	139.598	1.094%	3.932%
Init + PQ flow$_7$	0.270%	1.199%	31.774	120.206	31.347	131.873	1.518%	4.234%
Init + PQ flow$_8$	0.272%	1.227%	36.037	139.957	35.684	146.129	1.213%	4.279%
Init + PQ flow$_9$	0.269%	1.176%	31.883	138.178	31.476	147.972	1.134%	3.774%

Table 6 : Impact of PQ flow sensors on estimated variables in MV feeder 5

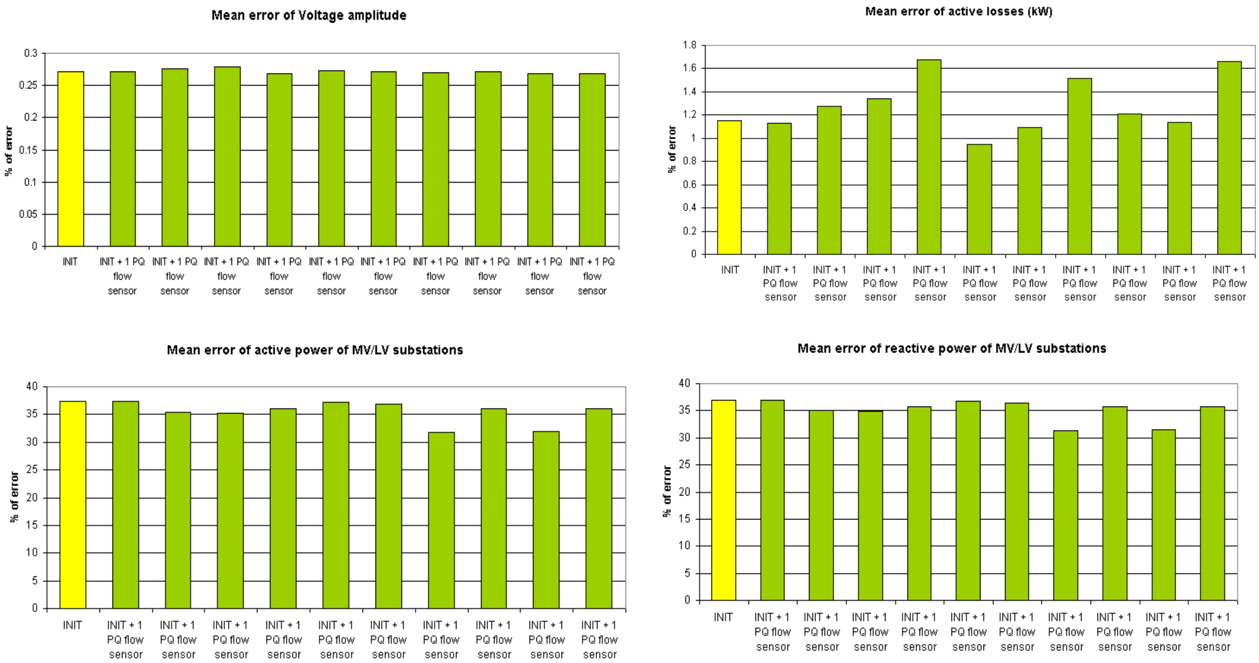


Figure 18 : Impact of PQ flow sensors on mean error of estimated variables in MV feeder 5

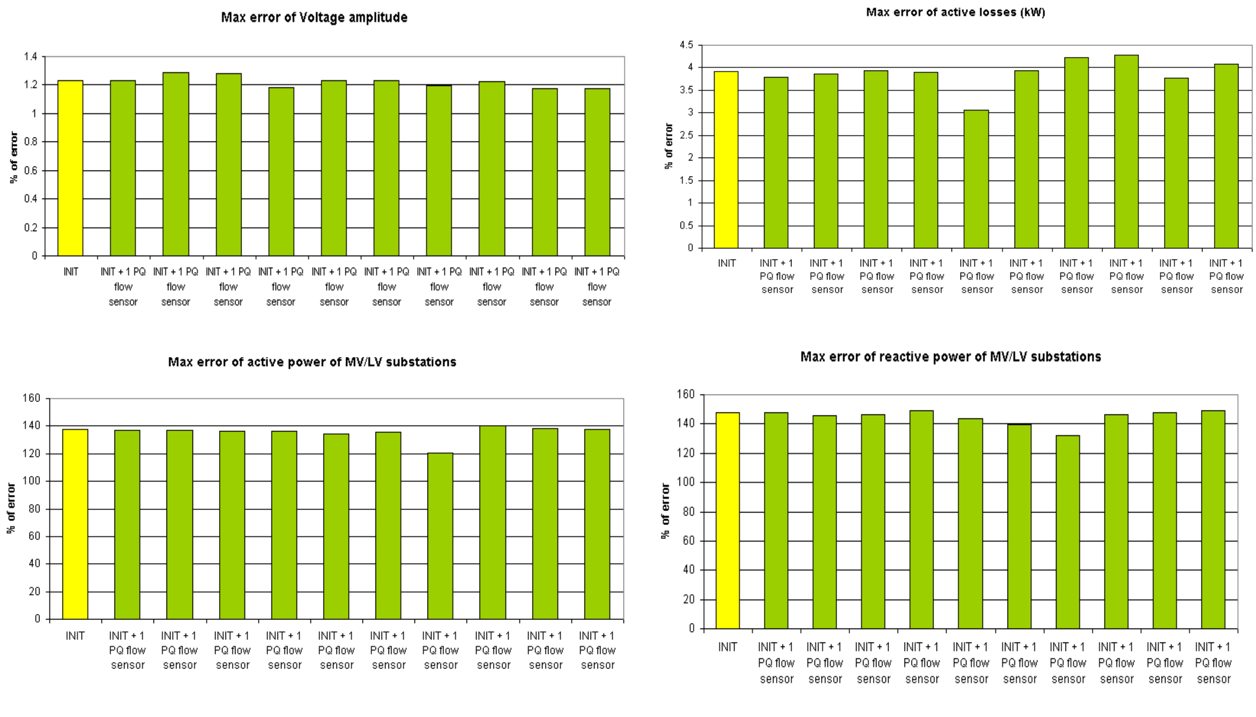


Figure 19 : Impact of PQ flow sensors on maximum error of estimated variables in MV feeder 5

The results obtained for the other MV feeders confirm the results for MV feeder 5 (for example, results for MV feeder 1 are in Appendix 1).

The impact of PQ flow sensors on estimated magnitudes can be summarized as follows:

- **Voltage amplitude : There is no impact of a PQ flow sensor on estimated voltage amplitudes.**
- **PQ loads : there is no impact of a PQ flow sensor on estimated loads' power except if the sensors measures a line that supplies only one load. In this case, the estimation of the active and reactive power of the load will be improved.**
- **Copper losses : one PQ flow sensor has no impact on Copper losses as it only improves the estimation of active and reactive power of the measured line. If several PQ flow sensors are placed in the network, the estimation of Copper losses will be improved.**

6. Impact of Voltage Phase sensors

These sensors measure the difference of phase between voltages of two nodes (Figure 20). In our case, it has been considered that all phases measurements are referred to the phase of voltage at the MV bus bar. For each node of the network, a simulation with a phase measurement at this point has been run.

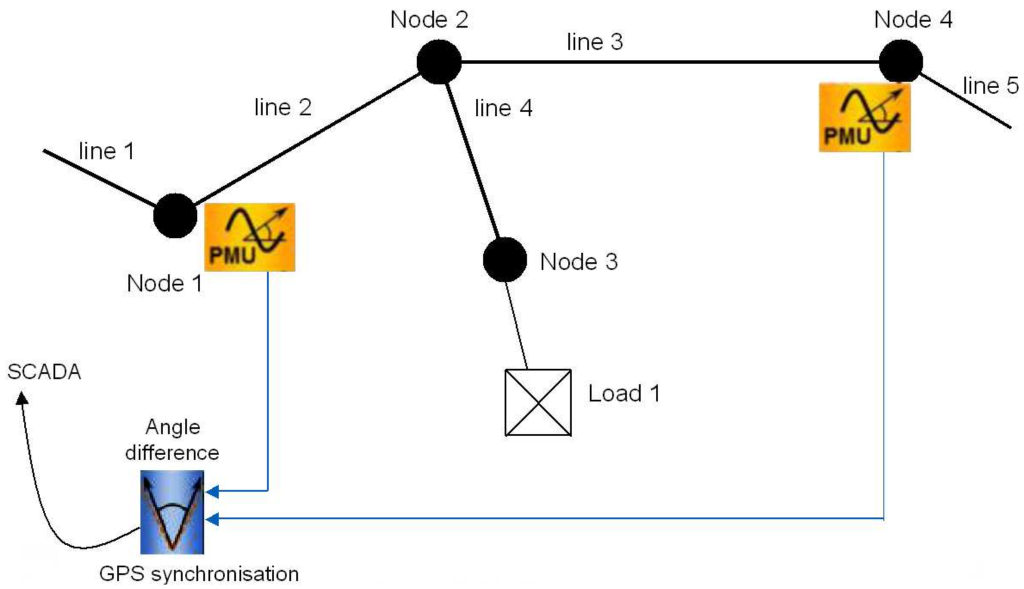


Figure 20 : Measure of Voltage phase angle

Table 7, Figure 21 and Figure 22 summarize the results obtained for MV feeder 5.

These results show that the Voltage Phase sensors can have an impact on estimated voltage amplitudes depending on its position.

It is also possible to see that there is no impact on estimated active and reactive power of loads.

It is also possible to observe that estimated Copper losses are improved when a phase sensor is installed. Its impact depends on its position.

Estimated variable / Sensors configuration	Voltage amplitude		P load		Q load		Copper losses	
	Mean error	Max error	Mean error	Max error	Mean error	Max error	Mean error	Max error
Initial	0.271 %	1.228 %	37.3 %	137.5 %	36.96 %	147.8 %	1.153 %	3.911 %
Init + $Phase_1$	0.174 %	0.580 %	37.3 %	137.5 %	36.96 %	147.8 %	0.910 %	3.373 %
Init + $Phase_2$	0.187 %	0.888 %	37.1 %	137.3 %	37.06 %	147.9 %	0.654 %	1.720 %
Init + $Phase_3$	0.211 %	1.021 %	36.9 %	137.2 %	37.17 %	148.1 %	0.604 %	1.943 %
Init + $Phase_4$	0.236 %	1.041 %	37.3 %	136.4 %	36.96 %	148.2 %	0.578 %	1.775 %
Init + $Phase_5$	0.244 %	1.032 %	37.3 %	134 %	36.97 %	149.2 %	0.559 %	1.826 %
Init + $Phase_6$	0.248 %	1.042 %	37.3 %	134.1 %	36.96 %	149.2 %	0.574 %	1.903 %
Init + $Phase_7$	0.248 %	1.036 %	37.3 %	134 %	36.96 %	149.2 %	0.581 %	1.944 %
Init + $Phase_8$	0.236 %	1.045 %	37.29 %	136.5 %	36.96 %	148.2 %	0.582 %	1.723 %
Init + $Phase_9$	0.234 %	1.033 %	37.29 %	136.6 %	36.96 %	148.2 %	0.573 %	1.716 %
Init + $Phase_{10}$	0.228 %	0.998 %	37.25 %	136.7 %	36.98 %	148.2 %	0.538 %	1.552 %

Table 7 : Impact of Voltage phase sensors on estimated variables in MV feeder 5

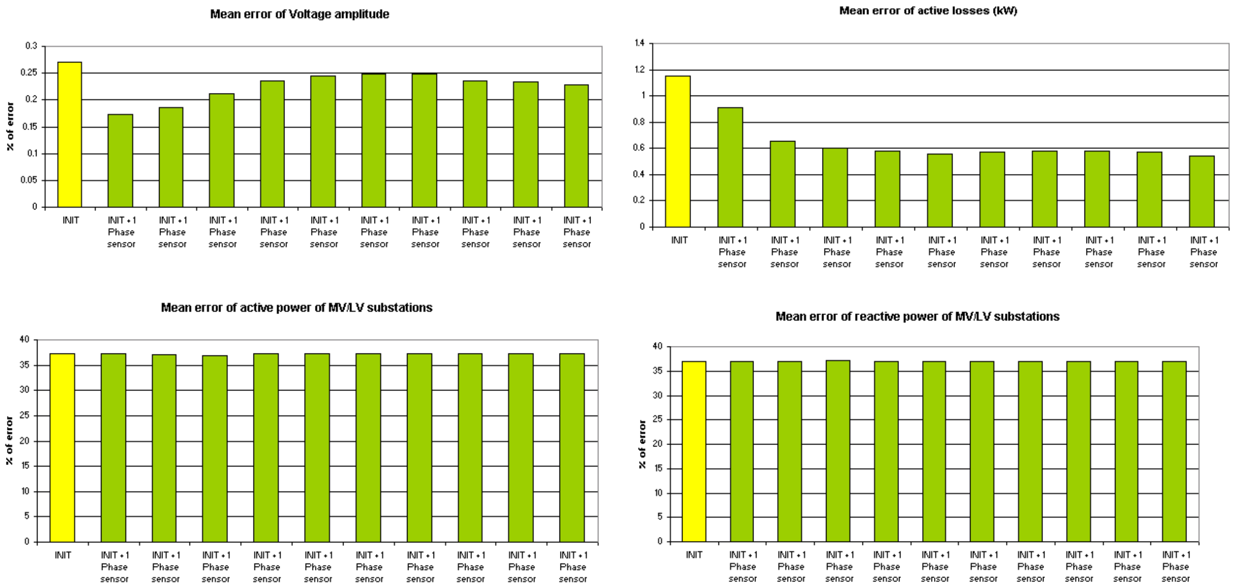


Figure 21 : Impact of Voltage Phase sensors on mean error of estimated variables in MV feeder 5

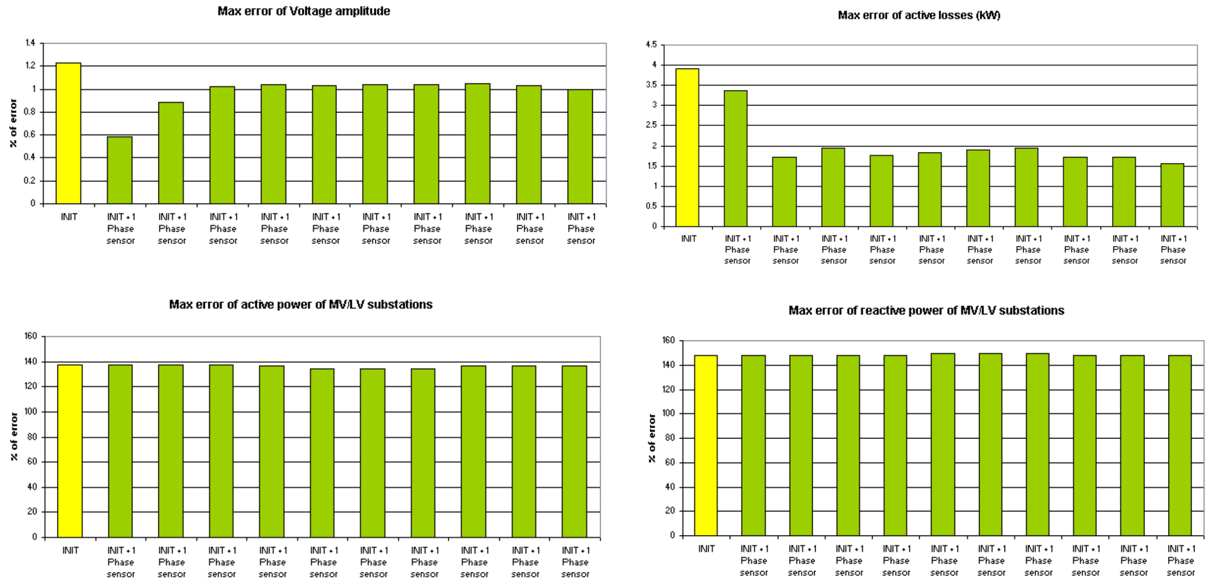


Figure 22 : Impact of Voltage Phase sensors on maximum error of estimated variables in MV feeder 5

The results obtained for the other MV feeders confirm the results for MV feeder 5 (for example, results for MV feeder 1 are in Appendix 1).

