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Modeling a Solution for Smart Space Planning Aiming for Energy Efficiency in Industry 4.0

Modelagem de uma Solução para Planejamento de Espaços Inteligentes Visando Eficiência Energética na Indústria 4.0

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Viviane Bessa Ferreira
ORCID: https://orcid.org/0000-0003-1393-2299
Instituto Federal de Goiás, Brazil
E-mail: viviane.ferreira@ifg.edu.br
Raphael de Aquino Gomes
ORCID: https://orcid.org/0000-0002-6036-7678
Instituto Federal de Goiás, Brazil
E-mail: raphael.gomes@ifg.edu.br
Wesley Pacheco Calixto
ORCID: https://orcid.org/0000-0002-1928-4432
Instituto Federal de Goiás, Brazil
E-mail: wpcalixto@ifg.edu.br

Resumo
A crescente demanda por energia no setor industrial gera desafios significativos, necessitando da exploração de soluções inovadoras. Em resposta, há uma inclinação crescente para aproveitar o potencial transformador das tecnologias da Indústria 4.0 para melhorar a eficiência energética nestes espaços. A integração de tecnologias inteligentes surge como uma alternativa promissora, suscitando um exame crítico de como os recursos, equipamentos e componentes computacionais podem ser estrategicamente organizados nesses ambientes. Com base nesta necessidade, o presente estudo procura contribuir, propondo uma solução abrangente para a concepção e planeamento de espaços inteligentes, alicerçada nas tecnologias da Indústria 4.0, com um foco específico na obtenção de eficiência energética. O trabalho não apenas conceitua o modelo proposto, mas também fornece resultados preliminares sobre sua implementação, preenchendo assim a lacuna entre as considerações teóricas e as aplicações práticas na busca de espaços industriais sustentáveis e inteligentes.
Palavras-chave: Eficiência Energética. Planejamento. Indústria 4.0.

Abstract
The escalating demand for energy in the industrial sector poses significant challenges, necessitating the exploration of innovative solutions. In response, there is a growing inclination towards leveraging the transformative potential of Industry 4.0 technologies to enhance energy efficiency in these spaces. The integration of smart technologies emerges as a promising alternative, prompting a critical examination of how computing resources, equipment, and components can be strategically arranged within these environments. Addressing this imperative, the present study endeavors to contribute to the discourse by proposing a comprehensive solution for the design and planning of smart spaces, grounded in Industry 4.0 technologies, with a specific focus on achieving energy efficiency. The research not only conceptualizes the proposed model but also provides insights into

its preliminary implementation, thereby bridging the gap between theoretical considerations and practical applications in the pursuit of sustainable and intelligent industrial spaces.
Keywords: Energy Efficiency. Planning. Industry 4.0.

1. Introduction

The increasingly complex energy production, distribution, and consumption challenges have established energy efficiency as a fundamental principle (Liu et al., 2023). In the industrial context, optimizing energy consumption is crucial for competitiveness and cost reduction, considering that the industrial sector is Brazil's leading energy consumer (Empresa de Pesquisa Energética, 2023).

According to data from the Energy Research Company (2023), national electricity consumption increased by 11.7% in May 2023, compared to the same period in 2020, in the industrial and commercial categories. 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 the exploration of new energy sources and the development of technologies that optimize the use of existing sources (Chatterjee, Keyhani & Kapoor, 2011; Barman et al., 2023). Renewable energy sources have gained prominence globally due to their positive impact on sustainability.

In this context, the fourth industrial revolution, known as Industry 4.0 (Lasi et al., 2014), was characterized by the convergence between digital technologies and industrial processes. 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 (Chen et al., 2021).

These solutions must be implemented in a way that guarantees satisfactory performance while seeking to reduce costs, for example, through sharing resources. Therefore, it is necessary to develop solutions that facilitate this complex task. Additionally, Industry 4.0 and the IoT encounter numerous hurdles, ranging from the development of skills to IT integration to the immaturity of some technologies (Saravanan *et al.*, 2022). Moreover, the impact of energy efficiency in Industry 4.0 has a dual nature. Firstly, considering the devices, which are limited in computational and communication resources, increased energy consumption may reduce the IoT's operational lifespan (Albreem *et al.*, 2017). Secondly, the sensing, computing, and communication processes executed by IoT devices can contribute to an expanding carbon footprint from a holistic system perspective (Wang *et al.*, 2016).

Among the approaches aimed at IoT planning, Wang (2011) addresses the problem of positioning canonical sensors to maximize the coverage area in wireless sensor networks. Similarly, Qiu (2004) presents algorithmic approaches to solving gateway placement problems to maximize throughput in wireless mesh networks. Jia (2021) explores in-depth analysis and research on the planning and design of smart gardens using Agricultural IoT technology, encompassing concepts, characteristics, related theories, and guidance methods. Furthermore, the QuIC-IoT platform (Chang et al., 2023) proposes model-driven planning to temporarily deploy a customized IoT infrastructure to monitor short-term events, using physics-based models to predict the propagation of phenomena.

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. The paper details the model of this solution and describes the implementation project. 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 paper is organized as follows: Section 2 presents the modeling proposal, while the implementation project is discussed in Section 3; conclusions are addressed in Section 4.

2. Problem Modeling

The proposed modeling is based on the proposal for the SmartParcels tool (Chang, 2021a; Chang, 2021b), a framework that generates the plan to instrument designated regions of smart communities. The problem is decomposed into four layers: application, information, infrastructure, and geophysics, as illustrated in Figure **1**.

