# A system-based framework for optimal sensor placement in smart grids


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***Abstract*—The number of sensors deployed in power systems unlocks the promising benefits and capabilities of digitalisation. Sensor-driven applications and communication technologies, which are the backbone of smart grids, present an unprecedented opportunity to improve grid observability and enable the integration of renewable energy sources cost-effectively. Observability is dependent on optimal sensor placement (OSP), which also relies on economic and technical constraints. To achieve observability optimally, past sensor placement studies have applied optimisation methods in power systems. However, these often neglect the broader and interdisciplinary scope in which sensor placement is included, as well as the interoperability between the phases of the OSP workflow. Therefore, there is a need to evaluate sensor placement from a system-based perspective and to structure the placement process into workflow categories, describing their interdependencies. This is to assess the technical, economic, business, social, and environmental factors affecting sensor placement and their impact on decision-making and the performance of digital applications using the collected data. Thus, this discussion paper proposes a system-based sensor placement framework addressing the main challenges, performance metrics, and the value of information for continuous sensor placement.**



***Index Terms*—optimal sensor placement, smart grids, IoT, optimisation, digitalisation, systems theory, and holistic framework design.**


## I. Introduction

Smart grids present a pivotal opportunity to enable decentralisation and decarbonisation of the power sector. Smart grids integrate higher levels of renewable energy into the existing grid and aim to build the grid's robustness, flexibility, and reliability. To harness these benefits, understanding the state of the grid (i.e., observability) is critical. In [1], power observability is defined as the ability of a system to make inferences about its critical processes using measurement data. Hence, sensors become increasingly important as measurement acquisition agents. Such measurements enable the analysis of the dynamic behaviour of electric power systems and, for instance, spur the development of more efficient control and automation processes [2]. Therefore Energy companies strive to deploy sensors for operation and event-based use cases such as (i) outage detection, recognition, and identification [3], [4], (ii) energy theft detection [5], (iii) asset monitoring [6] [7], fault prediction [8], fault diagnosis [9], [10], and (iv) early prediction optimization instabilities [11].

Power systems observability depends on the number, type, and location of sensors deployed to collect data from different points of interest (POI) [12], [13]. Furthermore, sensor placement relies on the economic feasibility and time-based performance constraints of energy companies carrying out the study of determining the most strategic POIs.

As a result, several methods have been explored for OSP design. For instance, Jiang et al [14] explore a modified binary particle swarm optimisation algorithm that determines the minimum number of sensors required for a power grid monitoring system based on the Internet of Things (IoT). Kesici et al [11] propose a feature selection classifier algorithm to determine the optimal locations for phasor measurement units (PMUs) placement in early transient instability prediction. Samudrala et al [3] propose a novel formulation of the OSP as a cost optimisation problem based on dynamic programming for outage detection. These studies propose novel strategies and approaches for OSP from a technical performance perspective, neglecting the business, social, and environmental factors [15].

Therefore, to address this multi-disciplinary and complex problem, systems theory brings a set of approaches and tools to rationalise the behaviour of large and complex systems such as power systems [16]. Thus, this paper aims to provide a comprehensive framework that addresses the OSP issue from a systems perspective and identifies the major steps for the sensors placement workflow ranging from problem formulation to sensors operation.

The contributions of this paper are detailed as follows:

- To provide a comprehensive overview of the OSP prob-

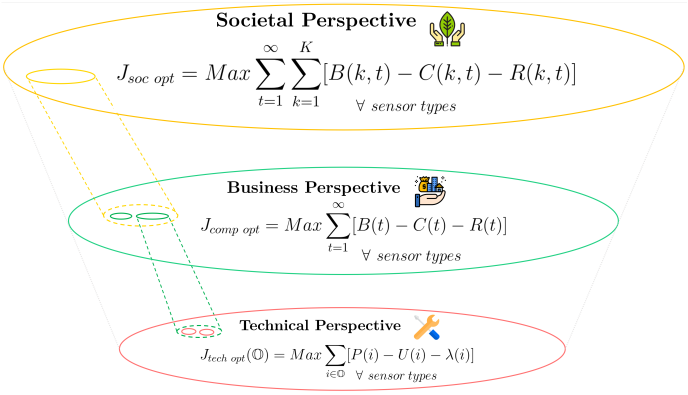


Fig. 1: Optimal sensor placement from a systems perspective.

lem from a systems perspective, combining societal, economic, and technical dimensions.