The impact of Voltage Phase sensors on estimated magnitudes can be summarized as follows:

- **Voltage amplitude : Voltage phase sensors can improve estimated voltages amplitudes. The impact depends on the position of the sensor.**
- **PQ loads : There is no impact of Voltage Phase sensors on estimated active and reactive power of loads.**
- **Copper losses : Voltage Phase sensors improve the estimation of Copper losses in the network.**

7. Relation between sensors and estimation improvements

The results obtained in previous paragraphs have led to conclusions on the impact of each type of sensor on estimated variables. These conclusions are summarized in Table 8.

Sensor type	**Estimated variables**			
	Voltage amplitude	Active power of loads	Reactive power of loads	Copper losses
PQ load	No impact	**Local impact**[3]	**Local impact**[3]	No impact
Voltage amplitude	**Global impact**	No impact	No impact	No impact
Current	No impact	No impact[4]	No impact[4]	No impact
PQ flow	No impact	No impact[4]	No impact[4]	No impact
Phase	**Global impact**	No impact	No impact	**Global impact**

Table 8 : Impact of different sensors' type in state variables

[3] The estimated values are only improved for the load that is measured.

[4] The estimation can be improved if the line in which the sensor is placed supplies only one load.

8. Impact of pseudo-measurements

The impact of load models on the accuracy of DSE results has been analysed to determine if an improvement of pseudo-measurements leads to an improvement of DSE results. To do so, pseudo-measurements have been calculated in four different ways:

- Mean value[5] of the load with a gaussian error of 50%
- $S_{load\ i}$ with a gaussian error of 50%
- $S_{load\ i}$ with a gaussian error of 30%
- $S_{load\ i}$ with a gaussian error of 15%

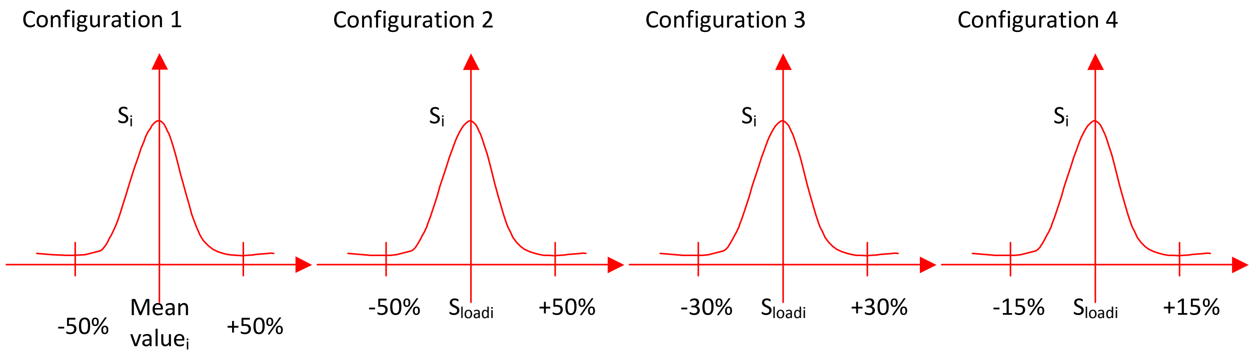


Figure 23 : Pseudo-measurements models for each configuration

$S_{load\ i}$ is calculated with the maximum value of all loads and the power flow at the beginning of the feeder[6].

$$S_{load\ i} = S_{flow\ at\ the\ beginning\ of\ MV\ feeder} \frac{S^*_{\max\ load\ i}}{\sum_{j \in non\ measured\ loads} S^*_{\max\ load\ j}}$$

[5] To determine the mean value, it is supposed that the load is at the maximum value during h hours and at 0 the rest of the time, so the mean value is: max. load * h/8760 (h depends of the type of the network)

[6] If a DG is connected to the feeder, its production is considered to determine the new "$S_{flow\ at\ the\ begining\ of\ the\ MV\ feeder}$". The relationships used to calculate this new value are:

$$P_{total} = P_{flow\ at\ the\ beginning\ of\ MV\ feeder} + \sum_{i \in DG} P_{DG\ i} \qquad Q_{total} = Q_{flow\ at\ the\ beginning\ of\ MV\ feeder} + \sum_{i \in DG} Q_{DG\ i}$$

$$S_{new\ flow\ at\ the\ beginning\ of\ MV\ feeder} = \sqrt{P_{total}^{\ 2} + Q_{total}^{\ 2}}$$

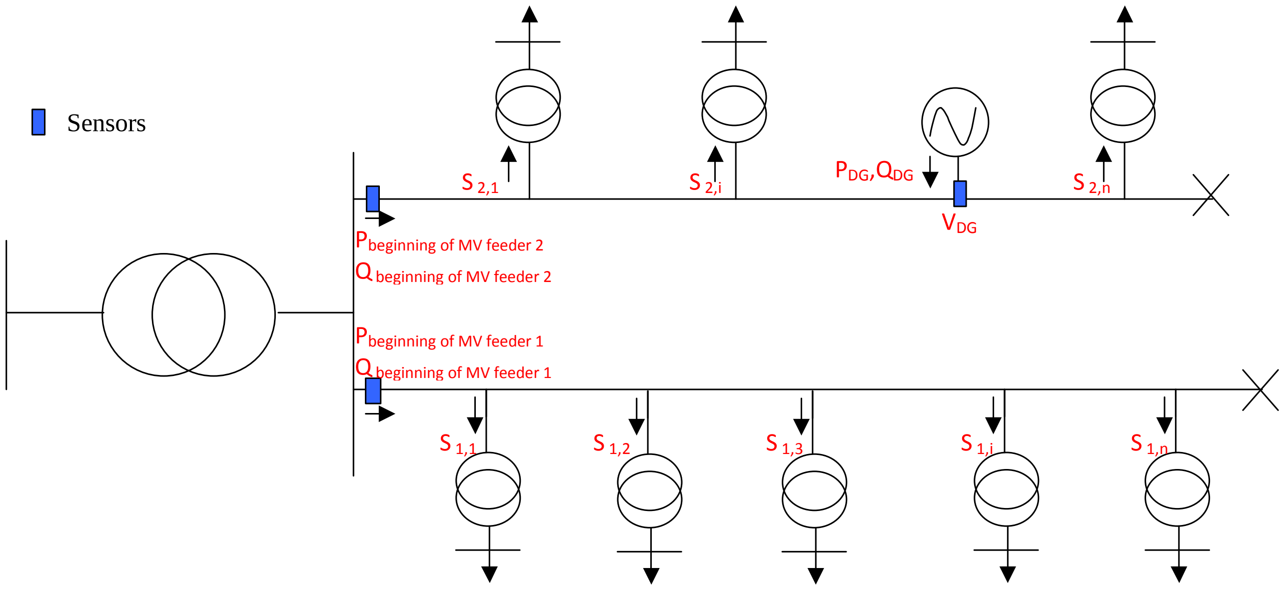


Figure 24 : Pseudo-measurements calculation

Regarding sensors, all the tests have been run with the same sensors' configuration : a PQV sensor at the beginning of the MV feeder[7] and PQV sensors at all remote controlled switches.

Table 9, Figure 25 and Figure 26 summarize results for MV feeder 5. For this MV feeder, the results of the four configurations are mostly the same. The only differences concern the maximum errors of active and reactive power of loads even if these differences are not really significant.

Estimated variable / Sensors configuration	Voltage amplitude		P load		Q load		Copper losses	
Pseudo-measurements	Mean error	Max error	Mean error	Max error	Mean error	Max error	Mean error	Max error
Mean value ± gaussian error 50%	0.271 %	1.228 %	37.30 %	137.5 %	36.96 %	147.8 %	1.153 %	3.911 %
S_{load} ± gaussian error 50%	0.271 %	1.201 %	40.44 %	154.5 %	40.13 %	166.2 %	1.183 %	3.590 %
S_{load} ± gaussian error 30%	0.272 %	1.210 %	39.53 %	124.2 %	39.26 %	131.1 %	0.950 %	2.957 %
S_{load} ± gaussian error 15%	0.277 %	1.254 %	39.28 %	101.4 %	39.12 %	104.7 %	0.842 %	2.757 %

Table 9 : Impact of pseudo-measurements on estimated variables in MV feeder 5

[7] For feeders with DG, a PQV sensor is placed at each DG.

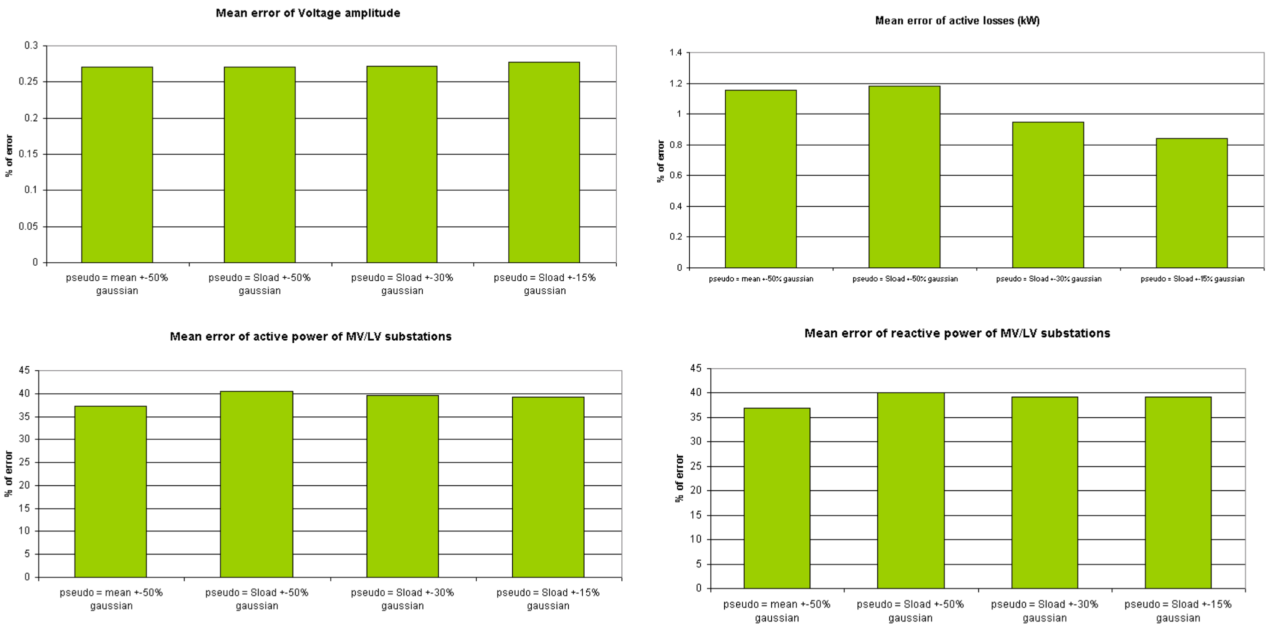


Figure 25 : Impact of pseudo-measurements on mean error of estimated variables in MV feeder 5

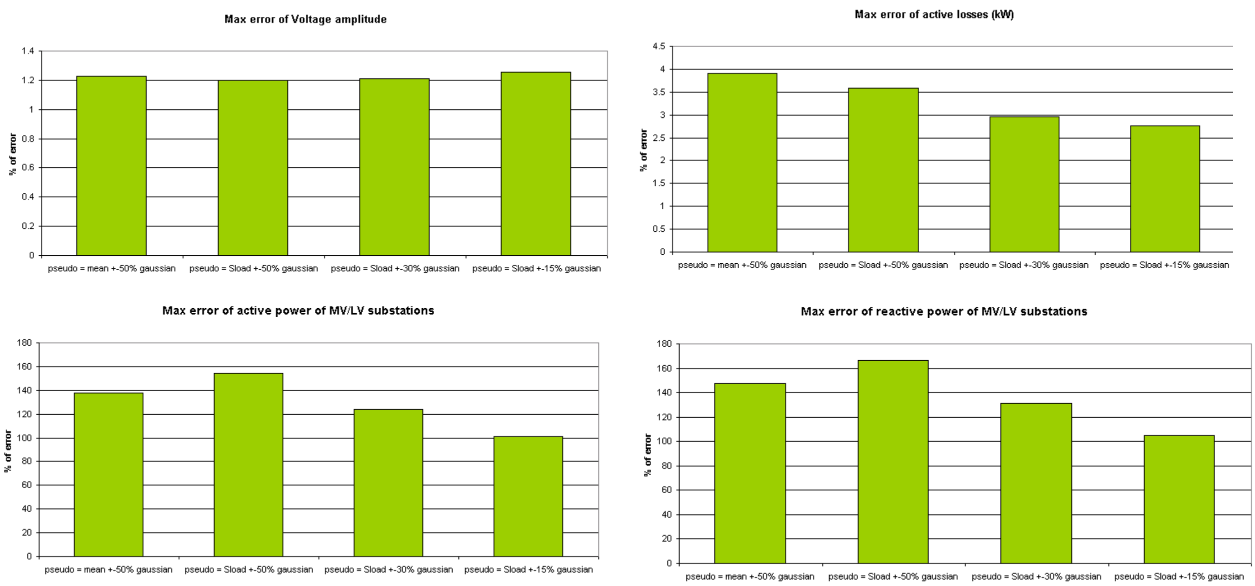


Figure 26 : Impact of pseudo-measurements on maximum error of estimated variables in MV feeder 5

The results for the other feeders show in some cases how the diminution of the pseudo-measurements errors (from 50% to 15%) can decrease the accuracy of voltage amplitudes as more confidence is attributed to unknown values (results for MV feeder 1 in Appendix 1 are an example of such case).