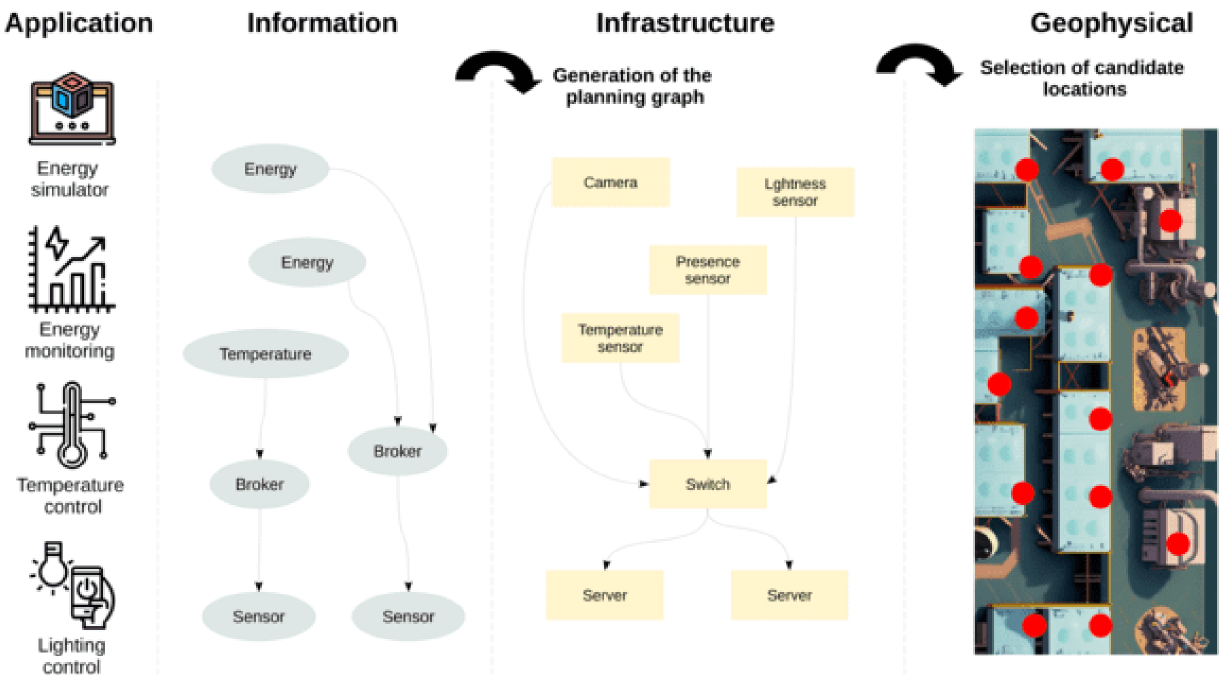

Figure 1: Overview of the proposed modeling.

The scenario is treated as an optimization problem that aims to maximize the overall utility of the required applications after deploying IoT devices, edge servers, and network switches in the generated planning. The service's usefulness is defined based on (i) coverage, which represents the geographic area where application events can be detected, and (ii) accuracy, which represents the probability of an event being detected correctly. Deployment plans must satisfy severe constraints, including deployment and operational budgets, detection ranges, computing power, network bandwidth, and application QoS requirements. Solving the resulting application planning problem is challenging due to the complex interaction between the four layers: application, information, infrastructure, and geophysics.

The premise for the solution to be developed is that it is a differentiator compared to other solutions for promoting energy efficiency, mainly because it is an alternative that seeks to optimize the quantity of equipment and components needed, considering aspects of functionality and coverage.

The proposed model considers a single industry with a set of rooms S, where $s_i \in S$ is the i-th room. s_i demands for a set of applications A_i, where $a_{i,j} \in A_i$ is the j-th application.

The industry is represented by a tuple $(S, \{A_i | \forall s_i \in S\})$, which indicates its rooms and corresponding applications. A room is represented by the center point within its boundary for simplicity. The industry has a set of candidate locations L, such as light bulbs, air conditioning, and computers, including IoT devices such as sensors, edge servers, and network devices. Different applications may have different levels of importance. Each room s_i is assigned a weight $\beta_{i,j}$ for each required application, representing its importance. Without loss of generality, it is assumed $\sum_{\forall a_{i,j} \in A_i} \beta_{i,j} = 1$, $\forall s_i$.

Modeling must be carried out for an industry, taking into account all its rooms. Assuming that an industry has 15 rooms, in the model developed $|S| = 15$ and $S = \{s_1, s_2, \ldots, s_{15}\}$. Suppose it is an administrative room requiring two applications, such as temperature control and consumption monitoring. In this case, $|A_1| = 2$ and $A_1 = \{a_{11}, a_{12}\}$, so a_{11} and a_{12} are the applications required for this room.

The other components of the modeling are described below.

2.1. Information flows for an application

Each required application can be realized through different combinations of sensor data from IoT devices and analytical algorithms on computing devices (edge servers) connected by directed graphs called information flows. Different information flows from the same application, allowing planning to balance the application's QoS and cost (deployment and operational), selecting the most appropriate one to meet industry requirements.

