Design and Implementation of a Solution for the Planning of Smart Spaces Aiming for Energy Efficiency in Industry 4.0☆

Projeto e Implementação de uma Solução para o Planejamento de Espaços Inteligentes Visando Eficiência Energética na Indústria 4.0

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Abstract

Given the significant increase in electricity consumption, especially in the industrial and commercial categories, exploring new energy sources and developing innovative technologies are essential. The fourth industrial revolution (Industry 4.0) and digital transformation are not just buzzwords, but they offer real opportunities for energy sustainability, using technologies such as artificial intelligence, the Internet of Things (IoT), and cloud computing. In this context, the paper presents an integrated approach that uses heterogeneous devices to cover the detection, communication, computation, and application layers, targeting application deployment efficiency. The implementation of this solution aims to reduce energy consumption by controlling connectivity and resource constraints. Preliminary results indicate its potential to assist in strategic planning and decision-making, promoting sustainability.

Keywords

Energy efficiency • Industry 4.0 • Deployment Planning • Internet of Things

Resumo

Dado o aumento significativo do consumo de energia elétrica, especialmente nas categorias industrial e comercial, explorar novas fontes de energia e desenvolver tecnologias inovadoras são essenciais. A quarta revolução industrial (Indústria 4.0) e a transformação digital não são apenas palavras da moda, mas oferecem oportunidades reais para a sustentabilidade energética, usando tecnologias como inteligência artificial, Internet das Coisas e computação em nuvem. Nesse contexto, o artigo apresenta uma abordagem integrada que usa dispositivos heterogêneos para cobrir as camadas de detecção, comunicação, computação e aplicação, visando a eficiência da implantação de aplicações. A implementação desta solução visa reduzir o consumo de energia controlando a conectividade e as restrições de recursos. Resultados preliminares indicam seu potencial para auxiliar no planejamento estratégico e na tomada de decisões, promovendo a sustentabilidade.

Palavras-chave

Eficiência energética • Indústria 4.0 • Planejamento de Implantação • Internet das Coisas

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1 Introduction

The increasingly complex energy production, distribution, and consumption challenges establish energy efficiency as a fundamental principle [1]. In the industrial context, optimizing energy consumption plays a crucial role in competitiveness and cost reduction, considering that the industrial sector is the leading consumer of energy in Brazil [2].

According to data provided by the Brazilian Energy Research Company [2], electricity consumption in Brazil grew 9% in May 2024 compared to the same period last year, representing the fourth highest electricity consumption since 2004, especially in the industrial and commercial. These categories showed significant growth rates that continue to rise. Although factors such as population growth and the proliferation of electronic equipment have contributed to this increase, inadequate management of these devices and the lack of measures to promote energy efficiency can be considered the main problems.

Given this scenario, the growing energy demand requires exploring new energy sources and developing technologies that optimize the use of existing sources [3]. The fourth industrial revolution, known as Industry 4.0, and the digital transformation of the business world are expected to offer immense opportunities for energy sustainability [4]. This paradigm reconfigures the design and implementation of industrial operations, extensively using artificial intelligence, the Internet of Things (IoT), cloud computing, and other technologies. The integration of these technologies enables highly interconnected and intelligent operating environments, creating an environment conducive to applying innovative solutions aimed at energy efficiency [5].

As discussed by Boyes et al. [6], the Industrial Internet of Things (IIoT) has been a milestone for the development of so-called smart factories. These factories are characterized by integrating sensors and various devices, which collect real-time information and analyze and generate response actions, a process highlighted by WEG Digital Solutions [7].

These solutions must be implemented in a way that guarantees satisfactory performance while seeking to reduce costs, for example, through sharing resources [8]. Therefore, it is necessary to develop solutions that facilitate this complex task. Among the approaches aimed at this goal, Wang [9] addresses the problem of positioning canonical sensors to maximize the coverage area in wireless sensor networks. Similarly, Qiu et al. [10] present algorithmic approaches to solving gateway placement problems to maximize throughput in wireless mesh networks. As another example, the QuIC-IoT platform [11] proposes model-driven planning to temporarily deploy a custom IoT infrastructure to monitor short-term events, using physics-based models to predict the propagation of phenomena. Furthermore, Sasikumar et al. [12] combines a blockchain-based distributed network with a digital twin for the IIoT applications. Other solutions for IoT-based smart space planning were proposed, targeting specific goals such as energy saving in communication [13] and reduce data transferring [14]. Despite these efforts, existing solutions have limitations in selecting and implementing applications that meet energy efficiency demands. Therefore, this work introduces an integrated approach that covers the sensing, communication, computing, and application layers, using heterogeneous devices and considering the structure and needs of applications. In Refs. [15, 16, 17], we detail the model of this solution and describe the solution design, and here we present new results related to its implementation. Through the planning provided by the software, it is expected that the implementation resulting from the project will enable the reduction of energy consumption by controlling restrictions on connectivity, resources, and equipment, among others. Furthermore, the software has the potential to assist in strategic planning and decision-making related to modeled spaces, aiming to save expenses and promote sustainability.