IV. Accuracy of DSE results regarding the number of sensors

Once the individual impact of different sensors has been analysed, the purpose of this chapter is to determine the number of sensors needed to obtain a required accuracy for different variables. To do so, several simulations have been run to determine DSE accuracy with different number of sensors. The sensitivity of DSE results to sensors' accuracy has also been analysed.

As described in chapter III, it is necessary to introduce voltage sensors in order to obtain accurate voltage amplitudes8 and it is necessary to use PQ sensors in order to obtain accurate load's active and reactive power. Therefore, it has been decided to use PQV sensors to obtain both, accurate voltage amplitudes and power loads. Two different positions of PQV sensors are available:

- remote controlled switches[9],
- MV/LV substations.

The placement rules were the following : firstly PQV sensors are placed in remote controlled switches; once all remote controlled switches of the MV feeder are instrumented, MV/LV substations are equipped with a PQV sensor. To decide the substation to be instrumented, the corresponding loads have been classed by decreasing electric moment[10].

To determine the impact of the accuracy of sensors on DSE results, three different accuracies have been considered :

- 0.5%,
- 1%,
- 2%.

1. Case study 1 : French network

For each MV feeder of the semi-urban French network that was chosen in section III. (Figure 4), all available positions have been sequentially equipped with a PQV sensor. Each simulation has the same sensor's configuration as the previous one and a new PQV sensor. In section 1.1, the results obtained for all feeders are depicted. Section 1.2 gives the number of sensors needed for each MV feeder depending on the accuracy required by automation functions. Finally in section 1.3, the use of previous results to determine the number of additional sensors required is explained.

1.1. Detailed results

- MV feeder 1

This feeder (Figure 27) has no remote controlled switches and 24 MV/LV substations. Figure 28 and Figure 29 illustrate how voltage accuracy is improved with the number of sensors. It is also possible to see that for a required accuracy the number of sensors needed depends highly on their accuracy[11].

[8] Phase sensors could also be used but their installation is more difficult so it has been decided that they will not be used.

[9] These sensors measure power flow in the line.

[10] The electric moment is defined as P*L. "P" is the loads' power and "L" the distance between the MV/LV substation and the MV bus bar.

[11] Introducing a PQV sensor with an accuracy of 0.5% is different from using 2 sensors of 1% accuracy.

Figure 27 : MV feeder 1

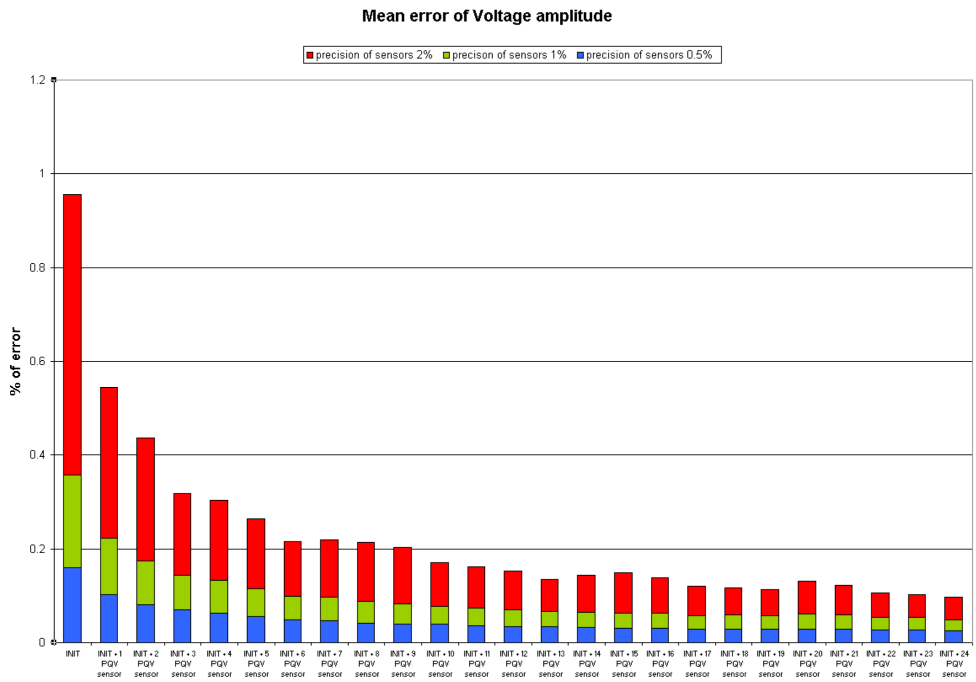


Figure 28 : Feeder 1 - Mean error of voltage amplitude with several sensors (accuracy 0.5%, 1%, 2%)

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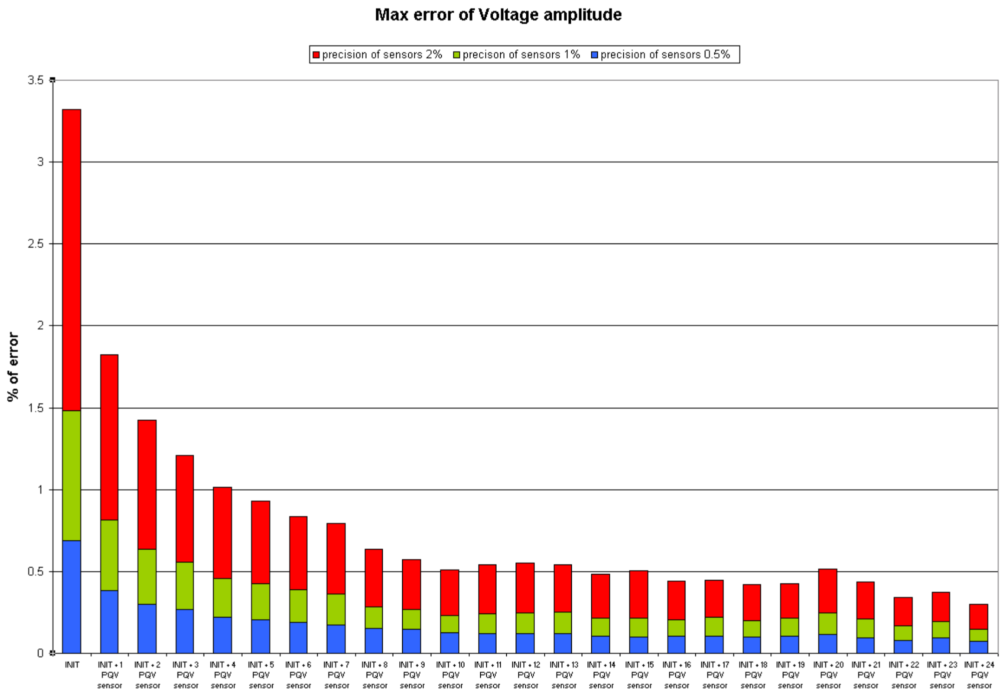

Figure 29 : Feeder 1 - Max error of voltage amplitude with several sensors (accuracy 0.5%, 1%, 2%)

In some cases, the results of the simulations show that the error increases when a new sensor is included. This augmentation is obtained only because a limited number of random configurations is used[12].

[12] In fact, only 100 random errors have been used for each sensors. If a higher number of errors is used, the error will always decrease when a new sensor is included.

- MV feeder 2

This feeder (Figure 30) has 2 remote controlled switches and 30 MV/LV substations. The same behaviour as for MV feeder 1 is observed. The accuracy of results is improved with the number of sensors and the number of sensors required for a certain accuracy of results depends on the accuracy of the sensors.

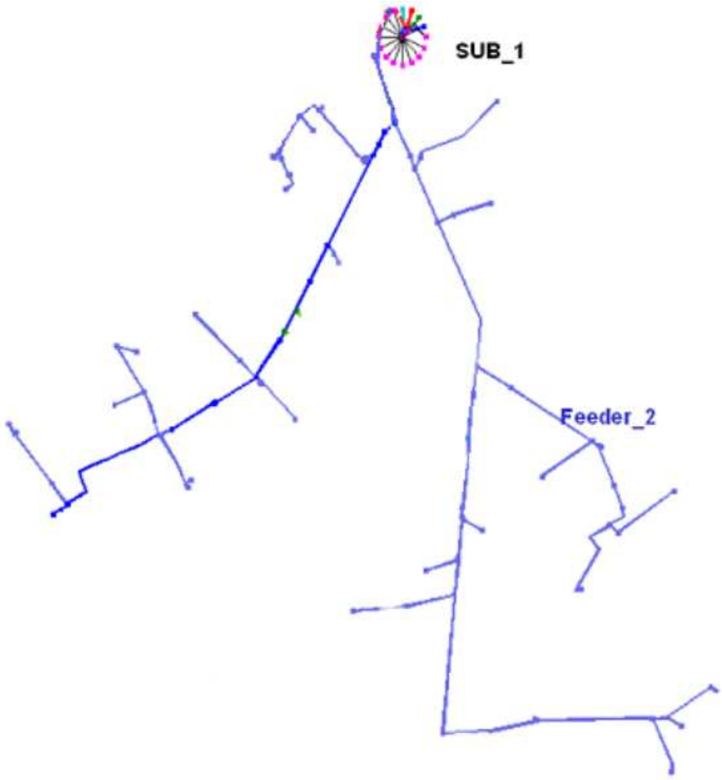

Figure 30 : MV feeder 2

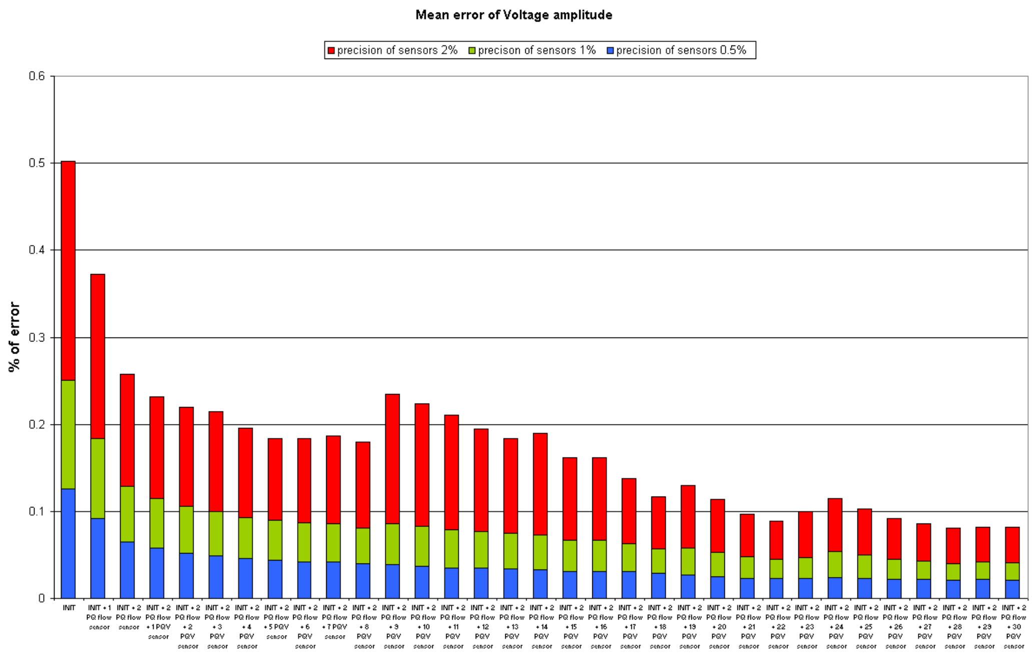

Figure 31 : Feeder 2 - Mean error of voltage amplitude with several sensors (accuracy 0.5%, 1%, 2%)

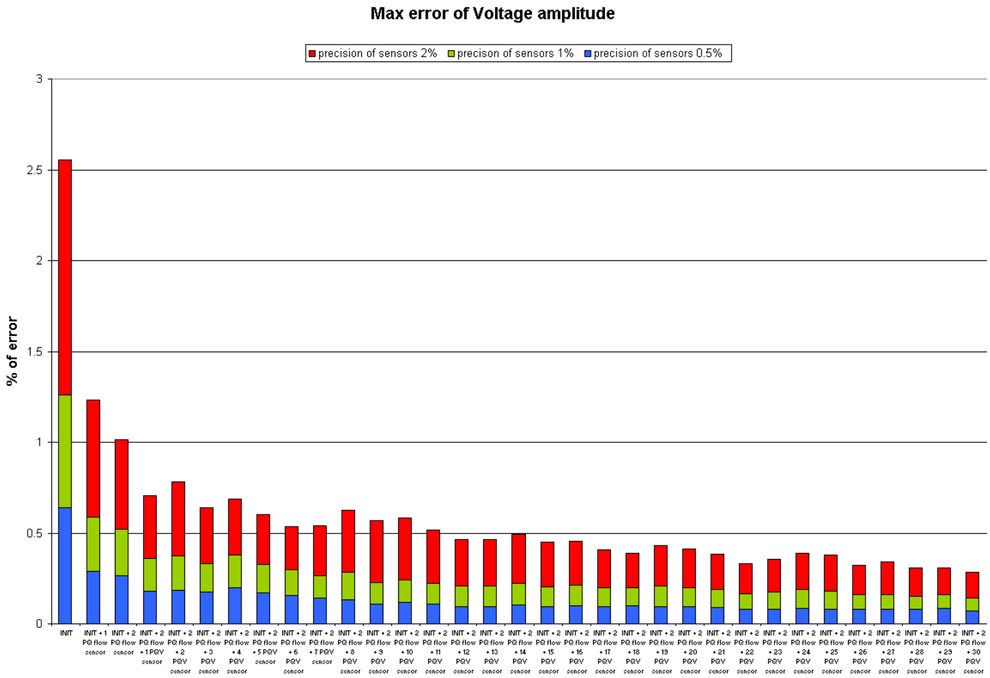

Figure 32 : Feeder 2 - Max error of voltage amplitude with several sensors (accuracy 0.5%, 1%, 2%)

- MV feeder 3

This feeder (Figure 33) has 1 remote controlled switches and 41 MV/LV substations. The same behaviour as for MV feeders 1 and 2 is observed.