To implement the application $a_{i,j}$, a set of information flows $F_{i,j}^{info}$ can be adopted, where $f_{i,j,k}^{info} \in F_{i,j}^{info}$ is the k-th information flow. More precisely, $f_{i,j,k}^{info} = (V^{info}, E^{info})$ is a weighted directed graph, where $v \in V^{info}$ represents a unit of information (raw data or components of communication middleware) and $e(u,v) \in E^{info}$ represents the data flow between two information units. Both vertices and edges are associated with weights. The weight of a vertex $w(v)$ represents the computing resources consumed by the information unit, while the weight of an edge $w(e(u,v))$ is the bandwidth consumption. Furthermore, each information stream specifies the number of sensors; for example, three microphones are required for sound source detection using triangulation. Figure **2** represents how each application can be implemented by a set of information flows.

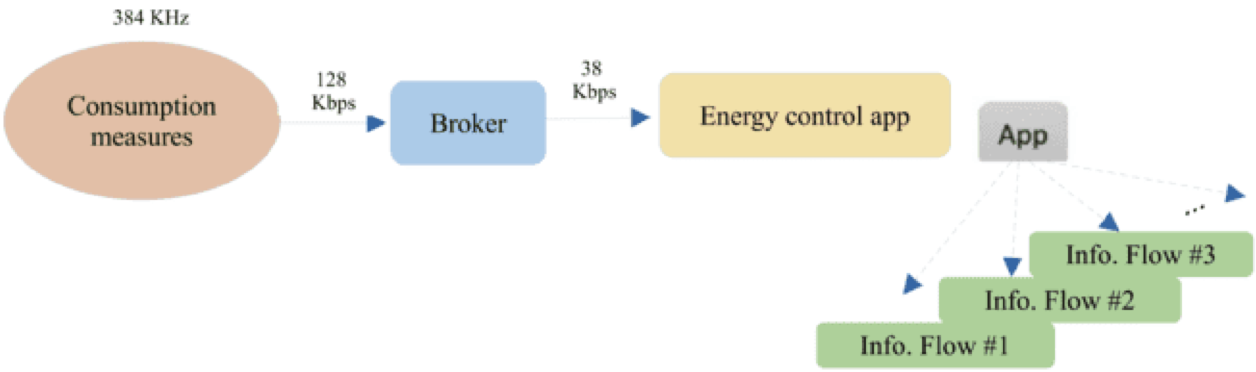

Figure 2: Representation of information flows for an application.

Figure **8** presents possible information flows for a temperature control application. As can be seen, a flow is distinguished from others considering the following aspects: modeled information unit: raw data (consumption measurement), middleware services such as broker or virtual sensor; QoS requirements of each information unit, such as bandwidth, measurement accuracy, minimum computing resources, and others; accuracy of each flow of information.

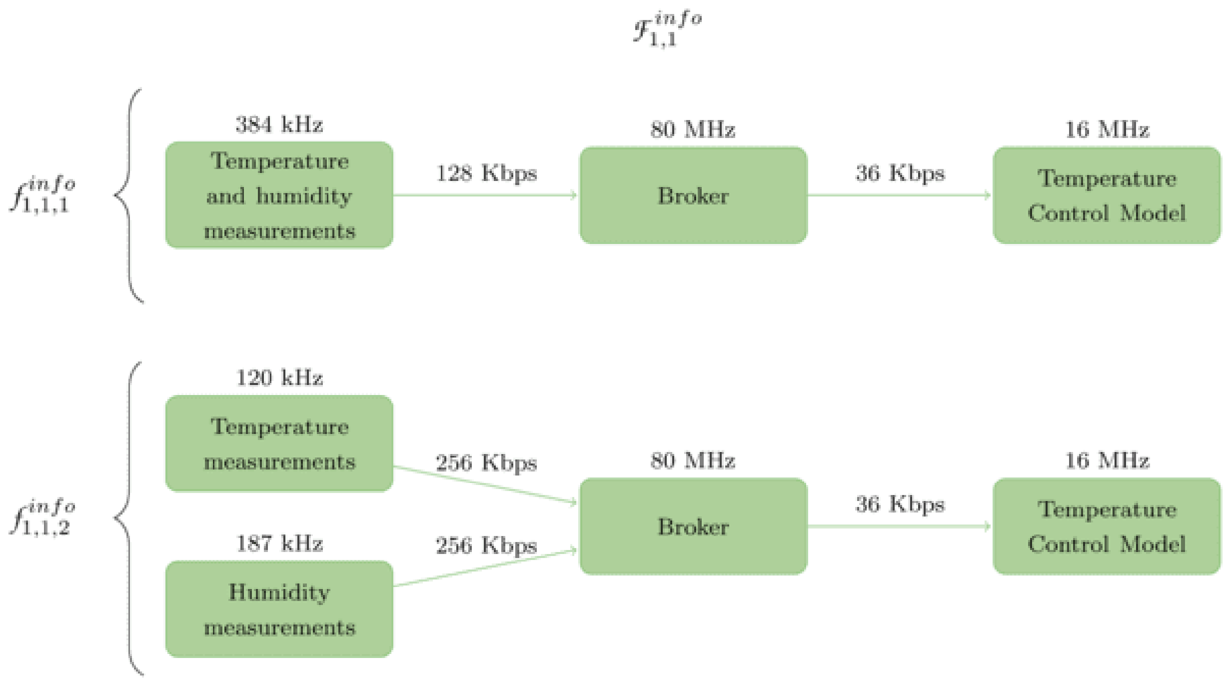

Figure 3: Set of information flows for a temperature control application

2.2. Infrastructure flows implementing an information flow

Each information flow can be installed on different combinations of sensors, edge servers, and network switches, called infrastructure flows. Different infrastructure flows from multiple information flows can lead to different resource (or device) sharing degrees, allowing planning to explore reuse for greater efficiency.