- To provide a holistic framework to guide future research on this complex and multi-disciplinary field.
- To identify the major steps in the OSP workflow merging technical, business, and societal perspectives and apply the proposed framework on a proactive maintenance use case.

This paper is organised into four sections. After the introduction provided in Section I, Section II details the proposed systems-based framework for OSP. Section III discusses industrial implications and future work. Finally, Section IV concludes the paper.

## II. Framework for optimal sensor placement

In this study, the proposed multi-level framework is composed of (A) a systems-based description of the different perspectives to be considered in OSP and (B) an OSP workflow based on the system-based framework to present the sensor placement as a multi-level continuous optimisation problem.

### A. Systems perspective for optimal sensor placement

Traditionally, the OSP design has been considered mostly from a technical perspective. However, the business perspective, socio-environmental factors must be considered as they affect the business models and technical performance metrics through regulation and policies. The proposed system-based view of the OSP is illustrated in Fig. 1, where the objective functions of the technical, business, and societal perspectives are shown. These perspectives are described using a bottom-up approach as:

*1) **Technical perspective**:* Grid operators deploy sensors to determine the state of a particular equipment, event, or process. For this purpose, accuracy and reliability are important parameters driving sensor performance. To meet the targeted performance metrics, several attributes of a sensor are considered: type (mechanical or electrical), sensor failure recovery, proximity to communication channels, especially in wireless configurations, energy consumption, and external disturbances. Let us denote a set of observed attributes by $\mathbb{O} \subseteq \{x_1, ..., x_n\}$. Each element $x$ is a vector of dimension $L \times N$, where $L$ is the number of considered placement schemes and $N$ is the number of considered sensor types. To maximise the performance of sensors in wide-area situation awareness, it is important to minimise the sensor's unreliability and faults, as displayed in Eq. 1:

$$J_{tech\_opt}(\mathbb{O}) = Max \sum_{i \in \mathbb{O}} [P(i) - U(i) - \lambda(i)] \tag{1}$$

where $J_{tech\_opt}(\mathbb{O})$ is the optimal solution obtained from the cost function considering only the technical perspective for that specific set of observable attributes. $P(\mathbb{O})$ is the performance index function, $U(\mathbb{O})$ is the uncertainty function, and $\lambda(\mathbb{O})$ represents the unreliability index function, for all considered sensor types and placement schemes. $P$, $U$, $\lambda$: $\mathbb{R}^{L \times N} \rightarrow \mathbb{R}^{L \times N}$. For the business and societal perspectives, a similar mathematical formulation would be applicable. However, to facilitate the understanding, only a subset of the observable attributes were considered, such as time and the number of stakeholders.

OSP goes beyond improving grid observability. In so doing, the approaches focus on the ability of these sensors to adapt to disturbances and uncertainties $U(\mathbb{O})$ without increasing O&M costs. Grid operators seek to comprehend how their sensor network configuration behaves if (n+1) sensing devices fail. They run predictive models to detect and run a root-cause analysis for device failure to enable self-reconfiguration [17] of the sensing network for continued data acquisition before the faulty device(s) are replaced or repaired [18].

Another figure of merit for sensor performance is power management. Most sensors and microprocessor-based intelligent electronic devices draw an input voltage of $5V - 24V$ from the battery sources, Power over the Ethernet (PoE), or energy harvesting options like miniature sensor-fit solar panels or energy conservation modes that place idle devices to sleep [19].

While the system-based framework considers all sensor types, heterogeneity raises performance and interoperability concerns when deploying sensors from different vendors with varying compute resources and storage capacity. This challenge is resolved by standardization.