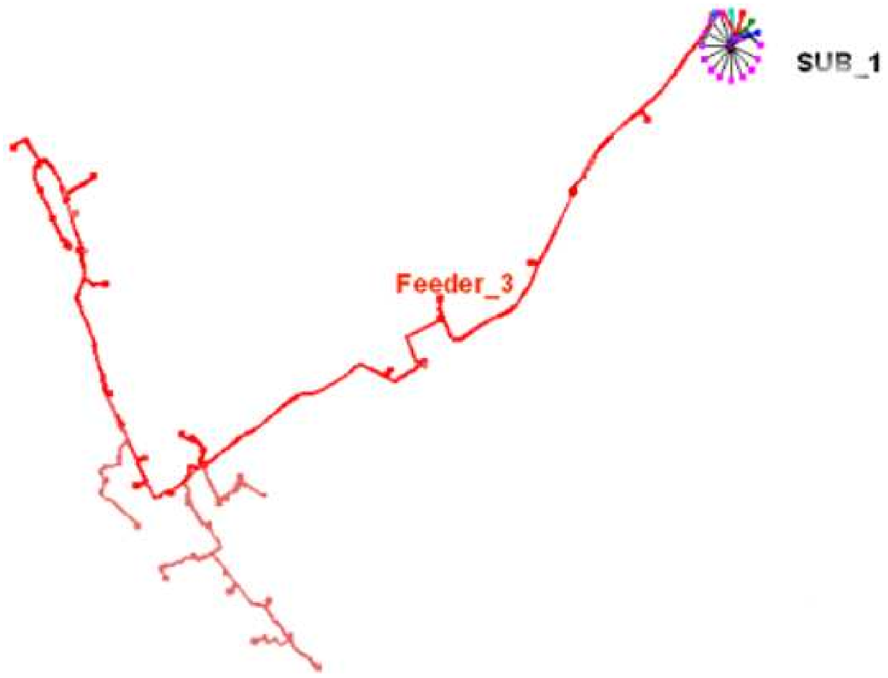

Figure 33 : MV feeder 3

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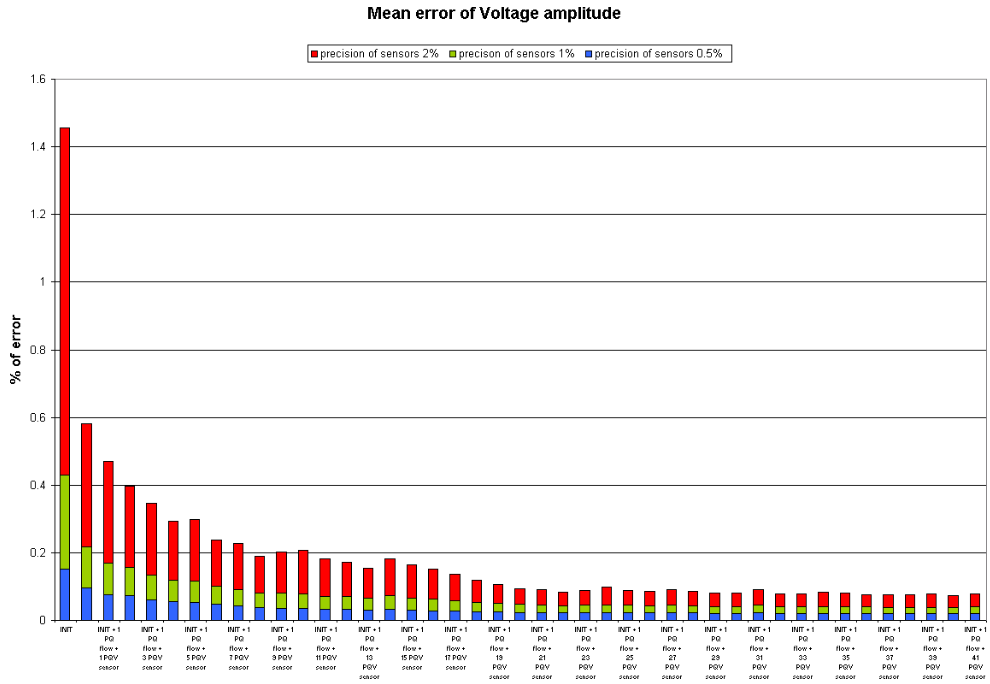

Figure 34 : Feeder 3 - Mean error of voltage amplitude with several sensors (accuracy 0.5%, 1%, 2%)

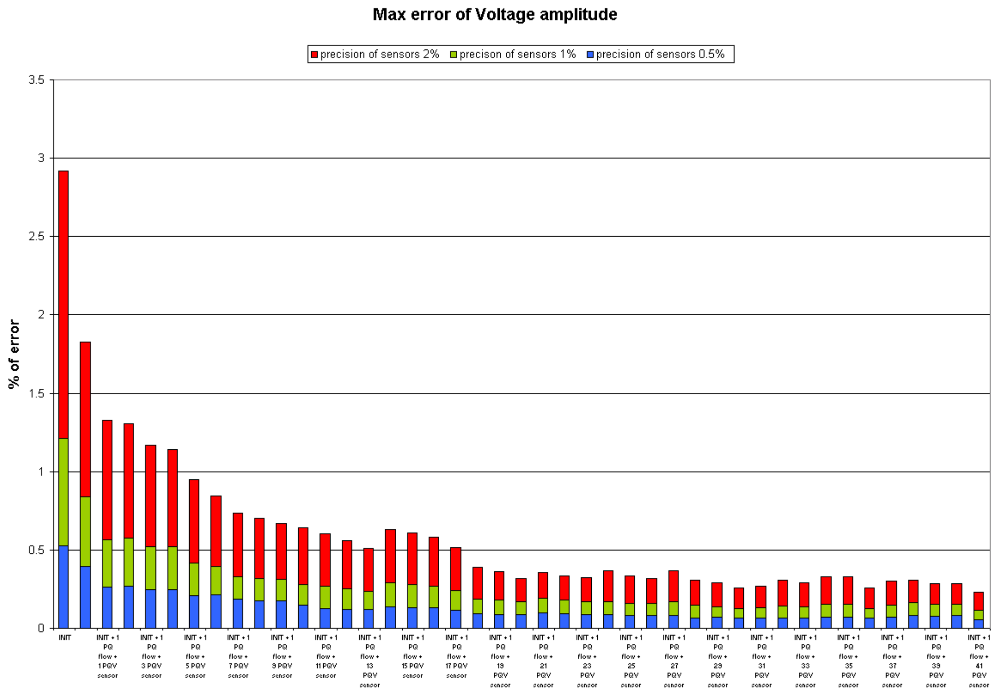

Figure 35 : Feeder 3 - Max error of voltage amplitude with several sensors (accuracy 0.5%, 1%, 2%)

- MV feeder 4

This feeder (Figure 36) has 2 remote controlled switches and 36 MV/LV substations. The same behaviour as for previous MV feeders is observed.

Figure 36 : MV feeder 4

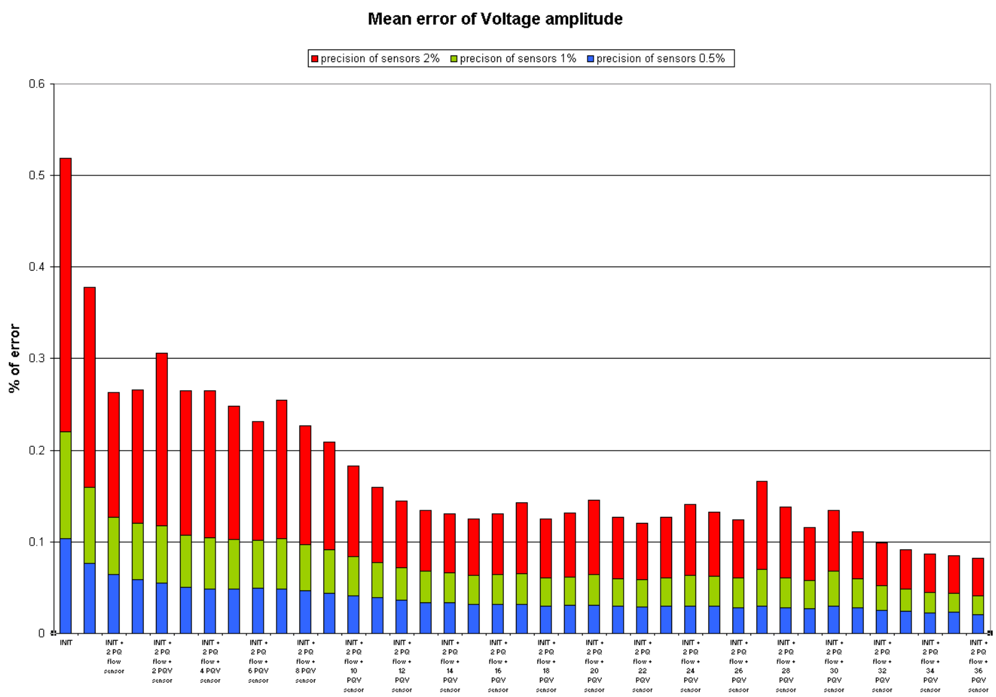

Figure 37 : Feeder 4 - Mean error of voltage amplitude with several sensors (accuracy 0.5%, 1%, 2%)

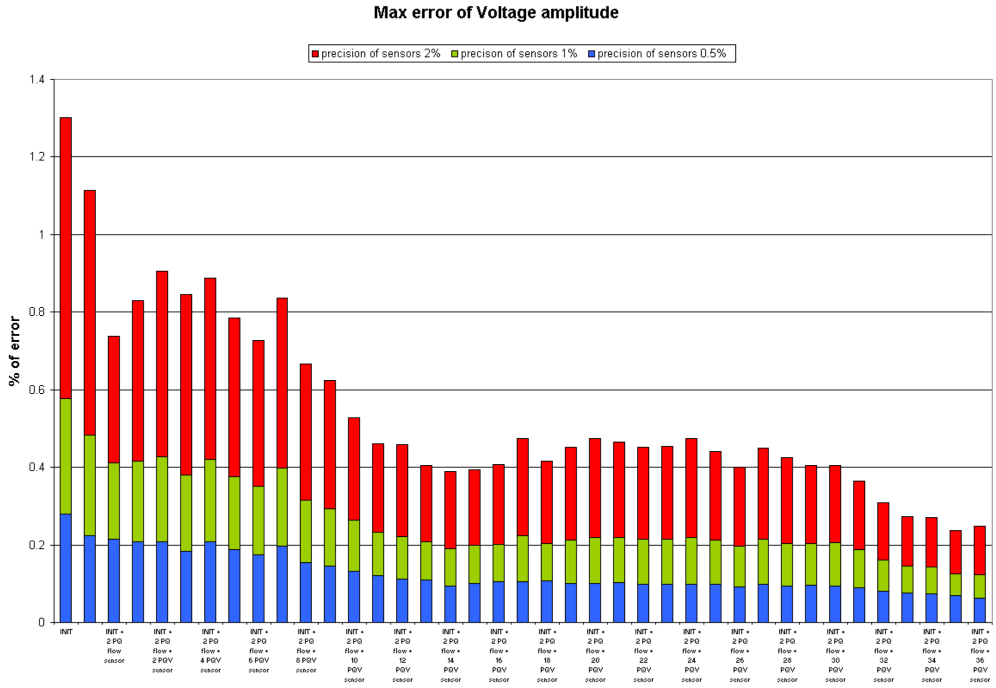

Figure 38 : Feeder 4 - Max error of voltage amplitude with several sensors (accuracy 0.5%, 1%, 2%)

- MV feeder 5

This feeder (Figure 39) has no remote controlled switches and 9 MV/LV substations. The same behaviour as for previous MV feeders is observed. For this particular feeder, it is also possible to see that in some cases (accuracy of sensor 2%), it is not possible to achieve the same accuracy of results as for the previous feeders. This is due to a limited number of available positions (the number of sensors required for the other feeders to achieve this accuracy is higher than the number of available positions in this feeder).

Figure 39 : MV feeder 5

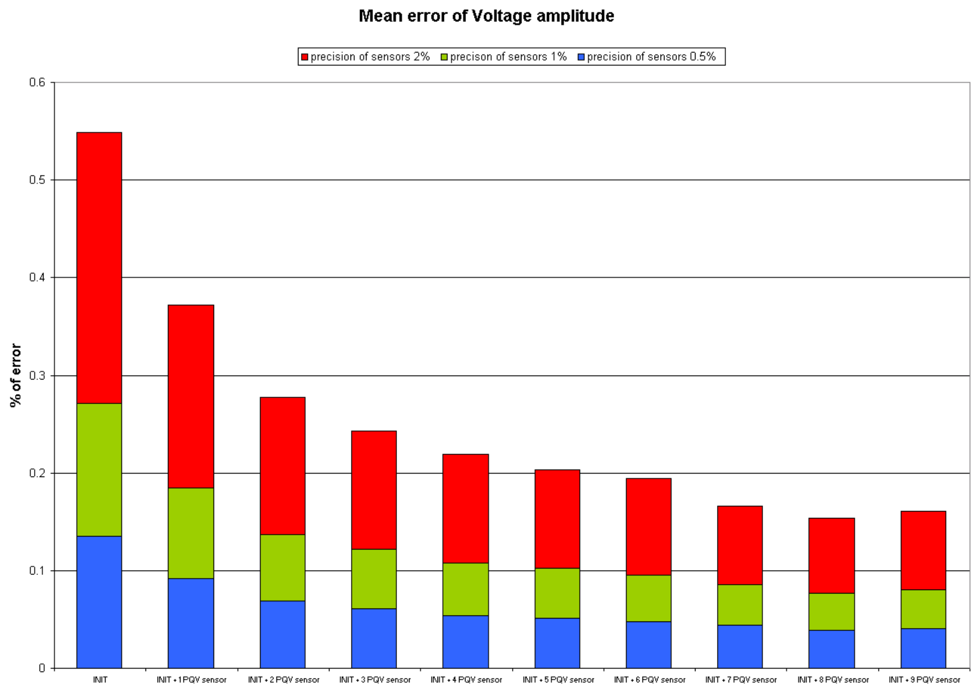

Figure 40 : Feeder 5 - Mean error of voltage amplitude with several sensors (accuracy 0.5%, 1%, 2%)

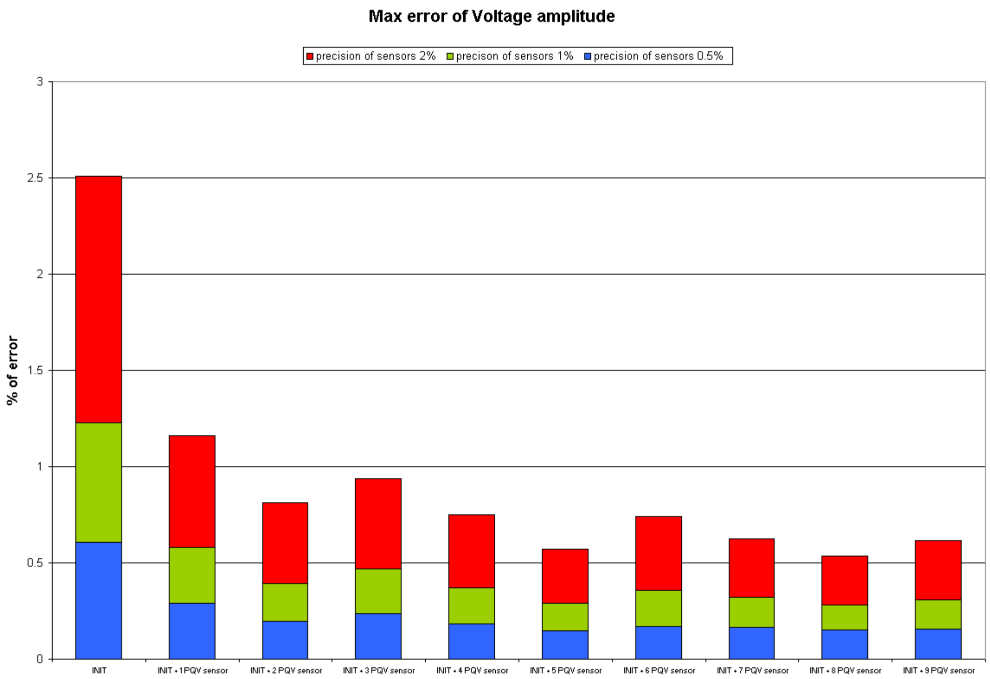

Figure 41 : Feeder 5 - Max error of voltage amplitude with several sensors (accuracy 0.5%, 1%, 2%)

- MV feeder 6

This feeder (Figure 42) has 3 remote controlled switches and 37 MV/LV substations. The same behaviour as for previous feeders is observed.