Each information flow $f_{i,j,k}^{info}$ can be implemented by a set of infrastructure flows $F_{i,j,k}^{ifr}$ where $f_{i,j,k,m}^{ifr} \in F_{i,j,k}^{ifr}$ is the m-th infrastructure flow. $f_{i,j,k,m}^{ifr} = (V^{ifr}, E^{ifr})$ 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 two devices. Here, general devices are considered, which can be sensors such as power meters or cameras, computing devices such as edge servers, and network switches such as LTE cells or Ethernet switches. The weights of a vertex $w(v)$ and an edge $w(e(u,v))$ represent the computing resource and network bandwidth they offer, respectively.

A tuple $(F_{i,j}^{info}, \{F_{i,j,k}^{ifr} | \forall f_{i,j,k}^{info} \in F_{i,j}^{info}\})$ summarizes all information flows and corresponding infrastructure flows for each application $a_{i,j}$.

Given a $f_{i,j,k}^{info}$ and a $f_{i,j,k,m}^{ifr}$, each processing unit $v \in V^{info}$ is assigned to a device $v' \in V^{ifr}$ by a function $R(v) = v'$. Furthermore, 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 involved devices, i.e., the actual data flow in the infrastructure layer. Without loss of generality, it is assumed $\langle R(u), R(v) \rangle$ contains at least one network switch unless $R(u)$ and $R(v)$ are the same device. If u and v run on the same device, the network bandwidth between them is exceptionally high, so it is assumed that $w(e(R(u), R(v))) = \infty$.

Figure **4** shows how infrastructure flows can carry out each information flow.

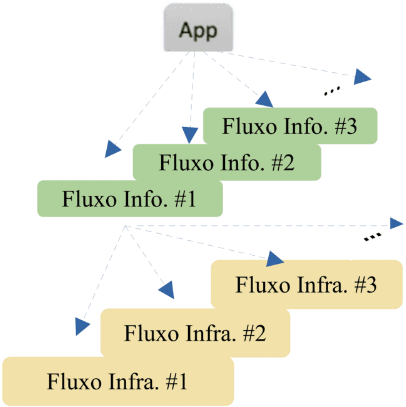

Figure 4: Representation of the Infrastructure flows.

Figure 4 shows different infrastructure flows for the same information flow. An infrastructure flow is distinguished from others considering the following aspects: number of devices; computing resource (CPU power) of a device; network resource (bandwidth) of a device; transmission range of a device; detection range of a device; cost of implementing each device; operating cost of each device.