The technical perspective implies not only performance maximisation but also cost minimisation. Sensors, such as PMUs, may represent a significant capital investment in IoT-based power monitoring systems [20]. Likewise, maintenance costs of sensors through firmware updates and resolving sensor hardware issues or updating security patches due to cyber threats and unauthorized access control are a major concern for the grid operator who aims to keep operational costs at a minimum.

*2) **Business perspective**:* Budget constraints and cost minimization are relevant aspects affecting decisions in the current frames of OSP. However, these represent a limited set of the drivers affecting decisions within energy companies, for which benefits seeking and risk reduction play a crucial role. Thus, to extend the purely technical and cost-based perspective, the OSP issue may be integrated into the overall company perspective. This perspective considers that optimal decisions regarding OSP rely on benefits $B(t)$ maximisation, costs $C(t)$ minimisation, and economic risks $R(t)$ minimisation over time, for all sensor types, as detailed in Eq. 2:

$$J_{comp\_opt} = Max \sum_{t=1}^{\infty} [B(t) - C(t) - R(t)] \tag{2}$$

Businesses thrive on data-rich operations, hence, the need for OSP to collect accurate measurements. In this context, a certain layout for OSP may help to increase cost-effectiveness, and efficiency, enhance existing revenue streams (e.g., logistics, optimal pricing, asset management), and develop new business models. With the continued decrease in the cost of sensors over the years, businesses are incentivised to capture the value of data analytics and data-driven decision-making, as detailed in [21] for power distribution grids. Thus, the strategies of companies encompass digital transformation, employing Big Data and Machine Learning solutions to decrease costs and provide new services. This strategic position drives new decisions for OSP, as a crucial aspect to build the digital capabilities of companies and leverage new benefits such as sales, talent retention, and business competitiveness.

To assess the benefits of more diverse and granular information from power systems, a life cycle thinking is required to capture the metrics evaluating the process along the information value chain, ranging from the deployment of the sensors to the application of new control and optimisation methods, changes in operations [22], and decision-making. Here, examples of business cases are the optimisation of maintenance schedules, better planning to postpone investments in grid infrastructure, decisions to avoid power outages, and anomalous operation modes. Sensor data not only finds application in addressing some recurring and costly grid challenges (e.g., early detection of faults in distribution grids) but also in fostering the capture of intangible benefits such as the development of digital skills for in-house technical personnel [23].

*3) **Societal perspective**:* In addition to the company-based perspective, sensor placement may be certainly affected by high-level social, regulatory, and environmental aspects. These are described from the societal perspective and should be considered within an ideal OSP procedure, in which balancing objectives and constraints are relevant. OSP design is considered to be optimal for society whether it maximises environmental and social benefits $B(k,t)$ and minimises risks $R(k,t)$ and costs $C(k,t)$ for all the stakeholders $k \subseteq \{1, ..., K\}$, as described in Eq. 3:

$$J_{soc\_opt} = Max \sum_{t=1}^{\infty} \sum_{k=1}^{K} [B(k,t) - C(k,t) - R(k,t)] \tag{3}$$

Here, the stakeholders considered may be generalised as environment, society, power system companies, and regulators.

Regarding environmental impacts, information gathering may have a significantly positive environmental impact, leading to improvements in energy efficiency,and asset lifetime, and allowing better planning toward the integration of renewable energies. On the one hand, the environmental footprint of sensors may represent a barrier to deploying such technologies, which may require considerable materials and energy for their manufacturing, transportation, use, and disposal; factors of growing importance nowadays. Therefore, OSP must consider the energy consumption and the features of sensors while minimising hardware roll-out to limit environmental impacts.