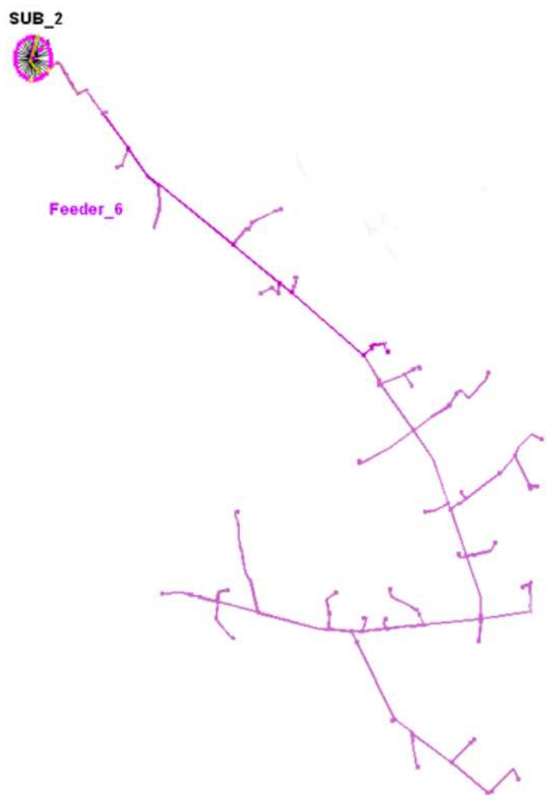

Figure 42 : MV feeder 6

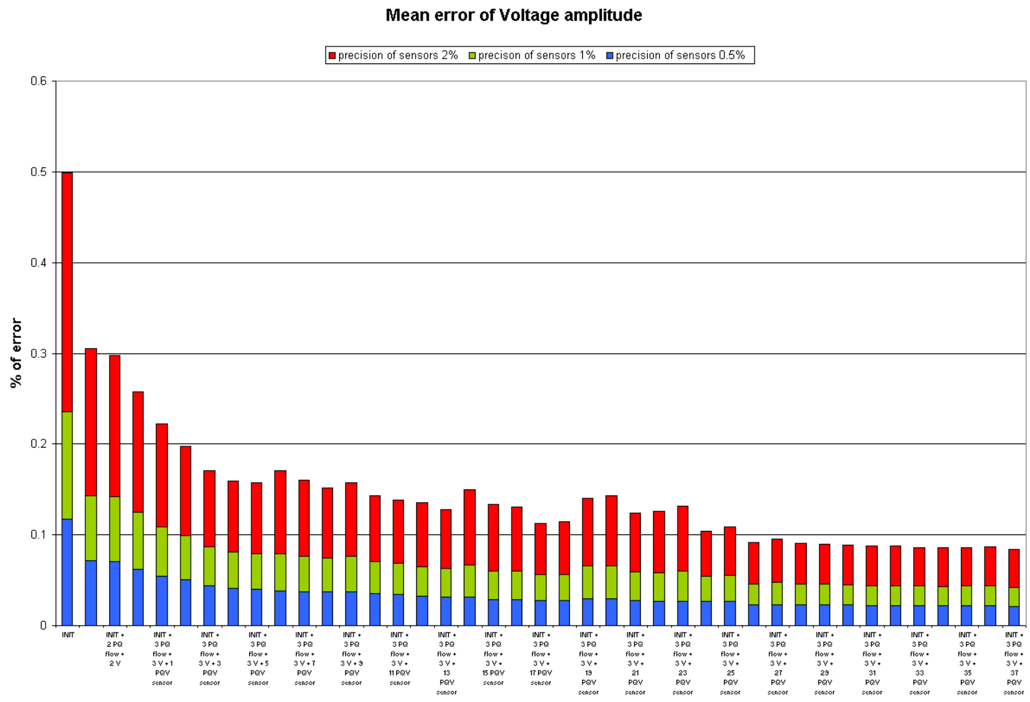

Figure 43 : Feeder 6 - Mean error of voltage amplitude with several sensors (accuracy 0.5%, 1%, 2%)

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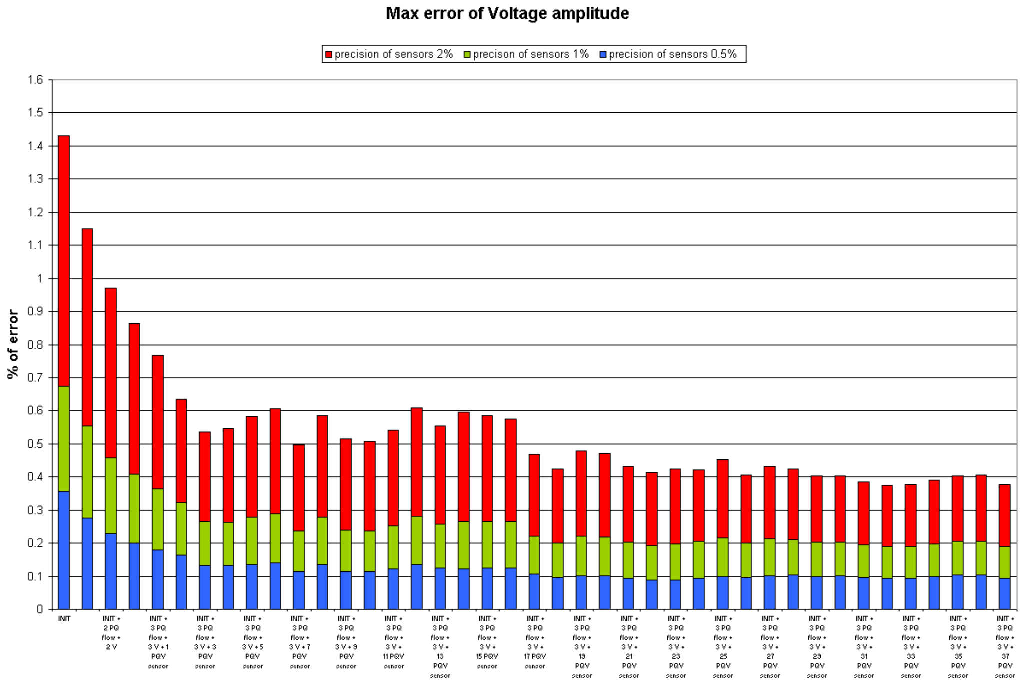

Figure 44 : Feeder 6 - Max error of voltage amplitude with several sensors (accuracy 0.5%, 1%, 2%)

The results obtained for all feeders show that the improvement of DSE results is not linear with the number of sensors. This non-linearity implies that if the accuracy of sensors is divided by 2 (from 1% to 2%), the number of required sensors is multiplied by a much higher factor. This result justifies using accurate sensors to reduce their number and the corresponding cost of instrumentation.

1.2. Results for the whole network

Once we know the accuracy of input data required by automation functions, the previous results give the number of sensors to be installed in the network in order to implement the automation function. Table 10 and Table 11 summarize the number of sensors needed for different accuracies of estimated voltage amplitudes[13] (mean and maximum error). These tables show how the number of additional[14] sensors that is required to get the same accuracy of DSE results is highly increased when the accuracy is divided by 2.

[13] The accuracy of active and reactive power of loads is not analysed as a sensor in the MV/LV substation is needed to obtain accurate results.

[14] It has been considered that a PQV sensor is available at the beginning of the feeder. These sensors have the same accuracy as the ones that are going to be added : 0.5%, 1% or 2%.

MV feeder	Sensors' accuracy	Number of additional sensors required for				
		0.1% mean error	0.2% mean error	0.3% mean error	0.4% mean error	0.5% mean error
MV feeder 1	0.5%	2	0	0	0	0
	1%	6	2	1	0	0
	2%	24	10	5	3	2
MV feeder 2	0.5%	1	0	0	0	0
	1%	5	1	0	0	0
	2%	28	14	2	1	1
MV feeder 3	0.5%	1	0	0	0	0
	1%	8	2	1	1	1
	2%	26	12	6	3	2
MV feeder 4	0.5%	1	0	0	0	0
	1%	10	1	0	0	0
	2%	34	12	5	1	1
MV feeder 5	0.5%	1	0	0	0	0
	1%	6	1	0	0	0
	2%	*impossible*	6	2	1	1
MV feeder 6	0.5%	1	0	0	0	0
	1%	5	1	0	0	0
	2%	29	5	2	1	0

Table 10 : Number of additional sensors required to achieve a pre-defined accuracy on voltage amplitude

MV feeder	Sensors' accuracy	Number of additional sensors required for					
		0.5% max error	0.6% max error	0.7% max error	0.8% max error	0.9% max error	1% max error
MV feeder 1	0.5%	1	1	0	0	0	0
	1%	4	3	2	2	1	1
	2%	21	9	8	7	6	5
MV feeder 2	0.5%	1	1	0	0	0	0
	1%	3	1	1	1	1	1
	2%	16	11	5	3	3	3
MV feeder 3	0.5%	1	0	0	0	0	0
	1%	6	2	2	2	1	1
	2%	19	17	10	8	7	6
MV feeder 4	0.5%	0	0	0	0	0	0
	1%	1	0	0	0	0	0
	2%	13	12	10	10	6	2
MV feeder 5	0.5%	1	1	0	0	0	0
	1%	2	1	1	1	1	1
	2%	*impossible*	*impossible*	7	4	4	2
MV feeder 6	0.5%	0	0	0	0	0	0
	1%	2	1	0	0	0	0
	2%	20	16	5	4	3	2

Table 11 : Number of additional sensors required to achieve a pre-defined accuracy on voltage amplitude

1.3. Link with WP2.2

To show the use of previous results, we are considering that voltage regulation developed in WP2.2 is going to be applied to the same network and it will be fed in with DSE results.

For the case studies, it has been considered that this automation function requires voltage profiles with a maximum error of 0.7%[15].

This information will be enough to determine the number of additional sensors required depending on the sensors' accuracy. For all tests, it has been considered that the initial sensor configuration has a PQV sensor at the beginning of each MV feeder with the same accuracy as additional sensors.

1.3.1. With no zonal approach

To determine the number of sensors required for a good behaviour of the voltage regulation function, results summarized in Table 10 and Table 11 have been used. The number of additional required sensors (to achieve a maximum error of 0.7%) depending on their accuracy is :

- 0.5% → no additional sensors are required[16].
- 1% → six[17] additional sensors are required.
- 2% → forty five[18] additional sensors are required.

The number of required sensors is highly dependant on their accuracy. To achieve the same accuracy, no additional sensors are required when using 0.5% sensors and 45 additional sensors are required when using 2% sensors.

These results justify using accurate sensors to reduce their number and the corresponding cost of instrumentation.

1.3.2. Zonal approach

The zonal approach described in D.2.1.2 proposes to split the network into several zones to decrease calculation time of DSE. In this deliverable, two different approaches (parallel and series) were presented depending on available sensors.

In this paragraph the number of additional sensors needed to achieve the required accuracy for the voltage regulation is calculated depending on the retained zonal approach:

- Serial approach: In this case the number of additional sensors required to achieve accurate results is the same as previously as this approach can be run with only one PQV sensor at the beginning of each MV feeder (this is considered as the initial configuration).
- Parallel approach: To apply this approach, a PQV sensor has to be installed at each remote controlled switch (for the French network 8 sensors[19] have to be installed). The number of additional sensors[20] to be installed to have the required accuracy to run voltage regulation are (depending on their accuracy) :

[15] The 0.7% maximum error has been chosen as an example as the voltage regulation function is not finished yet.
[16] The initial configuration provides voltage profile with less than 0.7% of error.
[17] MV feeder 1 : 2; MV feeder 2 : 1; MV feeder 3 : 2; MV feeder 4 : 0; MV feeder 5 : 1; MV feeder 6 : 0
[18] MV feeder 1 : 8; MV feeder 2 : 5; MV feeder 3 : 10; MV feeder 4 : 10; MV feeder 5 : 7; MV feeder 6 : 5
[19] MV feeder 1 : 0; MV feeder 2 : 2; MV feeder 3 : 1; MV feeder 4 : 2; MV feeder 5 : 0; MV feeder 6 : 3
[20] The PQV sensors at remote controlled switches are considered as already installed.

- 0.5% → no additional sensors are required.
- 1% → four[21] additional sensors are required.
- 2% → thirty seven[22] additional sensors are required.

The number of required sensors is highly dependant on their accuracy. To achieve the same accuracy, no additional sensors are required when using 0.5% sensors and 37 additional sensors are required when using 2% sensors.

These results justify using accurate sensors to reduce their number and the corresponding cost of instrumentation.

2. Case study 2 : Slovenian EG network

In this case, two rural feeders (Cerklje -Figure 45- and Sencur -Figure 46-) provided by EG have been used to determine the number of additional sensors needed to have accurate estimated variables. The same approach as for the French network has been used.