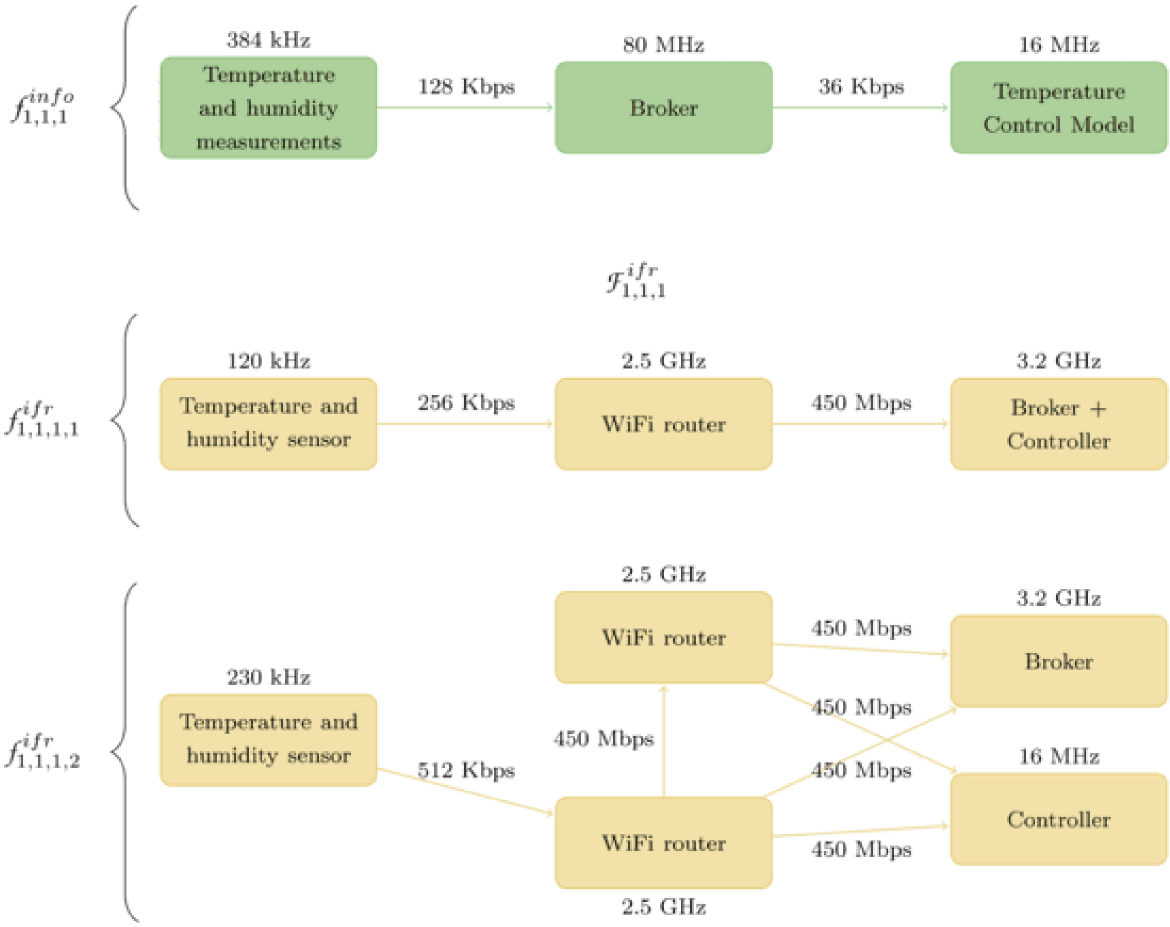

Figure 5: Set of infrastructure flows for an information flow.

2.3. Planning graph

Application deployment planning can be carried out based on information flows and infrastructure flows. There are two types of deployments: (i) initial, where no previous IoT infrastructure exists (e.g., a whole new industry), and (ii) retrofit, where some IoT devices, edge servers, and network switches are already integrated into place (e.g., a growing industry).

Based on this, an auxiliary structure called a planning graph, defined as a two-layer graph $G^p = (V^p, E^p)$, is established, where the first layer $G_1^p = (V_1^p, E_1^p)$ contains a set of information flows and the second layer $G_2^p = (V_2^p, E_2^p)$ consists of a set of 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 from $v \in V^{info} \subset V_1^p$ to $R(v) \in V^{ifr} \subset V_2^p$ to $f_{i,j,k}^{info}$ and $f_{i,j,k,m}^{ifr}$. The planning graph can be written as $V^p = \{V_1^p, V_2^p\}$ e $E^p = \{E_1^p, E_2^p, E^r\}$. Figure **6** illustrates this structure, with the edges in red representing E^r.

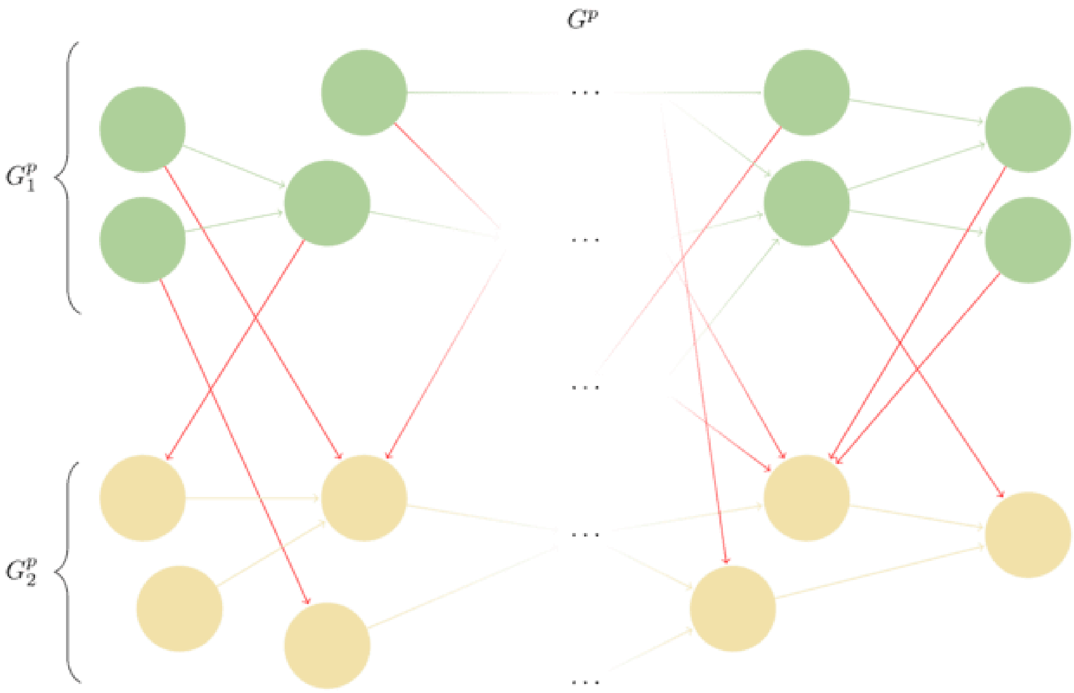

Figure 6: Planning graph.

2.4. Infrastructure geophysical mapping function

To select candidate locations, a geophysical mapping function $f(v)$ maps a vertex $v \in V_2^p$ of the infrastructure layer of a planning graph G^p to a candidate location $l \in L$.

A tuple $t_v = (r_v^{tr}, r_v^{sen}, \tau_v)$ captures each $v \in V_2^p$. The device's transmission and detection ranges are represented by r_v^{tr} and r_v^{sen}, respectively. τ_v indicates the type of device, which can be sensor, computing, or network. If $\tau_v \neq$ network, r_v^{tr} is equal to the transmission range of its connected network device u, i.e. $r_v^{tr} = r_u^{tr}, e(v, u) \in E_2^p$. Additionally, multiple devices can be mapped to the exact candidate location. For the sake of presentation, it is defined $V_{i,j,k,m}^{sen}$ to denote the sensors of $f_{i,j,k,m}^{ifr}$, i.e., $\forall v \in V_{i,j,k,m}^{sen}$, $\tau_v =$ sensor. Figure *7* presents the geophysical mapping for an infrastructure flow.