The remainder of the article is organized as follows: Section 2 summarizes the modeling proposal, while the problem solution is discussed in Section 3 and the implementation in Section 4. Section 5 presents final remarks.

2 Materials and Methods

The methodology employed in this research involves the design and implementation of an integrated solution that leverages the capabilities of Industry 4.0 technologies to improve energy efficiency in industrial environments. By combining IoT devices, edge computing, and network infrastructure, the solution aims to optimize the detection, communication, and processing of data within smart spaces, ultimately reducing energy consumption and enhancing system performance.

The proposed modeling is based on the *SmartParcels* [18, 19] tool, which generates plans to instrument smart community regions. The problem is decomposed into four layers: application, information, infrastructure, and geophysics. The application layer defines the tasks and objectives of the deployed devices, the information layer handles the flow of data between sensors and processing units, the infrastructure layer focuses on the physical devices and their placement, and the geophysics layer manages the spatial distribution and environmental constraints of the deployment.

In this work, a modified version of the SmartParcels tool was implemented to generate deployment plans for the IoT devices. The goal was to maximize the utility of applications after deployment by optimizing both the coverage area for event detection and the precision of event identification. The model accounted for various constraints, including budget, detection ranges, computational power, and Quality of Service (QoS) requirements.

The solution decomposed the problem into several sub-tasks, each addressed by specific algorithms. First, candidate locations for device deployment were selected based on coverage and cost considerations. Then, information flows, representing data combinations from sensors, were mapped onto infrastructure flows, which represent the physical devices like sensors and edge servers. The final deployment plans balanced resource use, cost, and performance to achieve efficient and reliable system operations.

The proposed model was validated through a realistic scenario. Further details on the modeling structures, algorithms, and performance metrics used in the study can be found in previous works by the authors [15, 16].

The goal is to maximize the utility of applications after deploying IoT devices, edge servers, and network switches. Utility is defined by (i) coverage, representing the area where application events are detected, and (ii) precision, representing the probability of correct event detection. Deployment plans must meet constraints such as budget, detection ranges, computing power, network bandwidth, and QoS requirements.

The proposed model defines an industry as a structure composed of the tuple $(\mathcal{S}, \mathcal{A}_i | \forall s_i \in \mathcal{S})$, where $\mathcal{S}$ is the set of rooms and $\mathcal{A}_i$ is the set of applications for each room s_i. Each application $a_{i,j}$ in room s_i has a weight $\beta_{i,j}$, with $\sum_{\forall a_{i,j} \in \mathcal{A}_i} \beta_{i,j} = 1, \forall s_i$. The set $\mathcal{L}$ represents candidate locations in the industry for installing devices.

As shown in Fig. 1, the model uses three data structures that represent functional and non-functional aspects of an application: **Information Flow**, **Infrastructure Flow** and **Mapped Infrastructure Flow (MIF)**.

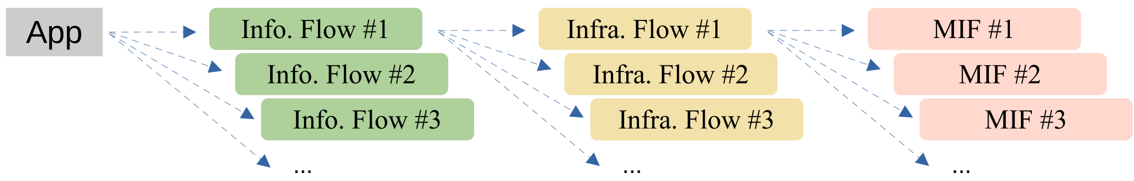

Figure 1: Main modeling structures.

Information flows are directed graphs representing different data combinations from sensors and algorithms on computing devices that perform an application. These flows, denoted by $\mathcal{F}_{i,j}^{info}$ for an application $a_{i,j}$, allow compensating the application's QoS and the cost, selecting the most appropriate combination.