Sensor placement may be considerably affected by regulation, which drives the adoption of modernization actions in power systems and the integration of new standards. Likewise, customers are directly and indirectly affected by sensor placement. Costs of operation are regulated by policy-makers and indirectly paid by customers in their electricity bills. Thus, despite the potentially high up-front costs of sensors, they have the ability to reduce prices in the long term and allow a better service by means of enhanced power quality and security of supply. These aspects are influenced by the installation, design, and operation of sensors. Thus, to further describe the nuances of current approaches, the workflow of the technical perspective is presented.

### *B. System perspective in the sensor placement workflow*

Designing a sequential OSP workflow serves as a guide for grid operators, planners, and researchers for the implementation of sensors for a given use case. The OSP workflow is mapped sequentially into phases as illustrated in Fig. 2. These phases interact with each other sequentially and iteratively forming a mesh representation of the proposed OSP system-based workflow. The OSP workflow phases are:

*1) **Use Case Definition**:* At the inception of the OSP workflow, the grid operators define their use cases for the data collection by (i) the challenge (e.g., wide area monitoring, predictive maintenance, or power quality monitoring), (ii) availability of sensor technology in the market (e.g., while exploring in-house customised sensor fabrication - verification process), and (iii) assessing the environmental, social, and economic feasibility of adopting sensors. This phase is quite crucial as it involves key stakeholders and factors in all the system perspectives. The phase results in feasibility studies, geo-mapping of sensor placement sample area, and planning reports which are crucial in building a clear understanding of the problem to consider reliable alternatives [24].

*2) **Data collection, enrichment, and pre-processing**:* Having identified the need for sensor placement and conducted feasibility studies, grid operators gather data from different stakeholders to formulate a relevant objective function for optimal sensor placement. This data (either internally or externally sourced) is analysed to draw out the key metrics, constraints, benefits, and risks associated with the deployment. As such, this data needs to be accurate, complete, and consistent which may not be the case with externally sourced data. To cope with these issues, [25] provides a data enrichment framework to guide the selection of sources.

The quality of the accessible data (e.g., data accuracy, and consistency) correlates strongly with the quality of the OSP process output and thus, with the aimed business process improvements [26]. Therefore, before starting with the design of the required sensor network, data enrichment and pre-processing tasks must be carried out. The latter tasks are shared with other data-driven problem formulations such as artificial intelligence, in which high data quality is highlighted as a key prerequisite for modelling success, as stated in [27].

For this purpose, this paper leverages existing studies measuring the degree of data quality, characterised by feature selection [28] and data completeness [29], to foster the use of data quality assessment methods [30] and frameworks [31] in OSP. From the data obtained, operators define the relevant constraints metrics and constraints to define a multi-objective function for OSP.

*3) **Optimal Sensor placement design**:* In section I, the paper discusses several use cases and OSP design methods such as swarm optimisation algorithms [14] and data-driven approaches [11]. In this workflow, the system-based perspectives metrics, and constraints are considered when formulating the multi-objective function. Here, the design phase explores trade-offs when the OSP objective function is subject to economic, socio-environmental, and technical constraints. Case in point, the technical objective functions could determine the best location points for sensors but that would tip the economic scale as businesses incur huge costs in the initial sensor deployment, feature updates, or maintenance activities. The costs of sensors installation and maintenance may significantly