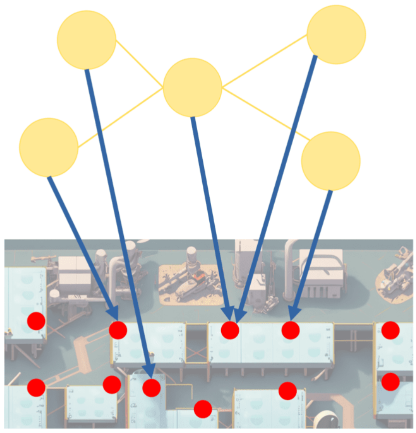

Figure 7: Representation of Geophysical Mapping.

2.5. Utility of a service in an infrastructure flow

The Euclidean distance between two candidate locations $l_1, l_2 \in L$ is defined as $dist(l_1, l_2)$. By definition, the Euclidean distance between two two-dimensional points (x_1, y_1) and (x_2, y_2) is defined according to Equation 1:

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

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

$$U(f_{i,j,k,m}^{ifr}, s_i) = A(f_{i,j,k,m}^{ifr}) \times P(V_{i,j,k,m}^{sen}, s_i) \tag{2}$$

where $A(f_{i,j,k,m}^{ifr})$ and $P(V_{i,j,k,m}^{sen}, s_j)$ are the detection accuracy and probability.

If $f_{i,j,k,m}^{ifr}$ is not connected, $U(f_{i,j,k,m}^{ifr}, s_i)$ is set to 0. Each $f_{i,j,k,m}^{ifr}$ for an application $a_{i,j}$ refers to an accuracy model $A(f_{i,j,k,m}^{ifr})$ that depends on the implemented method. For example, presence sensor-based detection has higher accuracy for presence detection than image-based detection.

As with SmartParcels, the detection probability models used here are inspired by the attenuated truncated model (Wang, 2011), which establishes that the coverage measure becomes very small when the distance between a spatial point and a sensor becomes very small. In these cases, the coverage measure can be neglected, and some approximations can be made by truncating the coverage measure for larger distance values. Initially, for a sensor $v \in V_{i,j,k,m}^{sen}$, the probability is attenuated (decayed) with its distance $s_i, dist(f(v), s_i$ and truncated by its detection range r_v^{sen}. Therefore, if $dist(f(v), s_i) \leq r_v^{sen}, \forall v \in V_{i,j,k,m}^{sen}$, the average truncated attenuated detection probability is given by Equation 3:

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

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

The detection probability is then limited by the detection range of the sensors as defined in Equation 4:

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

These definitions complete what was called the usefulness of a service. It is important to emphasize that the proposed algorithms do not depend on the mathematical properties of a service's usefulness. Thus, one has complete freedom to apply different models, for example, refining the analysis using detection ranges outside the line of sight (Adeyeye et al., 2022).

2.6. Costs

Each device $v \in V_2^p$ in the infrastructure layer is subject to two costs: (i) deployment cost $\delta_{deploy}(v, l)$ due to deploying the device v at the candidate location $l \in L$ and (ii) operational cost $\delta_{op}(v)$ due to maintaining its operation.

The implementation cost occurs once, while the operational cost is recurring. Furthermore, B_{dp} and B_{op} defines the budgets for the deployment and operation of the devices.

2.7. Problem Formulation

Given the industry profile, information flows, and infrastructure flows, the energy efficiency planning problem aims to maximize the overall quality of services under cost budgets, generating the optimal planning graph G^{p^*} and selecting the optimal geophysical mapping functions $F^* = \{f^*(v) | \forall v \in V_2^{p^*}\}$. More specifically, the energy efficiency planning problem is formulated as follows:

$$\text{Maximize} \sum_{\forall s_i \in S} \sum_{\forall f_{i,j,k,m}^{ifr^*} \in G_2^{p^*}} \beta_{i,j} U(f_{i,j,k,m}^{ifr^*}, s_i), \tag{5}$$

$$\text{subject to:} \sum_{\forall v \in V_2^{p^*}} \delta_{deploy}(v, f^*(v) \leq B_{dp}, \tag{6}$$

$$\sum_{\forall v \in V_2^{p^*}} \delta_{op}(v) \leq B_{op}, \tag{7}$$

$$\sum_{\forall e(u,v) \in E^{r^*}} w(u) \leq w(v), \forall v \in V_2^{p^*}, \tag{8}$$

$$\sum_{\forall e(u,v) \in E_2^{p^*}} w(e(u,v)) \leq \sum_{\forall e(v,u') \in E_2^{p^*}} w(e(v,u')), \forall v \in V_2^{p^*}, \tag{9}$$

$$w(e(u,v)) \leq \min_{\forall e' \in \langle R(u), R(v) \rangle} w(e'), \forall e(u,v) \in E_1^{p^*}. \tag{10}$$

The objective function in Equation 5 finds G^{p^*} and F^* that maximizes total utility. Equations 6 and 7 are the budget constraints for deployment cost (B_{dp}) and operational cost (B_{op}). For each device $v \in V_2^{p^*}$, Equation 8 guarantees that v has sufficient computational resources to process all assigned units of information u, that is, the weight $w(v)$ of v is not less than the sum of all the weights of u. Furthermore, Equation 9 guarantees that v's output bandwidth is not less than its input bandwidth. Equation 10 ensures that the minimum bandwidth within the assigned path $\langle R(u), R(v) \rangle$ meets its bandwidth requirement for each data stream $e(u,v) \in E_1^{p^*}$.