Each piece of equipment's transmission capacity and monitoring range are considered. In this context, $f_{i,j,k}^{info} \in \mathcal{F}_{i,j}^{info}$ represents the k-th information flow, indicating the data transmission sequence of the equipment in the application.

The model uses the expression $f_{i,j,k}^{info} = (V^{info}, E^{info})$ to structure information flow in terms of vertices (V^{info}), which represent units of information, including sensor data and middleware components for organization and processing; directed edges (E^{info}), which represent data transfers between vertices, showing the circulation of information and communication in the system; and weights on edges ($w(e(u,v))$) and vertices ($w(v)$), which represent bandwidth consumption for data transfer and use of computational resources for processing or storage.

Each information flow can be installed on different combinations of sensors, servers, and network switches, called **infrastructure flows**. Each information flow $f_{i,j,k}^{info}$ can be implemented by a set of infrastructure flows $\mathcal{F}_{i,j,k}^{ifr}$, where $f_{i,j,k,m}^{ifr} \in \mathcal{F}_{i,j,k}^{ifr}$ is the m-th infrastructure flow. Different infrastructure flows concerning an information flow can result in different degrees of resource sharing, allowing reuse for greater efficiency. The term $f_{i,j,k,m}^{ifr} = (V^{ifr}, E^{ifr})$ is a weighted directed graph, where $v \in V^{ifr}$ represents a device and $e(u,v) \in E^{ifr}$ represents the data flow between devices. Devices can be sensors, computing devices (such as edge servers), and network switches. The weights of a vertex $w(v)$ and an edge $w(e(u,v))$ represent the computing resource and the offered network bandwidth, respectively.

Each infrastructure flow is characterized and differentiated based on different attributes: the number of devices, computing, and network resources used, transmission range, detection range, deployment cost, and operational cost. Considering these aspects, it is possible to select the most appropriate infrastructure flow to support the specific needs of an information flow, balancing performance, cost, and efficiency.

For an information flow $f_{i,j,k}^{info}$ and an infrastructure set $f_{i,j,k,m}^{ifr}$, each processing unit $v \in V^{info}$ is assigned to a device $v' \in V^{ifr}$ by a function $R(v) = v'$. For an edge $e(u,v) \in E^{info}$, $\langle R(u), R(v) \rangle$ denotes the shortest path in $f_{i,j,k,m}^{ifr}$ consisting of the devices involved, i.e., the actual data flow at the infrastructure layer. $\langle R(u), R(v) \rangle$ is assumed to contain at least one network switch, unless $R(u)$ and $R(v)$ are the same device. If u and v are on the same device, the network bandwidth between them is extremely high, denoted by $w(e(R(u), R(v))) = \infty$. An infrastructure flow $f^{ifr}_{i,j,k,m}$ with mapping $f(v)$ for each device $v \in f^{ifr}_{i,j,k,m}$ is defined as a **Mapped Infrastructure Flow (MIF)**.

Application deployment planning can be carried out based on information flows and infrastructure flows. For this, an auxiliary structure called a planning graph is established, defined as a two-layer graph $G^p = (V^p, E^p)$, where the first layer $G^p_1 = (V^p_1, E^p_1)$ contains the information flows. The second layer $G^p_2 = (V^p_2, E^p_2)$ comprises the infrastructure flows. In both layers, flows can share vertices or edges. Furthermore, a set of assignment edges E^r is defined, where each edge $e(v, R(v))$ indicates the assignment of $v \in V^{info} \subset V^p_1$ for $R(v) \in V^{ifr} \subset V^p_2$ for $f^{info}_{i,j,k}$ and $f^{ifr}_{i,j,k,m}$. Based on these definitions, the planning graph can be written as $V^p = \{V^p_1, V^p_2\}$ and $E^p = \{E^p_1, E^p_2, E^r\}$.

To select candidate locations, a geophysical mapping function $f(v)$ is defined that maps a vertex $v \in V^p_2$ of the infrastructure layer of a planning graph G^p for a candidate location $l \in \mathcal{L}$.

Each $v \in V^p_2$ is captured by a tuple $t_v = (r^{tr}_v, r^{sen}_v, \tau_v)$. The device's transmission and detection ranges are represented by r^{tr}_v and r^{sen}_v, respectively. τ_v indicates the type of device, which can be *sensor*, *computing* or *network*. If $\tau_v \neq$ *network*, r^{tr}_v is equal to the transmission range of your connected network device u, i.e., $r^{tr}_v = r^{tr}_u, e(v, u) \in E^p_2$.