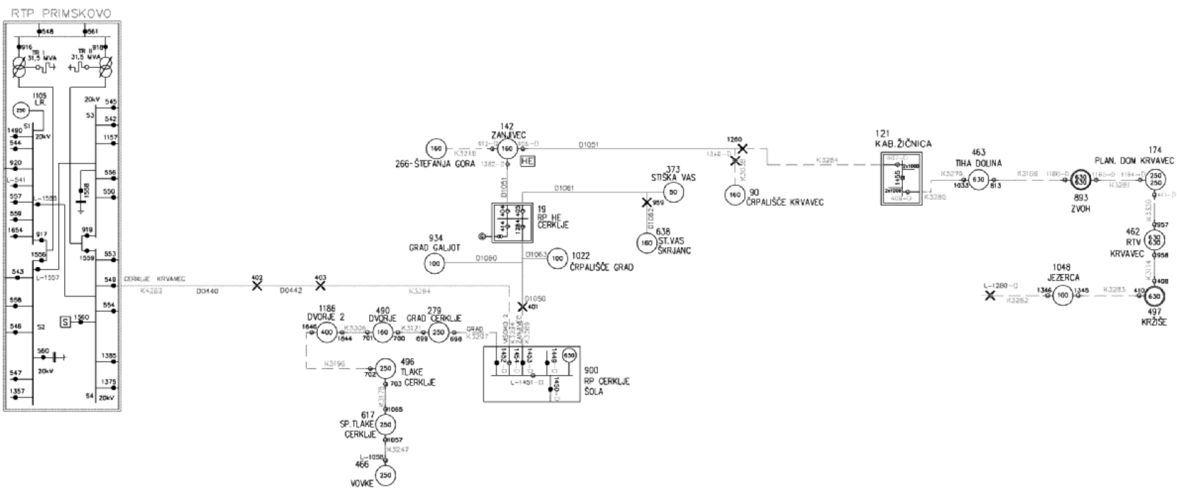

Figure 45 : Ceklje feeder

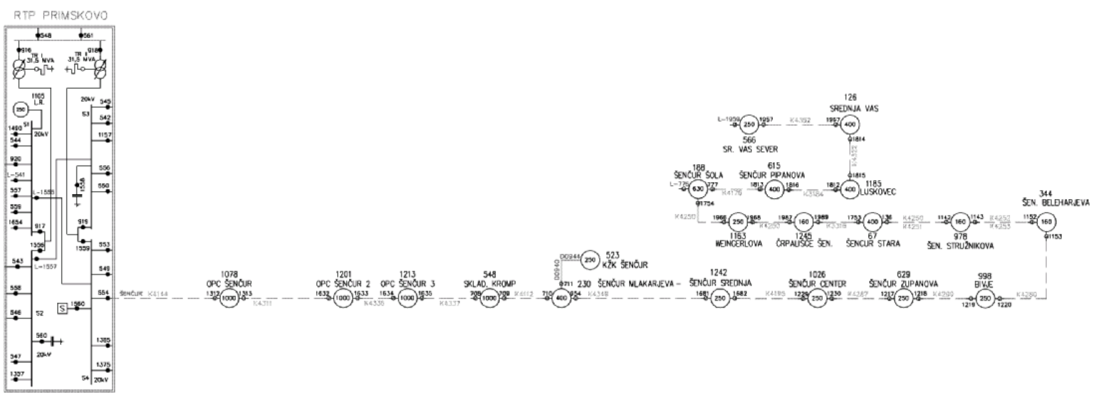

Figure 46 : Sencur feeder

[21] MV feeder 1 : 2; MV feeder 2 : 0; MV feeder 3 : 1; MV feeder 4 : 0; MV feeder 5 : 1; MV feeder 6 : 0.

[22] MV feeder 1 : 8; MV feeder 2 : 3; MV feeder 3 : 9; MV feeder 4 : 8; MV feeder 5 : 7; MV feeder 6 : 2

2.1. Detailed results

For these two feeders, PQV sensors have been added sequentially to MV/LV substations. To determine the order in which the PQV sensors are added, the substations have been classed by rated power[23], so the first sensors are placed in the substation with the highest power and the last ones in the substation with the lowest rated power.

- Cerklje MV feeder (Figure 45)

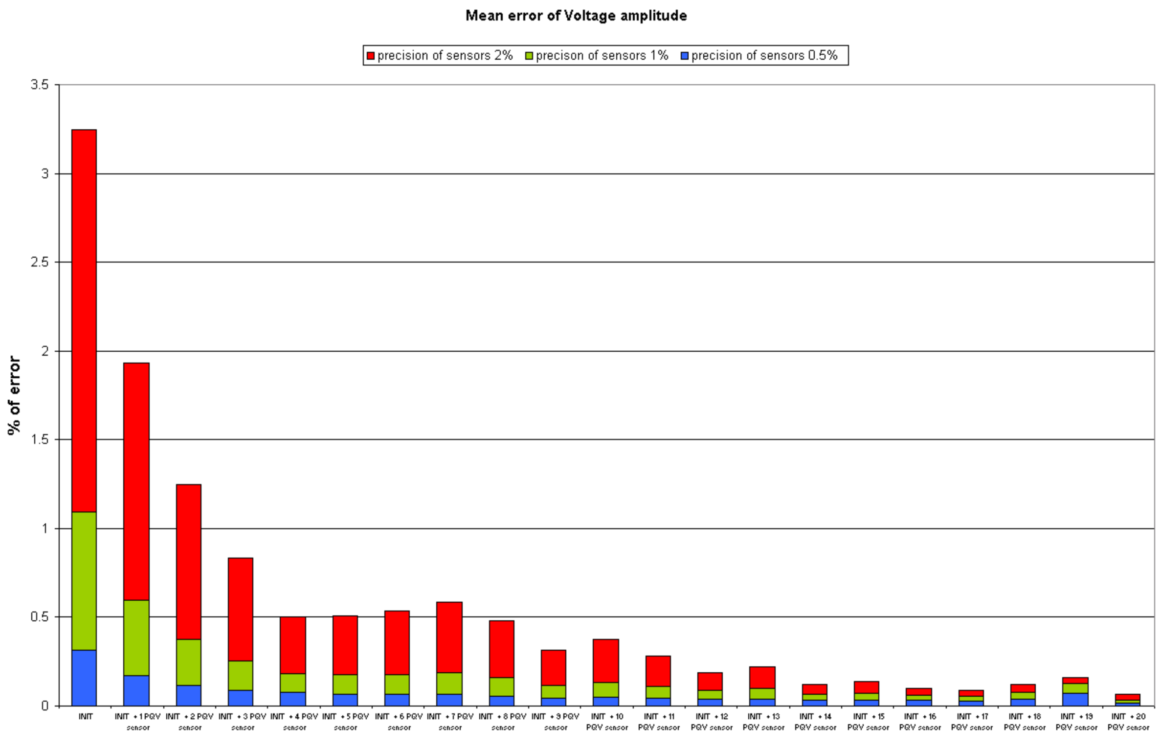

Figure 47 : Cerklje Feeder - Mean error of voltage amplitude with several sensors (accuracy 0.5%, 1%, 2%)

[23] The way the calssification is done is different from the one used for the French network as no information about distance was available.

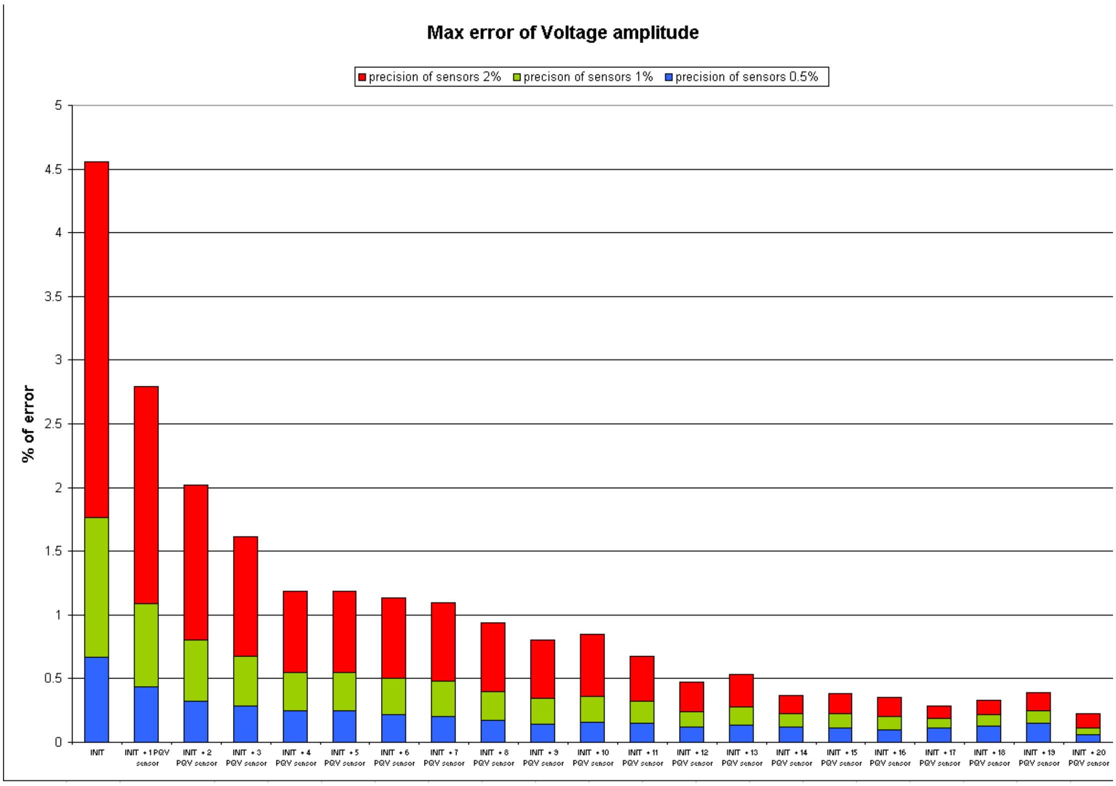

Figure 48 : Cerklje Feeder - Max error of voltage amplitude with several sensors (accuracy 0.5%, 1%, 2%)

- Sencur MV feeder (Figure 46)

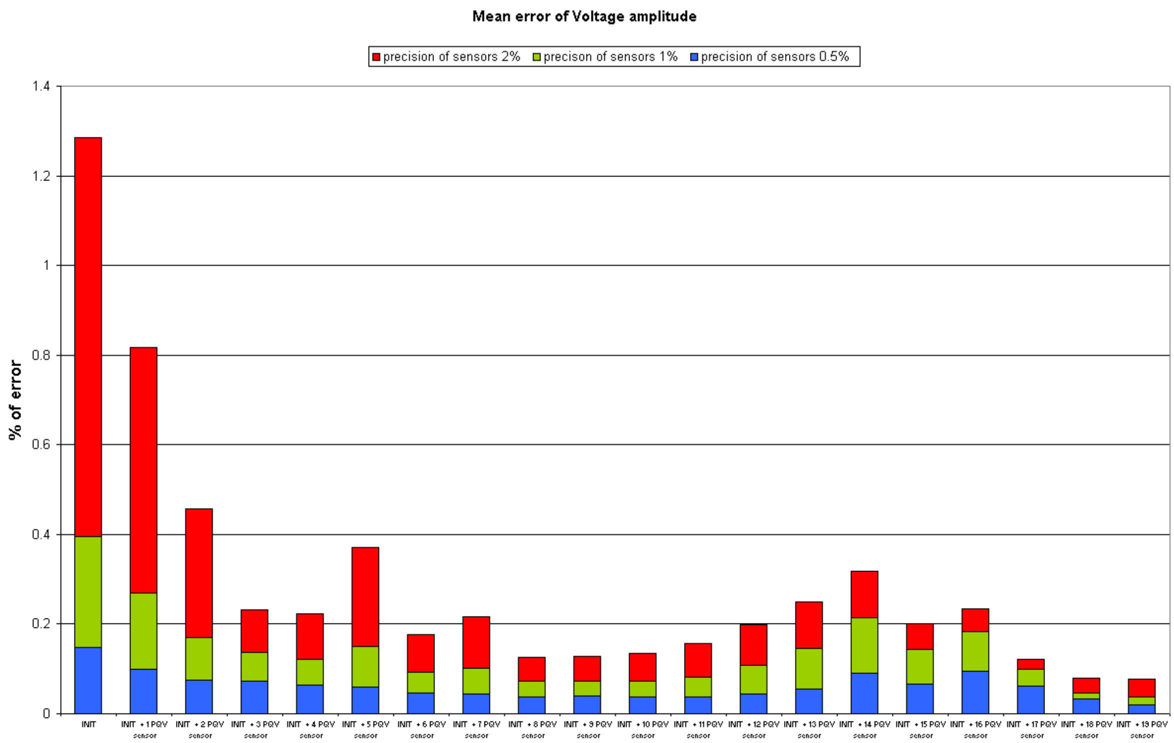

Figure 49 : Sencur Feeder - Mean error of voltage amplitude with several sensors (accuracy 0.5%, 1%, 2%)

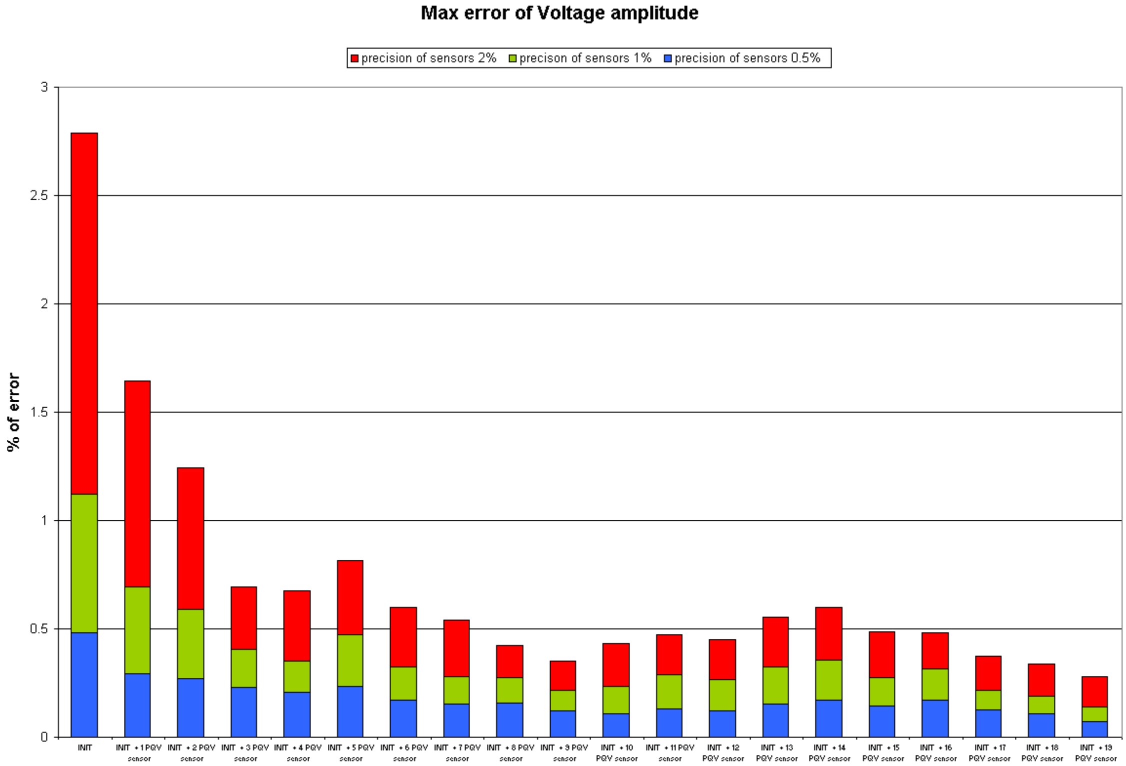

Figure 50 : Sencur Feeder - Max error of voltage amplitude with several sensors (accuracy 0.5%, 1%, 2%)

2.2. Results for the whole network

Once we know the accuracy of input measurement data required by automation functions, the previous results give the number of sensors to be installed in the network in order to implement the automation function.