3. Solution Design

Planning a space so that, using industry 4.0 technologies, it is possible to outline actions to promote energy efficiency is the main contribution of the proposed tool, whose architecture is presented in Figure **8**.

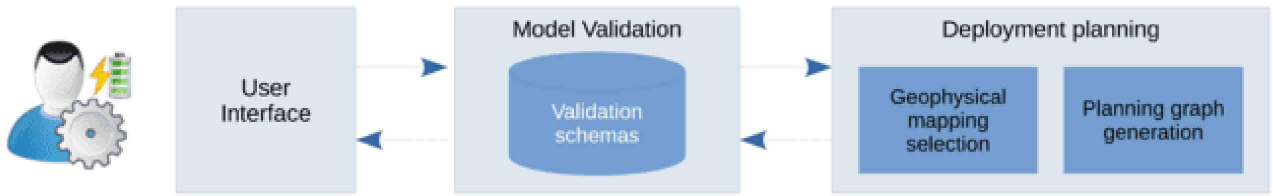

Figure 8: Proposed architecture.

The first component constitutes the user interface, through which physical spaces are modeled, energy consumption and generation characteristics. The input provided in models is then validated using a set of specifications. To this end, Smart Data Models (2023) are used, a set of standards and specifications developed to promote interoperability and data exchange between systems and devices in IoT environments. These models establish standardized, semantically understandable structures for representing information across multiple domains, enabling efficient integration and data sharing.

Based on the specified models, a component that uses combinatorial optimization allows deciding the distribution of equipment and software components to promote energy efficiency and improve costs. In the proposed solution, the energy efficiency planning problem is decomposed into two subproblems, *geophysical mapping selection*, and *planning graph generation*, aiming for reuse and better efficiency.

Let $G^{p^*} = (V^{p^*}, E^{p^*})$ be the optimal planning graph, where $G_1^{p^*} = (V_1^{p^*}, E_1^{p^*})$ contains a set of information flows and $G_2^{p^*} = (V_2^{p^*}, E_2^{p^*})$ contains a set of infrastructure flows. The main reason decomposition is proposed is that geophysical mappings are generated and examined repeatedly when searching for the optimal planning graph G^{p^*}. However, geophysical mappings are mostly static and can and should be stored and reused. Further details of these two subproblems are discussed below.

3.1. Geophysical mapping selection

This solution phase aims to select the optimal geophysical mapping functions F^* containing a mapping $f^*(v)$ for each device $v \in V_2^{p^*}$, i.e. $F^* = \{f^*(v)|\forall v \in V_2^{p^*}\}$.

The geophysical mapping selection has the following inputs: (i) a tuple $(S, \{A_j|\forall s_i \in S\})$ indicating the set of rooms and each application required in the room, (ii) a tuple $(F_{i,j}^{info}, \{F_{i,j,k}^{ifr} \in F_{i,j}^{info}\})$ representing the set of information flows and the infrastructure flows implementing each information flow for each application $a_{i,j} \in A_i$, (iii) a set of candidate locations L for implementing the infrastructures and (iv) a set of devices D already deployed in the industry (for retrofit).

Based on these inputs, a set of possible mappings of each infrastructure flow is selected. For each infrastructure flow $f_{i,j,k,m}^{ifr} = (V^{ifr}, E^{ifr}) \in F_{i,j,k}^{ifr}$, a geophysical mapping function $f(v)$ for each device $v \in V^{ifr}$ is selected as follows: (i) for a pair of devices u and v on the edge $(u,v) \in E^{ifr}$, they must be within the transmission range of each other r_u^{tr} and r_v^{tr} after mapping, i.e., $dist(f(u), f(v)) \le \min(r_u^{tr}, r_v^{tr})$, and (ii) if v is a sensor, the room s_i must be within its sensing range r_v^{sen}, i.e., $dist(f(v), s_i) < r_v^{sen}$.

An infrastructure flow $f_{i,j,k,m}^{ifr}$ and mapping $f(v)$ for each device $v \in f_{i,j,k,m}^{ifr}$ is defined as a *Mapped Infrastructure Flow (MIF)*.

3.2. Generation of the planning graph

This step aims to calculate the optimal planning graph G^{p^*} based on the outputs of the geophysical mapping selection, i.e., multiple sets of MIFs for each application $a_{i,j} \in A_i$. The set of all MIF sets $M^{ifr}_{i,j,k,m}$ generated for $a_{i,j}$ is denoted by $\hat{M}^{ifr}_{i,j,k,m} = \{M^{ifr}_{i,j,k,m} | \forall f^{ifr}_{i,j,k,m} \in F^{ifr}_{i,j,k,m}, \forall f^{info}_{i,j,k,m} \in F^{info}_{i,j,k,m}\}$. Furthermore, the set of all required applications in all rooms is denoted by $\hat{A} = \{a_{i,j} | \forall a_{i,j} \in A_i, \forall s_i \in S\}$.