To represent the service utility, that is, how advantageous a solution is compared to others, it is necessary to consider the distance between two candidate locations $l_1, l_2 \in \mathcal{L}$, defined as $dist(l_1, l_2)$. In modeling, distance is represented using the Euclidean distance between the two candidate locations. By definition [20], the Euclidean distance between two two-dimensional points (x_1, y_1) and (x_2, y_2) is defined according to Eq. (1):

$$d = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \tag{1}$$

An infrastructure flow is **connected** if all its devices are connected after mapping, that is, $dist(f(u), f(v)) \leq min(r^{tr}_u, r^{tr}_v), \forall e = (u, v) \in f^{ifr}_{i,j,k,m}$; otherwise, the stream is not connected. If $f^{ifr}_{i,j,k,m}$ is connected, the **service utility** in a room s_i is given by Eq. (2):

$$U(f^{ifr}_{i,j,k,m}, s_i) = A(f^{ifr}_{i,j,k,m}) \cdot P(V^{sen}_{i,j,k,m}, s_i) \tag{2}$$

where $A(f^{ifr}_{i,j,k,m})$ and $P(V^{sen}_{i,j,k,m}, s_i)$ are the accuracy and probability of detection.

If $f^{ifr}_{i,j,k,m}$ is not connected, $U(f^{ifr}_{i,j,k,m}, s_i)$ is set to 0. Each $f^{ifr}_{i,j,k,m}$ associated with the application $a_{i,j}$ has a precision model $A(f^{ifr}_{i,j,k,m})$ which depends on the implemented method. For example, for presence detection, presence sensor-based detection is more accurate than image-based detection.

Initially, for a sensor $v \in V^{sen}_{i,j,k,m}$, the probability is attenuated (decayed) with its distance denoted by s_i, $dist(f(v), s_i)$ and truncated by its detection range r^{sen}_v. Therefore, if $dist(f(v), s_i) \leq r^{sen}_v, \forall v \in V^{sen}_{i,j,k,m}$, the attenuated detection probability Truncated mean is given by Eq. (3):

$$\bar{p} = \frac{\sum_{\forall v \in V^{sen}_{i,j,k,m}} e^{-\alpha_v \cdot dist(f(v), s_i)}}{\mid V^{sen}_{i,j,k,m} \mid} \tag{3}$$

where α_v is a parameter related to v. Otherwise, $\bar{p} = 0$.

The probability of detection is then limited by the range of the sensors as defined in Eq. (4):

$$P(V^{sen}_{i,j,k,m}, s_i) = \begin{cases} \bar{p}, & \text{if } dist(f(v), s_i) \leq r^{sen}_v, \forall v \in V^{sen}_{i,j,k,m}; \\ 0, & \text{otherwise.} \end{cases} \tag{4}$$

To complete the modeling, each device $v \in V^p_2$ in the infrastructure layer is subject to two types of costs: deployment $\delta_{dp}(v, l)$ due to device deployment v in the candidate location $l \in \mathcal{L}$ and operational $\delta_{op}(v)$ due to the maintenance of its operation. Furthermore, B_{dp} and B_{op} are defined as the budgets for deploying and operating the devices.

3 Results and Discussion

Let $G^{p^*} = (V^{p^*}, E^{p^*})$ be the optimal planning graph, where $G^{p^*}_1 = (V^{p^*}_1, E^{p^*}_1)$ contains a set of information flows and $G^{p^*}_2 = (V^{p^*}_2, E^{p^*}_2)$ contains a set of infrastructure flows. The main reason decomposition is proposed is that when searching for the optimal planning graph, G^{p^*} geophysical mappings are generated and examined repeatedly. However, geophysical mappings are mostly static and can and should be stored and reused. Fig. 2 shows the relationship between these two subproblems and the algorithms that solve them: Selection (SEL), which chooses the most promising mappings with greater expected service utility and greater communication coverage, aiming to reduce the number of equipment; and Maximum Reusability (MR), which iteratively selects the infrastructure flow with maximum device reuse.