Table 12 and Table 13 summarize the number of sensors needed for different accuracies of estimated voltage amplitudes[24] (mean and maximum error). These tables show how the number of additional[25] sensors that is required for a same accuracy of DSE results is highly increased when the accuracy is divided by 2.

[24] The accuracy of active and reactive power of loads is not analysed as a sensor in the MV/LV substation is needed to obtain accurate results.

[25] It has been considered that a PQV sensor is available at the beginning of the feeder. These sensors have the same accuracy as the ones that are going to be added : 0.5%, 1% or 2%.

MV feeder	Sensors' accuracy	Number of additional sensors required for				
		0.1% mean error	0.2% mean error	0.3% mean error	0.4% mean error	0.5% mean error
Cerklje MV feeder	0.5%	3	1	1	0	0
	1%	12	4	3	2	2
	2%	16	14	11	9	4
Sencur MV feeder	0.5%	1	0	0	0	0
	1%	6	2	1	0	0
	2%	18	6	3	3	2

Table 12 : Number of additional sensors required to achieve a pre-defined accuracy on voltage amplitude

MV feeder	Sensors' accuracy	Number of additional sensors required for					
		0.5% max error	0.6% max error	0.7% max error	0.8% max error	0.9% max error	1% max error
Cerklje MV feeder	0.5%	1	1	0	0	0	0
	1%	7	4	3	3	2	2
	2%	12	12	11	11	9	8
Sencur MV feeder	0.5%	0	0	0	0	0	0
	1%	3	2	1	1	1	1
	2%	8	6	3	3	3	3

Table 13 : Number of additional sensors required to achieve a pre-defined accuracy on voltage amplitude

2.3. Link with WP2.2

To show the use of previous results, we are considering that voltage regulation developed in WP2.2 is going to be applied to the same network and it will be fed in with DSE results.

For the case studies, it has been considered that this automation function requires voltage profiles with a maximum error of 0.7%[26].

This information will be enough to determine the number of additional sensors required depending on the sensors' accuracy. For all tests, it has been considered that the initial sensor configuration has a PQV sensor at the beginning of each MV feeder with the same accuracy as additional sensors.

To determine the number of additional sensors to run the voltage regulation in EG rural feeders, it is necessary to look at results summarized in Table 12 and Table 13. Depending on the accuracy of the sensors, the number of additional sensor required (for a maximum error of 0.7%) is:

- 0.5% → no additional sensors are required[27].
- 1% → four[28] additional sensors are required.
- 2% → fourteen[29] additional sensors are required.

[26] The 0.7% maximum error has been chosen as an example as the voltage regulation function is not finished yet.
[27] The initial configuration provides voltage profile with less than 0.7% of error.
[28] Cerklje MV feeder : 3; Sencur MV feeder : 1
[29] Cerklje MV feeder : 11; Sencur MV feeder : 3

The number of required sensors is highly dependant on their accuracy. To achieve the same accuracy, no additional sensors are required when using 0.5% sensors and 14 additional sensors are required when using 2% sensors.

These results justify using accurate sensors to reduce their number and the corresponding cost of instrumentation.

V. Cost analysis

To determine the cost of a DSE function for DNOs, several costs must be taken into account. In one hand there are instrumentation costs and on the other hand there are development costs.

Regarding instrumentation costs, several aspects have to be integrated in the total cost of each sensor:

- cost of the equipment, this is the cost of the purchase of the sensor,
- cost of installation,
- maintenance cost,
- telecom's cost, this cost is associated to the telecommunication infrastructure needed to send the information of the sensor to the control center.

1. Cost analysis for the French network

In this paragraph a cost analysis is run for the semi-urban French network. This analysis takes only into account instrumentation costs. These costs depend on the required accuracy as more sensors are needed to achieve more accurate results. In this case, only the cost of additional sensors[30] has been taken into account. The global[31] cost of each PQV sensor with 1% accuracy has been considered as 3000 €.

As seen in §1.2, the number of additional PQV sensors[32] to be installed to achieve a certain accuracy for the French semi-urban network is summarized in Table 14.

Estimated Voltage amplitude Max error	**MV feeders**						**Number of sensors required**	**Instrumentation cost (in k€)**
	MV feeder 1	MV feeder 2	MV feeder 3	MV feeder 4	MV feeder 5	MV feeder 6		
1.00%	1	1	1	0	1	0	4	**12**
0.90%	1	1	1	0	1	0	4	**12**
0.80%	2	1	2	0	1	0	6	**18**
0.70%	2	1	2	0	1	0	6	**18**
0.60%	3	1	2	0	1	1	8	**24**
0.50%	4	3	6	1	2	2	18	**54**

Table 14 : Instrumentation cost

It is possible to see the instrumentation cost required for a DSE function depending on the requested maximum error in Figure 51. The previous instrumentation cost is calculated only for the 6 MV feeders of the French semi-urban network. To determine the overall cost of a DSE function, the instrumentation cost for all MV feeders has to be taken into account. It is important to keep in mind that several aspects as the characteristics of the network, the type of automation function developed and the accuracy of sensors will impact the instrumentation cost.

[30] PQV sensors of 1% accuracy at the beginning of the MV feeder are considered as already available.
[31] This cost integrates all different costs detailed previously.
[32] Considering 1% accuracy sensors.

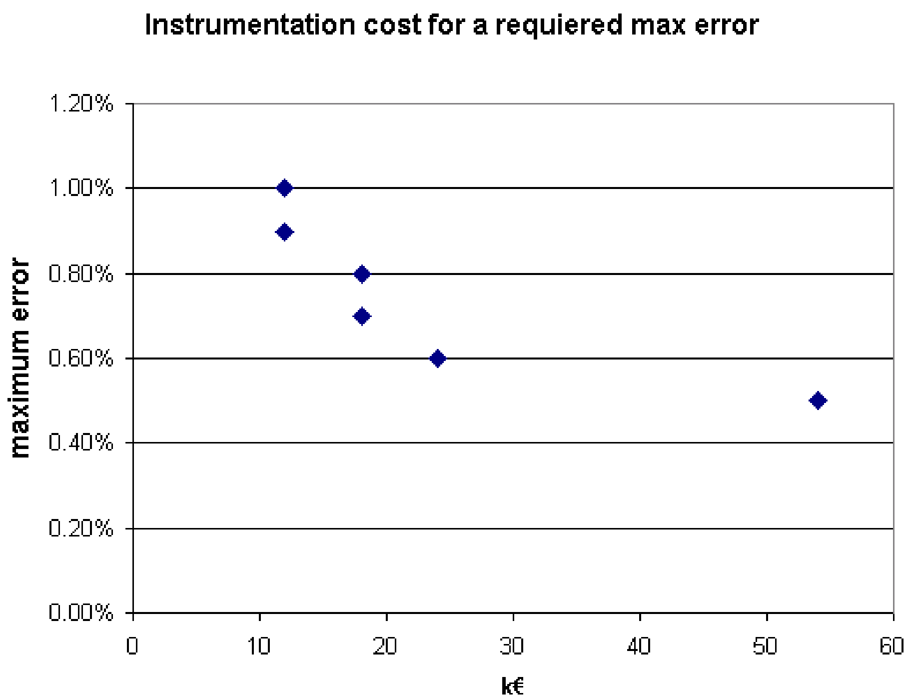

Figure 51 : Instrumentation cost depending on the maximum error

VI. Conclusion

This document is focused on the positioning of sensors in the network for state estimation accuracy and cost effectiveness.

To do so, a first analysis of the impact of each type of sensor on estimated variables has been run. This analysis has shown that **estimated voltage amplitudes can be improved with voltage amplitude or voltage phase sensors**. Regarding active and reactive loads of MV/LV substations, **only PQ sensors measuring the load can improve estimated powers**. Current and PQ flow sensors improve PQ loads estimations only if they measure a line supplying only one load.

Once the impact of each single sensor is analysed, it has been decided to investigate the impact of adding sensors sequentially on estimated variables. To do so, PQV sensors (to improve estimated voltage amplitudes as well as active and reactive powers) have been added sequentially into a French semi-urban network and a network provided by Elecktro Gorenjska. Case studies have been run with different sensors' accuracy (0.5%, 1% and 2%) to determine the number of additional sensors required depending on their accuracy.
These results are summarized in tables allowing to determine the number of additional sensors required to achieve a mean or a maximum error for voltage amplitudes.

Finally a cost analysis has been run to determine the cost of instrumentation required by a DSE function. This analysis takes into account instrumentation costs. Regarding instrumentation costs, it depends on the number of additional sensors to be installed. The number of sensors is directly related to the accuracy required by automation functions that use DSE results as input data.

VII. References

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HiPerDNO report D.2.1.1 “Proposed Approaches and Data Requirements for Distribution System State Estimation tool” 2010.

HiPerDNO report D.2.1.2 “Scalability of distribution state estimation : Implementation and assessment of a zonal approach” 2011.

VIII. Appendix

i. Appendix 1. Detailed results

PQ sensors

The results obtained for MV feeder 1 and with all possible PQ sensors are summarized in the following tables.

Estimated variable / Sensors configuration	Voltage amplitude		P load		Q load		Copper losses	
	Mean error	Max error	Mean error	Max error	Mean error	Max error	Mean error	Max error
Initial	0.357%	1.481%	36.60%	155.0%	35.94%	182.6%	2.43%	5.23%
Init + PQ_1	0.352%	1.454%	36.00%	154.1%	35.32%	180.7%	2.61%	5.63%
Init + PQ_2	0.384%	1.523%	34.76%	160.1%	34.28%	188.4%	3.01%	5.82%
Init + PQ_3	0.346%	1.453%	35.16%	149.3%	34.63%	177.6%	2.93%	5.87%
Init + PQ_4	0.375%	1.507%	33.48%	158.6%	32.89%	186.7%	1.75%	4.81%
Init + PQ_5	0.359%	1.496%	36.17%	156.1%	35.57%	182.4%	2.42%	5.11%
Init + PQ_6	0.347%	1.473%	35.20%	150.5%	34.64%	179.2%	2.35%	5.20%
Init + PQ_7	0.374%	1.514%	33.44%	155.0%	33.00%	185.9%	1.82%	4.34%
Init + PQ_8	0.370%	1.492%	33.53%	156.8%	33.11%	186.0%	1.81%	4.54%
Init + PQ_9	0.353%	1.470%	35.95%	154.0%	35.36%	180.7%	2.38%	5.21%
Init + PQ_{10}	0.345%	1.453%	35.28%	149.7%	34.52%	179.0%	2.12%	4.80%
Init + PQ_{11}	0.353%	1.479%	36.04%	154.2%	35.39%	182.2%	2.38%	5.16%
Init + PQ_{12}	0.360%	1.464%	36.26%	156.1%	35.58%	181.7%	2.48%	5.15%
Init + PQ_{13}	0.345%	1.463%	35.27%	152.1%	34.51%	180.7%	2.36%	5.16%
Init + PQ_{14}	0.368%	1.509%	33.88%	158.6%	33.12%	170.2%	2.49%	5.32%
Init + PQ_{15}	0.364%	1.495%	33.89%	157.2%	33.41%	183.5%	2.11%	4.70%
Init + PQ_{16}	0.351%	1.468%	35.13%	151.8%	34.50%	180.8%	2.59%	5.34%
Init + PQ_{17}	0.350%	1.456%	35.16%	154.1%	34.52%	181.3%	2.36%	5.17%
Init + PQ_{18}	0.354%	1.462%	35.72%	153.4%	35.16%	182.7%	2.13%	4.82%
Init + PQ_{19}	0.354%	1.468%	35.83%	153.8%	35.22%	182.5%	1.80%	4.65%
Init + PQ_{20}	0.352%	1.470%	35.17%	153.7%	34.51%	181.4%	2.32%	5.12%
Init + PQ_{21}	0.359%	1.486%	35.73%	155.3%	34.99%	183.3%	2.42%	5.23%
Init + PQ_{22}	0.364%	1.499%	34.00%	156.3%	33.33%	184.1%	2.90%	5.69%
Init + PQ_{23}	0.360%	1.486%	34.22%	155.6%	33.41%	183.0%	2.69%	5.32%
Init + PQ_{24}	0.355%	1.476%	35.60%	154.5%	34.95%	182.2%	1.92%	4.72%

Table 15 : Impact of PQ sensors on estimated variables in MV feeder 1

Voltage amplitude sensors

The results obtained for MV feeder 1 and with all possible Voltage amplitude sensors are summarized in the following tables.

Sensors configuration \ Estimated variable	Voltage amplitude		P load		Q load		Copper losses	
	Mean error	Max error	Mean error	Max error	Mean error	Max error	Mean error	Max error
Initial	0.357 %	1.481 %	36.6 %	155 %	35.94 %	182.6 %	2.426 %	5.232 %
Init + V_1	0.215 %	0.884 %	36.6 %	155 %	35.97 %	182.4 %	2.122 %	4.905 %
Init + V_2	0.208 %	0.919 %	36.6 %	155 %	35.96 %	183 %	2.151 %	4.703 %
Init + V_3	0.211 %	0.760 %	36.6 %	155 %	35.96 %	182.2 %	2.198 %	4.674 %
Init + V_4	0.212 %	0.734 %	36.6 %	155 %	35.97 %	182.3 %	2.140 %	4.567 %
Init + V_5	0.231 %	0.842 %	36.6 %	155 %	35.96 %	182.5 %	2.182 %	4.819 %
Init + V_6	0.213 %	0.811 %	36.6 %	155 %	35.96 %	183 %	2.166 %	4.877 %
Init + V_7	0.224 %	0.787 %	36.6 %	155 %	35.97 %	182.2 %	2.122 %	4.551 %
Init + V_8	0.233 %	0.788 %	36.6 %	155 %	35.97 %	182.7 %	2.125 %	4.552 %
Init + V_9	0.224 %	0.939 %	36.6 %	154.9 %	35.97 %	182.7 %	2.137 %	5.016 %
Init + V_{10}	0.228 %	0.759 %	36.6 %	155 %	35.96 %	182.6 %	2.175 %	4.249 %
Init + V_{11}	0.237 %	0.809 %	36.6 %	155 %	35.96 %	182.9 %	2.190 %	4.582 %
Init + V_{12}	0.230 %	0.949 %	36.6 %	155 %	35.97 %	182.8 %	2.132 %	4.510 %
Init + V_{13}	0.226 %	0.829 %	36.6 %	155 %	35.97 %	182.3 %	2.114 %	4.589 %
Init + V_{14}	0.231 %	0.726 %	36.6 %	155 %	35.96 %	183 %	2.199 %	4.566 %
Init + V_{15}	0.185 %	0.733 %	36.6 %	155 %	35.97 %	182.8 %	2.128 %	4.866 %
Init + V_{16}	0.217 %	0.728 %	36.6 %	155 %	35.97 %	181.7 %	2.143 %	4.741 %
Init + V_{17}	0.231 %	0.859 %	36.6 %	155 %	35.97 %	182.6 %	2.093 %	4.804 %
Init + V_{18}	0.230 %	0.996 %	36.6 %	155 %	35.97 %	182.3 %	2.157 %	5.043 %
Init + V_{19}	0.223 %	0.757 %	36.6 %	155 %	35.96 %	183 %	2.175 %	4.851 %
Init + V_{20}	0.219 %	0.742 %	36.6 %	154.9 %	35.96 %	182.7 %	2.153 %	4.876 %
Init + V_{21}	0.224 %	0.872 %	36.6 %	155 %	35.96 %	182.8 %	2.145 %	4.565 %
Init + V_{22}	0.209 %	0.770 %	36.6 %	155 %	35.97 %	183.1 %	2.071 %	4.391 %
Init + V_{23}	0.226 %	0.613 %	36.6 %	155 %	35.96 %	182.1 %	2.183 %	4.819 %
Init + V_{24}	0.217 %	0.694 %	36.6 %	155 %	35.97 %	182.6 %	2.101 %	4.448 %
Init + V_{25}	0.214 %	0.884 %	36.6 %	155 %	35.96 %	182.8 %	2.187 %	4.868 %

Table 16 : Impact of Voltage amplitude sensors on estimated variables in MV feeder 1

Current sensors

The results obtained for MV feeder 1 and with all possible current sensors are summarized in following the tables.