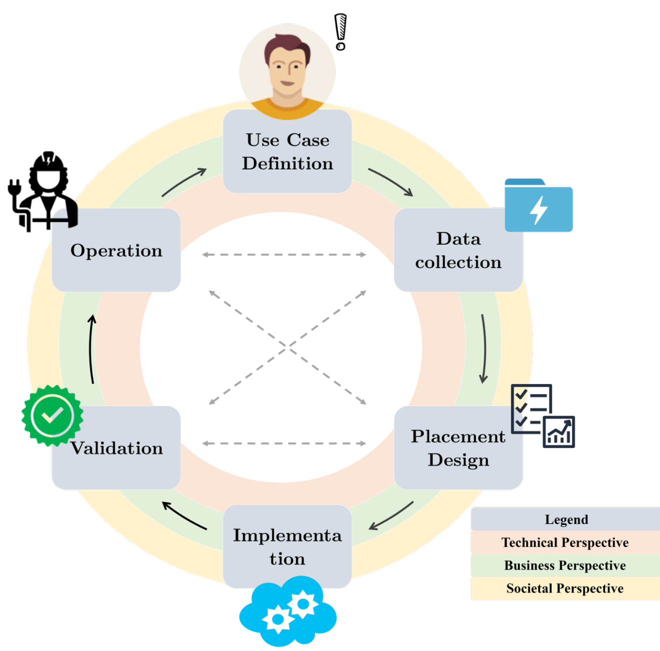


Fig. 2: Phases of an optimal sensor placement workflow.

influence the company's perspective, as detailed in [3].

As a result, additional methods for multi-criteria optimisation and decision analysis [32], where different weights may be assigned to the technical and economic constraints and objectives, become relevant. Sensor placement may be highly influenced by corporate strategy and regulation. In particular, standardisation strategies within companies or regulatory actions may force decision-makers to integrate sensors in all newly built components. In this context, the design phase may be entirely omitted, increasing the importance of other phases such as sensors implementation and operation, within the proposed OSP workflow. Ultimately, this phase defines the required number, type, and location of sensors for a particular use case taking into consideration all the system perspectives and trade-offs.

*4) **Implementation**:* Once the suitable location for the sensors has been selected, the next step is to install them in the real world. However, before a large-scale roll-out of the sensors, a pilot project or period is typically required [33] [6]. This is due to the large number of assets involved, which have significant economic implications and require practical insights and incremental improvements.

The implementation phase may differ with the existence of past sensor networks (i.e., brownfield) or the absence of previous sensors (i.e., greenfield), being in the former cases possible to retrieve insights from past sensor installations (e.g., disturbing factors, connectivity issues, reliability implications). For both greenfield and brownfield scenarios, the implementation (i.e., installation) phase must consider technical aspects such as the optimal installation of sensors and communication equipment, wiring, and the connection of sensors to primary assets (e.g., substation components), while addressing also societal and company issues such as safety procedures, quality, and standards compliance.

Lastly, the phase integrates the collected sensor data in cloud systems, SCADA systems, and applications and uses thereby for example digital twin information interface module. A remote-controlled patch and release management for all sensors will propel toward continuous deployment and allow future sensor design changes based on application development.

*5) **Sensor placement validation**:* After deploying the sensors, it is important to validate the sensor configuration to ensure that the sensor network meets the grid operators' needs and expectations as specified in the problem formulation phase. This proves that the specified objectives of the OSP are fulfilled, guaranteeing that data gathering is effectively providing the desired information to enable the expected business cases (i.e., business case validation). The authors of this study identify a lack of research for methods to validate optimal sensor placement. However, advanced methods and best practices for optimum sensor placement validation might boost distribution grid stratification by encouraging better-validated sensor placement initiatives towards digital twins [34].

*6) **Sensor operation**:* In the operation phase, sensor prediction models and device failure analysis, such as [17], ensure sensor reliability and enable self-reconfiguration and resilience. Meanwhile, the operation phase needs to ensure the quality (e.g., trustworthiness, consistency, and completeness) of the sensor data [35], as defined in the design phase. Further, this phase monitors the energy consumption of sensing systems and explores different power management optimisation methods that may provide substantial savings [36], contributing towards a more sustainable, carbon-neutral sensing network.

Finally, closing the iterative loop for OSP, the operation may provide insights to be used in current and future sensor placement elaborations, and the more extensive formulation domain problems. Subsequently, this workflow is modeled in a digital twin architecture where different phases of the sensor placement workflow interact with the information query services and the simulation of the digital twin. These can allow the identification of new domain issues or questions fostering the need for future OSP studies, triggering new OSP loops within the workflow.

## III. Discussion

To highlight the applicability of the proposed framework, the paper discusses proactive maintenance solutions in distribution grids. Thereafter, strengths, limitations, and future actions to expand the OSP framework for data collection towards digital twins are presented.