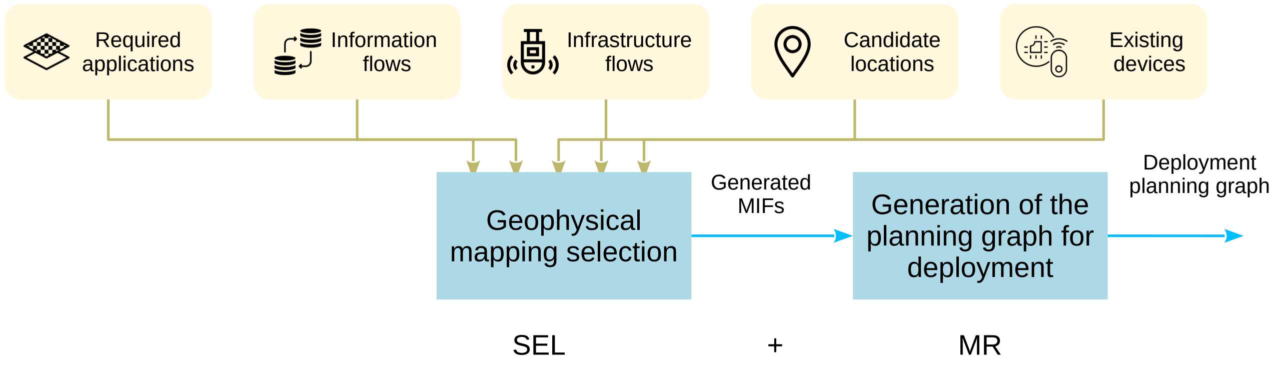

Figure 2: Problem decomposition, main inputs/outputs and proposed algorithms.

Based on the results from [19], it was possible to develop a solution approach based on dynamic programming that generates the planning graph with maximum service utility. However, the execution time increases dramatically when the number of rooms, required applications, implementation methods (information flows and infrastructure), or candidate locations increases. Therefore, the optimal solution is unfeasible due to its extremely long time to complete. As a result, the algorithms presented represent a heuristic solution for each subproblem.

The first heuristic, SEL, is based on selection policies to eliminate less promising mappings. The policies contain the following intuitions: (i) MIFs with more significant utilities should be included earlier, and (ii) MIFs with more excellent communication coverage should be included earlier.

For each $f^{ifr}_{i,j,k,m}$, the utility can be estimated by Eq. (2) after mapping all equipment (assuming that the graph is connected). Similarly, the communication coverage of a network device can be estimated after mapping. The Alg. 1 presents the adopted heuristic, using M and N to represent the user-specified pruning criteria for utility and communication coverage, respectively.

function SEL($\mathcal{S}$, $\mathcal{A}$, $\mathcal{F}^{info}$, $\mathcal{F}^{ifr}$)
Select all possible geophysical mapping functions $f(v)$ for each sensor $v \in V^{sen}_{i,j,k,m} \subset V^{ifr}$ where s_i is within the sensing radius of v, i.e., $dist(f(v), s_i) \leq r^{sen}_v$
Update $\widehat{\mathcal{F}}$ to contain only the M best service utilities
for each possible combination $\widehat{\mathcal{F}}$ **do**
Select all possible mappings $f(u)$ for each infrastructure u adjacent to the sensors in $f^{ifr}_{i,j,k,m}$, i.e., $dist(f(v), f(u)) \leq min(r^{tr}_v, r^{tr}_u)$
Update $\widehat{\mathcal{F}}$ to contain only the N best communication coverages if the examined infrastructure is a network device
end for
Recursively execute Step 4 for infrastructures adjacent to those previously examined until all have been examined
return u
end function

Algorithm 1: SEL Heuristic.

In the MR heuristic, instead of examining all possible combinations of MIFs, it iteratively: (i) selects an application $a_{i,j} \in \widehat{\mathcal{A}}$ to implement and (ii) merges an END $\widehat{\mathcal{F}} \in \mathcal{M}^{ifr}_{i,j,k,m}$, where $\mathcal{M}^{ifr}_{i,j,k,m} \in \widehat{\mathcal{M}_{i,j}}$, in the planning graph $\widehat{G}(K)$ according to the reusability of $\widehat{\mathcal{F}}$. A reusability index was defined, considering the investment efficiency and the gain in communication coverage when merging $\widehat{\mathcal{F}}$.