Estimated variable / Sensors configuration	Voltage amplitude		P load		Q load		Copper losses	
	Mean error	Max error	Mean error	Max error	Mean error	Max error	Mean error	Max error
Initial	0.357 %	1.481 %	36.6 %	155.0 %	35.9 %	182.6 %	2.426 %	5.232 %
Init + I_1	0.282 %	0.937 %	36.6 %	155.3 %	35.9 %	182.5 %	2.264 %	4.974 %
Init + I_2	0.247 %	0.957 %	36.5 %	154.6 %	36.0 %	182.7 %	1.831 %	3.943 %
Init + I_3	0.243 %	0.954 %	36.5 %	154.9 %	36.0 %	182.5 %	1.887 %	4.008 %
Init + I_4	0.329 %	1.397 %	29.7 %	155.4 %	34.9 %	184.9 %	1.107 %	3.541 %
Init + I_5	0.332 %	1.400 %	33.5 %	151.2 %	35.5 %	184.1 %	0.922 %	2.817 %
Init + I_6	0.377 %	1.513 %	36 %	151.6 %	35.9 %	184.1 %	2.441 %	5.242 %
Init + I_7	0.381 %	1.535 %	35.7 %	154.9 %	35.8 %	183.7 %	2.415 %	5.225 %
Init + I_8	0.330 %	1.399 %	34.8 %	149.1 %	35.7 %	183.6 %	0.949 %	2.863 %
Init + I_9	0.339 %	1.413 %	35.8 %	147.9 %	35.9 %	183.4 %	1.370 %	3.848 %
Init + I_{10}	0.352 %	1.478 %	34.4 %	158.9 %	35.0 %	168.6 %	2.431 %	5.241 %
Init + I_{11}	0.332 %	1.399 %	35 %	147.8 %	35.7 %	183.5 %	0.963 %	2.930 %
Init + I_{12}	0.242 %	1.040 %	36.0 %	153.3 %	35.9 %	182.7 %	1.218 %	2.792 %
Init + I_{13}	0.337 %	1.420 %	32.9 %	164.0 %	35.4 %	184.0 %	1.036 %	3.407 %
Init + I_{14}	0.373 %	1.510 %	36.4 %	152.9 %	35.9 %	183.1 %	2.459 %	5.265 %
Init + I_{15}	0.343 %	1.396 %	36.5 %	156.4 %	35.9 %	182.5 %	2.617 %	4.737 %
Init + I_{16}	0.304 %	1.305 %	36.5 %	154.2 %	35.9 %	182.5 %	1.944 %	3.999 %
Init + I_{17}	0.393 %	1.555 %	35.4 %	159.1 %	35.8 %	184.1 %	2.427 %	5.229 %
Init + I_{18}	0.356 %	1.496 %	36.5 %	154.4 %	35.9 %	183.3 %	2.401 %	5.298 %
Init + I_{19}	0.340 %	1.424 %	29.9 %	164.3 %	34.2 %	184.4 %	1.072 %	3.155 %
Init + I_{20}	0.354 %	1.435 %	36.4 %	152.5 %	35.9 %	183.0 %	2.172 %	4.666 %
Init + I_{21}	0.361 %	1.483 %	36.6 %	153.9 %	35.9 %	182.6 %	2.431 %	5.242 %
Init + I_{22}	0.375 %	1.496 %	35.2 %	151.7 %	35.8 %	182.5 %	2.695 %	5.416 %
Init + I_{23}	0.264 %	1.105 %	36.4 %	154.5 %	35.9 %	182.5 %	1.616 %	3.921 %
Init + I_{24}	0.351 %	1.469 %	34.1 %	157.4 %	35.5 %	182.9 %	2.055 %	4.653 %
Init + I_{25}	0.346 %	1.451 %	32.4 %	159.6 %	34.5 %	183.8 %	1.403 %	3.941 %

Table 17 : Impact of current sensors on estimated variables in MV feeder 1

PQ flow sensors

The results obtained for MV feeder 1 and with all possible PQ flow sensors are summarized in the following tables.

Estimated variable / Sensors configuration	Voltage amplitude		P load		Q load		Copper losses	
	Mean error	Max error	Mean error	Max error	Mean error	Max error	Mean error	Max error
Initial	0.357 %	1.481 %	36.6%	155.0%	35.9%	182.6%	2.426 %	5.232 %
Init + PQ flow$_1$	0.358 %	1.483 %	36.6%	156.0%	35.9%	182.6%	2.610 %	5.026 %
Init + PQ flow$_2$	0.386 %	1.522 %	36.6%	154.6%	35.7%	182.2%	2.424 %	5.056 %
Init + PQ flow$_3$	0.390 %	1.567 %	36.6%	155.0%	35.7%	182.1%	2.400 %	5.128 %
Init + PQ flow$_4$	0.382 %	1.504 %	30.0%	154.3%	30.0%	195.0%	1.030 %	3.318 %
Init + PQ flow$_5$	0.386 %	1.504 %	33.8%	150.2%	33.4%	189.5%	0.966 %	3.198 %
Init + PQ flow$_6$	0.353 %	1.476 %	36.0%	154.0%	35.4%	195.5%	2.345 %	5.190 %
Init + PQ flow$_7$	0.348 %	1.470 %	35.7%	157.1%	35.1%	193.5%	2.274 %	5.123 %
Init + PQ flow$_8$	0.371 %	1.496 %	34.9%	148.3%	34.1%	188.3%	1.039 %	3.150 %
Init + PQ flow$_9$	0.367 %	1.497 %	35.8%	147.7%	35.1%	185.3%	1.514 %	4.198 %
Init + PQ flow$_{10}$	0.368 %	1.509 %	33.9%	158.6%	33.1%	170.3%	2.493 %	5.318 %
Init + PQ flow$_{11}$	0.372 %	1.498 %	35.1%	147.3%	34.4%	187.1%	1.090 %	3.308 %
Init + PQ flow$_{12}$	0.389 %	1.523 %	36.1%	154.9%	35.2%	181.9%	1.743 %	4.226 %
Init + PQ flow$_{13}$	0.375 %	1.491 %	33.2%	162.7%	32.9%	190.4%	1.105 %	3.598 %
Init + PQ flow$_{14}$	0.358 %	1.480 %	36.4%	153.1%	35.7%	184.0%	2.404 %	5.218 %
Init + PQ flow$_{15}$	0.329 %	1.404 %	36.5%	155.7%	35.8%	184.0%	2.772 %	5.952 %
Init + PQ flow$_{16}$	0.357 %	1.496 %	36.5%	154.1%	35.9%	183.9%	2.219 %	5.397 %
Init + PQ flow$_{17}$	0.349 %	1.467 %	35.4%	162.2%	34.8%	198.9%	2.248 %	5.084 %
Init + PQ flow$_{18}$	0.356 %	1.490 %	36.5%	154.5%	35.9%	177.4%	2.374 %	5.279 %
Init + PQ flow$_{19}$	0.373 %	1.496 %	29.6%	163.1%	29.5%	191.7%	1.116 %	3.333 %
Init + PQ flow$_{20}$	0.357 %	1.487 %	36.5%	155.6%	35.8%	178.1%	2.269 %	4.886 %
Init + PQ flow$_{21}$	0.357 %	1.494 %	36.6%	154.3%	36.0%	170.5%	2.411 %	5.254 %
Init + PQ flow$_{22}$	0.360 %	1.486 %	35.1%	151.8%	34.5%	180.8%	2.633 %	5.379 %
Init + PQ flow$_{23}$	0.370 %	1.514 %	36.4%	154.9%	35.7%	182.5%	2.115 %	5.263 %
Init + PQ flow$_{24}$	0.356 %	1.478 %	33.9%	157.2%	33.4%	183.6%	2.089 %	4.685 %
Init + PQ flow$_{25}$	0.371 %	1.497 %	32.2%	159.2%	32.0%	187.0%	1.515 %	4.115 %

Table 18 : Impact of PQ flow sensors on estimated variables in MV feeder 1

Phase sensors

The results obtained for MV feeder 1 and with all possible Phase sensors are summarized in the following tables.

Sensors configuration \ Estimated variable	Voltage amplitude		P load		Q load		Copper losses	
	Mean error	Max error	Mean error	Max error	Mean error	Max error	Mean error	Max error
Initial	0.357 %	1.481 %	36.6 %	155 %	35.9 %	182.6 %	2.426 %	5.232 %
Init + $Phase_1$	0.206 %	0.854 %	36.6 %	155.2 %	36 %	182.2 %	1.968 %	4.845 %
Init + $Phase_2$	0.288 %	1.049 %	36.3 %	157 %	36.2 %	181.9 %	1.796 %	3.786 %
Init + $Phase_3$	0.243 %	1.016 %	36.6 %	154.9 %	35.9 %	180.9 %	2.088 %	3.942 %
Init + $Phase_4$	0.234 %	0.814 %	36.6 %	154.8 %	36 %	182 %	2.116 %	4.186 %
Init + $Phase_5$	0.248 %	0.825 %	36.4 %	156.3 %	36.1 %	182.7 %	1.806 %	3.526 %
Init + $Phase_6$	0.283 %	1.260 %	36.6 %	154.9 %	35.9 %	178.6 %	2.275 %	4.421 %
Init + $Phase_7$	0.263 %	0.987 %	36.4 %	156.7 %	36.1 %	182.6 %	1.821 %	4.137 %
Init + $Phase_8$	0.191 %	0.749 %	36.5 %	154.8 %	36 %	182.5 %	1.895 %	4.310 %
Init + $Phase_9$	0.284 %	1.048 %	36.2 %	154.6 %	36.3 %	181.9 %	1.713 %	3.962 %
Init + $Phase_{10}$	0.264 %	1.129 %	36.6 %	154.7 %	35.9 %	179.6 %	2.136 %	4.141 %
Init + $Phase_{11}$	0.200 %	0.660 %	36.5 %	155.1 %	36 %	182.6 %	1.841 %	3.840 %
Init + $Phase_{12}$	0.217 %	0.996 %	36.5 %	155 %	36 %	182.2 %	1.975 %	3.961 %
Init + $Phase_{13}$	0.296 %	1.093 %	36.1 %	154.2 %	36.3 %	181.6 %	1.691 %	4.133 %
Init + $Phase_{14}$	0.214 %	0.822 %	36.5 %	155.1 %	36 %	182.5 %	1.864 %	3.873 %
Init + $Phase_{15}$	0.285 %	1.252 %	36.6 %	155.6 %	35.9 %	178.9 %	2.301 %	4.595 %
Init + $Phase_{16}$	0.278 %	1.004 %	36.4 %	157 %	36.1 %	182.3 %	1.819 %	3.988 %
Init + $Phase_{17}$	0.221 %	0.874 %	36.5 %	155.8 %	36 %	182.6 %	1.844 %	3.543 %
Init + $Phase_{18}$	0.272 %	1.242 %	36.6 %	155.4 %	35.9 %	180.1 %	2.252 %	4.403 %
Init + $Phase_{19}$	0.188 %	0.643 %	36.5 %	155.1 %	36 %	182.1 %	1.816 %	4.026 %
Init + $Phase_{20}$	0.292 %	1.095 %	36.0 %	156.3 %	36.4 %	181.5 %	1.680 %	4.010 %
Init + $Phase_{21}$	0.294 %	1.102 %	36.1 %	156.8 %	36.3 %	181.5 %	1.681 %	3.832 %
Init + $Phase_{22}$	0.178 %	0.655 %	36.5 %	155.1 %	36 %	182.6 %	1.822 %	3.528 %
Init + $Phase_{23}$	0.239 %	1.061 %	36.5 %	155 %	35.9 %	181.5 %	2.008 %	3.773 %
Init + $Phase_{24}$	0.290 %	1.105 %	36 %	154.8 %	36.4 %	181.7 %	1.651 %	3.848 %
Init + $Phase_{25}$	0.279 %	0.990 %	36.4 %	157.9 %	36.1 %	182.3 %	1.819 %	4.046 %

Table 19 : Impact of Phase sensors on estimated variables in MV feeder 1

Pseudo-measurements

The results obtained for MV feeder 1 with four different calculations of pseudo-measurements are summarized in Table 20.

Estimated variable / Sensors configuration	Voltage amplitude		P load		Q load		Copper losses	
Pseudo-measurements	Mean error	Max error	Mean error	Max error	Mean error	Max error	Mean error	Max error
Mean value ± gaussian error 50%	0.357 %	1.481 %	36.6 %	155.0 %	35.9 %	182.6 %	2.426 %	5.232 %
S_{load} ± gaussian error 50%	0.308 %	1.324 %	38.0 %	164.9 %	37.3 %	200.4 %	1.957 %	4.769 %
S_{load} ± gaussian error 30%	0.339 %	1.446 %	37.1 %	130.4 %	36.6 %	152.1 %	1.878 %	4.466 %
S_{load} ± gaussian error 15%	0.682 %	1.860 %	36.7 %	105.8 %	36.4 %	115.0 %	1.915 %	4.611 %

Table 20 : Impact of pseudo-measurements on estimated variables in MV feeder 1