In this phase, the optimal planning graph is generated by determining (i) which application $a_{i,j} \in \hat{A}$ to deploy and (ii) which MIF $\hat{F}$ (i.e., mapping) of a set $M^{ifr}_{i,j,k,m} \in \hat{M}_{i,j}$ (i.e., infrastructure flows and information flows) selected to implement $a_{i,j}$.

While generating a planning graph, an intermediate planning graph $\hat{G}(K) = (\hat{V}(K), \hat{E}(K))$ is generated using MIFs, where $\hat{G}_1(K) = (\hat{V}_1(K), \hat{E}_1(K))$ is the first layer and $\hat{G}_2(K) = (\hat{V}_2(K), \hat{E}_2(K))$ is the second layer.

For each MIF $\hat{F}$, its infrastructure and corresponding information flow are included in $\hat{G}_2(K)$ and $\hat{G}_1(K)$, respectively. $\langle R(u_1), R(u_2)\rangle$ represents the actual data flow in the infrastructure layer for each edge $(u_1, u_2) \in \hat{E}_1(K)$, where information units u_1 and u_2 are assigned to the equipments $R(u_1) \in \hat{V}_2(K)$ and $R(u_2) \in \hat{V}_2(K)$, respectively. $\hat{\delta}_{dp}(K)$ and $\hat{\delta}_{op}(K)$denote the accumulated implementation and operational costs, respectively, of $\hat{G}(K)$. Finally, $\tau_K(l)$ represents the set of equipment mapped to a candidate location $l \in L$ for $\hat{G}(K)$.

To generate the planning graph, an extra MIF $\hat{F}$ is combined with the intermediate planning graph $\hat{G}(K)$, denoted as $\hat{G}(K) = \hat{G}(K-1) + \hat{F}. \hat{F} = \{f(u) | \forall u \in V^{ifr}\}$, which represents the resulting mapping of an infrastructure flow $f^{ifr}_{i,j,k,m} = (V^{ifr}, E^{ifr}) \in F^{ifr}_{i,j,k,m}$ implementing an information flow $f^{info}_{i,j,k,m} = (V^{info}, E^{info}) \in F^{info}_{i,j,k,m}$. In this process, $\hat{G}(K)$ and $\tau_K(l)$ are configured as $\hat{G}(K-1)$ and $\tau_{K-1}(l)$, initially. Similarly, the accumulated costs $\hat{\delta}_{dp}(K)$ and $\hat{\delta}_{op}(K)$ of $\hat{G}(K)$ are initialized as $\hat{\delta}_{dp}(K-1)$ and $\hat{\delta}_{op}(K-1)$. The operation includes each equipment $v \in V^{ifr}$ and the corresponding information unit $u \in V^{info}$ in $\hat{G}(K)$. When a device (previously included) $v' \in \tau_K(f(v))$ is identical to v in $\hat{G}(K)$, we have the following three cases.

1. u and v are merged into $\hat{G}(K)$, i.e., the existing device and information unit must be reused if one of the following conditions occurs: (i) v' has been assigned to an information unit u', i.e., $R(u') = v'$ and u' are identical to u, (ii) u and u' have the same internal information units, i.e., $\exists e(u'_{in}, u') \in \hat{E}_1(K)$, such that u'_{in} is identical to u_{in}, $\forall e(u_{in}, u) \in E^{info}$, and (iii) identical internal information units are mapped to the same device, $R(u'_{in}) = R(u_{in})$.
2. v is merged into $\hat{G}(K)$ while u is branched into $\hat{G}(K)$, i.e., reusing an existing device while adding an extra information unit into $\hat{G}(K)$ and an edge with v' if: (i) all information units assigned to v are distinct from those of u, i.e., u is different from u', $\forall u' \in \hat{V}_1(K)$ whose $R(u') = v$, and (ii) v has sufficient resources, that is, satisfy Equations 8 to 10. Furthermore, if u has an internal information unit u', that is, $\exists (u', u) \in f^{info}_{j,k,m}$, an edge between u' and u is added in $\hat{G}(K)$ after u' and u are included.
3. u and v are omitted if only condition (i) of case (2) is satisfied. So, $\hat{F}$ is deleted from $M^{ifr}_{i,j,k,m}$ as it has insufficient computing resources. For simplicity, a candidate location is assumed to host one device for each device type.

4. Final Remarks

In the complex scenario of the Internet of Things (IoT) applied to Industry 4.0, the effective deployment of multiple applications is a research topic of great importance. Interactions between physical devices and software components present significant challenges that require carefully crafted approaches. Factors such as satisfying QoS criteria and reducing costs through existing equipment make the task even more complex. Therefore, this work presented the modeling and initial results of implementing a solution for planning the implementation of applications in the context of Industry 4.0 aiming at energy efficiency.

The research focused on modeling these complex systems, aiming at energy optimization. The preliminary results presented in this study represent a significant advance. The study lays the foundation for future developments. The complete implementation of the proposed solution and its subsequent validation in real-use scenarios are crucial steps to be followed. In addition to solidifying the robustness of the model, practical validation will allow us to observe its applicability directly, generating essential indicators for subsequent refinements.

The research can contribute to overall energy efficiency, resource optimization, and improved service quality when deploying IoT applications in Industry 4.0. As research progresses, these efforts are expected to inspire other innovative approaches, triggering continued advances within the Industry 4.0 ecosystem.

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