### A. Industry Applications

To curb high O&M costs [21] and unbearably long power outages as a result of equipment failure, the energy sector is adopting proactive maintenance (PM) techniques in three models: (i) preventive maintenance, (ii) condition-based maintenance, and (iii) scheduled/periodic maintenance. These methods use sensor data to assess the state of the equipment, determine if there is a need for corrective action (repair or replacement), and, finally, restore the system to normalcy. Sensor data is used to determine the condition of the assets to assess the need for maintenance.

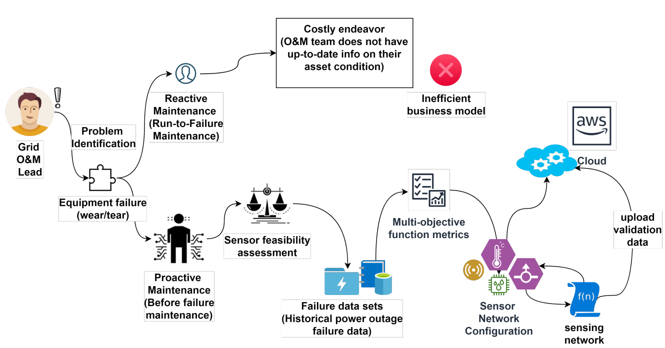


Fig. 3: Proactive maintenance optimal sensor placement: A system-based framework application

Fig. 3 customises the OSP workflow (as shown in Fig. 2) to capture the requirements and specifications for PM, and the need to monitor the condition of assets (grid equipment) is identified. In the first place, the problem formulation describes the boundary conditions (e.g., location, grid topology), stakeholders (e.g., grid operator, technical experts), and objectives of tackling issues in distribution grid components. For this, sensor placement can be beneficial to obtain the required information.

Historical data on failure in a given region comprises failure reports, components data (e.g., identification number, technical features), electrical parameters (e.g., loading, operation voltage, and current), and environmental conditions (e.g., ambient conditions, soil type, surrounding digging activities). These data categories are seldom completely available and, thus, require cooperation between different stakeholders for their collection. First-stage data quality is typically poor. Therefore, data enrichment and data pre-processing are required.

After processing the data, the OSP multi-objective function is formulated subject to business, technical, and socio-environmental constraints identified in the problem definition phase. Here, the maximisation of the health of grid components is included as a benefit in the objective function of the business perspective, together with the costs of implementation and risks of failures. The latter aspects affect positively the societal perspective, since the benefits of PM may increase power quality for customers and extend assets' lifetime.

### B. Discussion and future work

The proposed framework has provided a novel approach to map the proposed OSP workflow onto a multi-level system-based framework addressing technical, business, and societal aspects. For instance, adopting new sensors may be hindered by the economic risks of adopting one technology that may be replaced or obsolete in a short time. Here, real options theory [23] may be promising to assess the economic value of the options to delay sensor deployment if there is technological uncertainty or the option to expand the investment (i.e., increase the number of sensors deployed) if the socio-economic context is favourable. From the societal perspective, there is an increasing concern about the impacts of IoT on sustainability. Here, life cycle analysis [37] may be used to integrate the negative effects of IoT into the OSP calculations, highlighting the need to mitigate environmental impacts. This work can be advanced by developing a comprehensive test case involving stakeholders such as DSO, TSO, and grid planners. The test case results can be quantified (i.e., the benefits) to inform the best guidelines and policies to bridge the gap between current industrial practices and the novel framework developed in this paper.

## IV. Conclusion

This paper has proposed a system-based framework to discuss the technical, company and societal perspectives involved in the large-scale deployment of sensors for smart grids. Given the wide range of optimal sensor placement

(OSP) studies from a technical perspective, this paper has analyzed the nuances and identified the major steps of the OSP workflow. A prevalence use case in grid management, proactive maintenance, was modelled to demonstrate workflow application. The framework guides grid operators in sensor placement from a holistic view to attain economic, societal, environmental, and technical benefits.

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