Investment efficiency is the ratio between the application's utility gain and the cost gain after merging $\widehat{\mathcal{F}}$ into $\widehat{G}(K)$. In other words, the more infrastructures are reused, the lower the costs will be with merging $\widehat{\mathcal{F}}$. Specifically, whether $\Delta U(\widehat{\mathcal{F}}, \widehat{G}(K))$ the application's utility gain after merging $\widehat{\mathcal{F}}$ into $\widehat{G}(K)$. After merging $\widehat{\mathcal{F}}$ into $\widehat{G}(K)$, the cost gain is given by:

$$\Delta\delta(\widehat{\mathcal{F}}, \widehat{G}(K)) = \widehat{\delta}_{dp}(K) - \widehat{\delta}_{dp}(K-1) + \widehat{\delta}_{op}(K) - \widehat{\delta}_{op}(K-1) \tag{5}$$

Therefore, we have:

$$I_{eff}(\widehat{\mathcal{F}}, \widehat{G}(K)) = \frac{\Delta U(\widehat{\mathcal{F}}, \widehat{G}(K))}{\Delta\delta(\widehat{\mathcal{F}}, \widehat{G}(K))} \tag{6}$$

which is the investment efficiency of merging $\widehat{\mathcal{F}}$ into $\widehat{G}(K)$.

Communication coverage gain is determined by the locations of network devices. If a network device has greater communication coverage after deployment, fewer devices will be needed. Let $\mathcal{L}_{cov}(K) \subset \mathcal{L}$ be the candidate locations in the communication coverage of network devices in $\widehat{G}(K)$. The communication coverage gain after merging $\widehat{\mathcal{F}}$ into $\widehat{G}(K)$ is given by:

$$I_{cov}(\widehat{\mathcal{F}}, \widehat{G}(K)) = \mathcal{L}_{cov}(K) - \mathcal{L}_{cov}(K-1) \tag{7}$$

The reusability index is defined as a weighted sum of investment efficiency and communication coverage gain when merging an FIM $\widehat{\mathcal{F}}$ into the intermediate planning graph $\widehat{G}(K)$. Let α_{eff} and α_{cov} be the weights of investment efficiency and communication coverage gain, respectively. The reusability index is written as:

$$I(\widehat{\mathcal{F}}, \widehat{G}(K)) = \alpha_{eff}\, I_{eff}(\widehat{\mathcal{F}}, \widehat{G}(K)) + \alpha_{cov}\, I_{cov}(\widehat{\mathcal{F}}, \widehat{G}(K)) \tag{8}$$

Without loss of generality, it is assumed that $\alpha_{eff} + \alpha_{cov} = 1$.

With these definitions, MR starts with an empty planning graph $\widehat{G}(0)$ and iteratively selects an application $a_{i_j} \in \widehat{\mathcal{A}}$ to implement by merging an END $\widehat{\mathcal{F}} \in \mathcal{M}^{ifr}_{i,j,k,m}$, where $\mathcal{M}^{ifr}_{i,j,k,m} \in \widehat{\mathcal{M}_{i,j}}$, in the current intermediate planning graph $\widehat{G}(K)$ as established in the Alg. 2.

function MR($\mathcal{S}$, $\mathcal{A}$, $\mathcal{F}^{info}$, $\mathcal{F}^{ifr}$)
  for each $a_{i_j} \in \widehat{\mathcal{A}}$ **do**
    Examine the reusability index $I(\widehat{\mathcal{F}}, \widehat{G}(K))$ of each MIF $\widehat{\mathcal{F}} \in \mathcal{M}^{ifr}_{i,j,k,m}, \forall \mathcal{M}^{ifr}_{i,j,k,m} \in \widehat{\mathcal{M}_{i,j}}$
    Integrate $\widehat{\mathcal{F}}$ with the largest $I(\widehat{\mathcal{F}}, \widehat{G}(K))$ in $\widehat{G}(K)$ and delete the corresponding applications of $\mathcal{A}$
    while at least one of the constraints is not violated for all MIFs of the remaining applications or all reusability indices generated are zero **do**
      Repeat previous steps
    end while
  end for
  return u
end function

Algorithm 2: MR Heuristic.

In Lines 2 to 3, for each application $a_{i_j} \in \widehat{\mathcal{A}}$, the algorithm examines the reusability index $I(\widehat{\mathcal{F}}, \widehat{G}(K))$ for each END $\widehat{\mathcal{F}}$ within the set of possible mappings $\mathcal{M}i, j, k, m^{ifr}$, where $\widehat{\mathcal{M}}i, j$ represents the set of all mappings for the considered application. In Line 4, the END $\widehat{\mathcal{F}}$ with the highest reusability index $I(\widehat{\mathcal{F}}, \widehat{G}(K))$ is then incorporated into the planning graph $\widehat{G}(K)$. Applications corresponding to this END are excluded from the set $\mathcal{A}$, indicating that their infrastructure needs have already been met.

The process repeats the evaluation and selection steps as long as at least one of the constraints is not violated for the MIFs of the remaining applications, or until all calculated reusability indices are zero. This strategy ensures that planning continues to optimize component reuse without violating operational or design constraints. As output, the algorithm produces a planning graph representing the infrastructure and application mapping, prioritizing component reuse.

The proposed solution was implemented as a prototype made available through a Web API. The objective was to develop a flexible application for both local environments and cloud infrastructures. Based on this, the implemented architecture is presented in Fig. 3.

The first component is the user interface, designed to enable modeling and achieve planning. The interaction takes place through the REST API. Users' models are validated according to specifications intended for IoT models. This process is based on standards and specifications developed to facilitate interoperability and simplified data exchange between devices and systems in IoT environments.

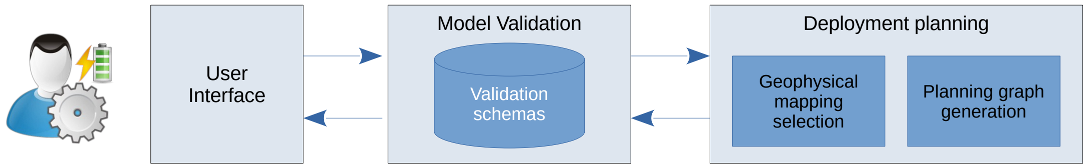

Figure 3: Solution architecture.

Among the standards used, a large part is used from [21], a collaborative initiative that aims to improve data models aimed at IoT. The data models are compatible with the *FIWARE* version 2 [22] and *Next Generation Service Interface - Linked Data* (NGSI-LD) [23] specifications, enabling their use by these standards. They encompass detailed definitions of properties, attributes, and the relationships between various data entities, ensuring that information is not only accessible but also meaningful and readily usable across diverse systems. In total, 15 application domains are available, and models from four of them were used: *Smart Energy*, *Smart Cities*, *Smart Robotics*, and *Smart Sensing*.

In addition to *Smart Data Models*, schemas from [24] are used, a collaborative initiative led by large search engines, aiming to structure information on the Internet through a standardized set of *tags Extensible Markup Language* (XML).

To represent information and infrastructure flows, [25] is used, a convention to describe the data structure in graphs using the JSON format, facilitating data storage, manipulation, and transfer. Fig.4 summarizes the models used in data representation.

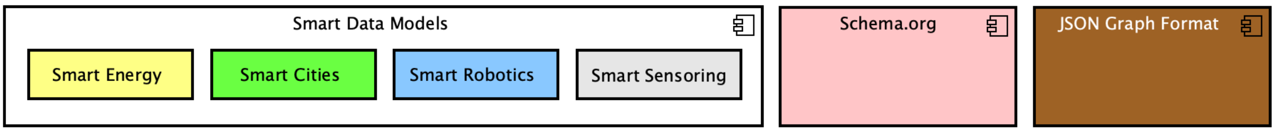

Figure 4: Models used in solution.

After validating the models, planning is carried out using the heuristic solution described in the previous section.

The industry and its rooms are represented using GeoJSON [26], an open standard format designed to represent simple geographic features along with their non-spatial attributes using JSON. Each candidate location is represented by the geographic coordinates of its location and the deployment cost for each type of equipment in that location.

In information and infrastructure flows, each node is assigned a `role` specifying its role. Vertices can be classified as `sensor`, representing sensors or any data collection device; `network` for components part of the network; or `compute` indicating devices with processing capacity. For vertices categorized as sensors, attributes `attribute` list the data types the device can collect.

Specific attributes were introduced, `r_tr` and `r_sen` which represent the transmission range (r_v^{tr}) and sensing range (r_v^{sin}), respectively. Additionally, `precision_model` is introduced as a representation of the precision model $A(f_{i,j,k,m}^{ifr})$. The procedure starts by selecting all possible geophysical mapping functions for each room, considering the sensors whose sensing area includes part of the room. In this analysis, candidate locations in the room and external locations are considered as long as the room is in the sensing coverage area of a sensor in these locations.

The application was implemented in Python using the *framework* Django [27]. The choice for these tools is because the Python language has a clear and readable syntax and is a robust option with a vast number of libraries available.

In the implementation, the `Shapely` libraries were used. and `Geopy` of Python. `Shapely` is used to manipulate and analyze plane geometry. It allows the creation, manipulation, and analysis of geometries, in addition to performing operations such as union, intersection, difference, and many others on geometric objects. While `Geopy` provides a simple and consistent interface to perform various geographic operations such as geocoding, distance calculation between geographic points, route calculation between locations, and more, it is often used in applications involving geographic data analysis, geolocation, and geocoding.

The tool's output is a set of mapped infrastructure flows in JSON, along with the metrics of this mapping, as shown in the Fig. 5.

Each mapped infrastructure flow contains detailed information about different deployment options, including:

- `deployCost`: Deployment cost (in US$), with monetary variations, indicating different levels of initial investment required for each deployment;

```json
{
    "mifs": [
        {
            "mif": {
                "ifr1-1-1-3a": {
                    "deployCost": 35.7,
                    "operationalCost": 12.3,
                    "r_tr": 180,
                    "r_sen": 180,
                    "location": [
                        -16.826468,
                        -49.218952
                    ]
                },
                "ifr1-1-1-3b": {
                    "deployCost": 560.0,
                    "operationalCost": 12.3,
                    "r_tr": 46,
                    "location": [
                        -16.826468,
                        -49.218952
                    ]
                },
                "ifr1-1-1-3c": {
                    "deployCost": 35.7,
                    "operationalCost": 12.3,
                    "r_tr": 46,
                    "location": [
                        -16.826216,
                        -49.21929
                    ]
                }
            },
            "utility": 0.02947237571446263,
            "coverage": 115114.88117861019,
            "application": "temperature-control-application"
        },
        ...
    ],
    "cost": 1348.8999999999999,
    "utility": 0.04912062619077105,
    "coverage": 149391.44354599537,
    "investmentEfficiency": 3.64153207730529e-05,
    "coverageLocations": 4,
    "reusabilityIndex": 1.6000218491924638
}
```


Figure 5: A possible output from the tool.

- `operationalCost`: Operational cost (in US$), constant for all instances, suggesting that, regardless of the deployment choice, the operating cost will be the same;
- `r_tr`: Transmission range (in meters), which varies significantly between instances, indicating different data transmission capacities;
- `r_sen`: Sensing range (in meters), constant between instances, being an important criterion for deployment choice;
- `location`: Geographic coordinates that vary slightly between instances, indicating different physical locations for deployment.

To plan and calculate performance metrics, the following parameters are used:

- `utility`: utility, presented as a high-precision numerical value for the specific application, suggesting a measure of efficiency or relative benefit of the implementation;
- `coverage`: coverage, expressed in area units, representing the extent of the area covered by the implementation;

- `application`: application identifier, indicating the specific context of the implementation.

To perform the financial and efficiency metrics, the output variables are as follows:

- `cost`: total cost (in US$), representing the investment required for complete implementation;
- `investmentEfficiency`: investment efficiency (floating number), indicating the relationship between the cost and the benefit obtained;
- `coverageLocations`: number of locations covered, indicating the geographic distribution of the implementation;
- `reusabilityIndex`: reusability index (floating number), indicating the reusability of the components or infrastructure.

The analysis of the results presented in the output represents planning with several implementation options, each with its own costs, transmission rates, and locations. Performance metrics, such as utility and coverage, provide a clear view of the implementation's efficiency and scope. Financial and efficiency metrics, such as total cost and investment efficiency, help assess the project's economic viability.

4 Conclusion

The implementation of an integrated solution that covers the detection, communication, computing, and application layers using heterogeneous devices presents significant potential for improving energy efficiency in the context of Industry 4.0. By optimizing the deployment of IoT devices and leveraging advanced computational models, this approach aims to reduce energy consumption while maintaining high levels of performance and operational efficiency.

The results achieved during the implementation phase indicate promising outcomes, particularly in the areas of strategic planning and decision-making related to smart space management. The solution has shown potential to assist industrial environments in controlling resource constraints, connectivity, and equipment use, leading to more sustainable operations.

However, while the initial results are encouraging, a comprehensive evaluation of the developed solution is necessary to fully demonstrate its efficacy. Future work will focus on conducting extensive testing in real-world industrial environments. This will include long-term performance analysis, benchmarking against other existing solutions, and evaluating the system's adaptability to various industrial settings. Such an evaluation is essential for consolidating the proposed model's effectiveness and ensuring its practical applicability on a larger scale.

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