

PROPOSAL OF A DATA MODEL FOR A DYNAMIC ADAPTATION OF RESOURCES IN IOTs (ADR-IoT)

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ABSTRACT

In this work, the main objective is to provide a contribution of resources adaptation to consumption demand in IOT environments. To do this, we have proposed a data model including the entities "resource", "load", "event", "policy" and "device" as well as the different relationships between IOT devices and others. This data model, an adaptation process is proposed as well as a mathematical model based on the optimization of resource consumption on requests while, taking into account certain constraints including the Maximum Capacity of resources, the Satisfaction of user or IOT device requests and the Energy Constraints have been proposed.

The simulation results regarding the optimization of resource consumption show that our model could be beneficial for smart city management, industry 4.0 and e-health.

KEYWORDS

Resource adaptation – data model – IOT resource

1. INTRODUCTION

This paper on data models for dynamic resource adaptation in the Internet of Things (IoT) mainly focuses on methods for resource management and optimization in an environment often limited in energy, bandwidth and processing power. These models aim to ensure efficient resource utilization while maintaining performance and quality of service (QoS) for IoT applications. Thus, talking about dynamic resource adaptation in an IoT context deserves some explanations. Indeed, in order to understand the activity of resource adaptations, our explanation would focus on the following points:

- Data Models for Dynamic Resource Adaptation
- Approaches and Techniques for Dynamic Resource Adaptation
- Current Issues and Challenges Related to Resource Adaptation in IOTs

1.1. Data Models for Dynamic Resource Adaptation [1]

For data models dealing with the dynamic adaptation of IoT resources, we can cite:

- **Event-driven and contextual data models:** They use real-time data such as **location, sensor status** , and **user preferences** to dynamically adapt available resources (bandwidth, storage, processing). This type of model allows for near-instantaneous adaptation according to changes in the IoT environment.
- **Agent-centric architecture patterns** : These patterns implement autonomous agents that make decisions based on the resource needs of IoT devices. Agents dynamically adjust allocations based on network load, traffic, and device processing capacity.
- **Ontology-based models** [2]: Ontologies are used to create common semantics across different IoT devices, facilitating understanding and interoperability. These models are able to adapt resources based on the contextual understanding of the IoT network, for example by adjusting data quality based on network conditions.

1.2. Approaches and Techniques for Dynamic Resource Adaptation [3], [4]

In this part of our explanations, we will present some techniques and approaches used to carry out adaptation work. Among these techniques, we will present those which are known to our knowledge are:

- **Multi-criteria optimization** : This approach is used to allocate resources considering multiple criteria such as **latency** , **energy**, and **bandwidth** . Also, mathematical models, such as those based on linear and nonlinear programming, allow to adjust allocations optimally according to priority.
- **Machine learning and neural networks** : In this approach, reinforcement learning techniques are applied to anticipate and adjust resource consumption based on usage trends. These models are able to predict resource **demand** and **reallocate capacity in real time** .
- **Edge computing and fog computing** : These are computing models that relocate processing to edge nodes to reduce latency and load on a central cloud. In IoT, the use of edge computing enables faster and more decentralized adaptation of resources , according to network constraints and local needs.
- **Blockchain for resource management** : The use of blockchain in IoT is growing to securely manage access to resources. For example, it can be used to manage resource transactions between different IoT devices in a decentralized manner, thus enabling reliable dynamic adaptation.

1.3. Current issues and challenges related to resource adaptation in IoT

The adaptation of resources in IOTS could arise from issues and challenges among which we can cite:

- **Interoperability and standardization** : At this level, IoT devices are often of different brands and come from different standards. To achieve this, interoperable data models are required to enable seamless adaptation of resources.
- **Security and Privacy** : Deploying adaptive models poses security challenges as access to resources can become a security vulnerability. Also, secure data models are crucial to avoid intrusion risks.

- **Energy optimization** : Since many IoT devices are powered by batteries, energy optimization is essential. Designs must therefore be able to adapt resources in a way that minimizes energy consumption while ensuring adequate performance.

Thus presenting the contextual elements of understanding, the rest of our paper is organized as follows:

- Section 2 is devoted to the state of the art,
- Section 4 to our problem,
- Section 5 presents our contribution,
- Section 6 concludes this paper while providing perspectives.

2. STATE OF THE ART OF DATA MODELS FOR DYNAMIC ADAPTATION OF RESOURCES IN IOTS

In this part of our work, we will present the different works from the literature to our knowledge. These works range from models based on knowledge and ontologies, models based on events and contexts of IoT objects, possibilities offered by AI and different forms of learning to Edge Computing and Fog Computing. Also in this momentum, we will present the works resulting from the use of Blockchain technology for Resource Management in IoT as well as the opportunities offered by optimization tools. In this part, we will then present the models related to these different works while identifying the contributions, the different approaches, the limits and the associated challenges.

2.1. Knowledge and Ontology-based Models

- **Contributions** : The contributions made by knowledge-based models and ontologies help to create a common basis of understanding between different IoT devices. These contributions are mostly from works, such as those of [Bandyopadhyay and Sen (2011)] and [Nambi et al. (2014)]. Indeed, they explore ontologies to improve interoperability and flexibility in resource adaptation.
- **Approaches** : The different approaches of these IoT-specific ontological models allow to standardize the descriptions of resources, devices and services, thus simplifying their adaptation. In this respect, the work of [Ruta et al. (2017)] illustrates these ontology models for the management of resources and data in dynamic environments.
- **Limitations and Challenges** : In terms of limitations, these ontology-based models require intensive processing to interpret and adapt the data, which could be a challenge for resource-constrained IoT devices.

2.2. Event and Context Based Models [1]

- **Contributions** : Contextual and event-driven management is commonly used to enable dynamic adaptation. The work of [Perera et al. (2014)] proposes a contextual model, where IoT devices adjust their resources according to changes in their environment (temperature, position, user activity).
- **Approaches** : In their approach, contextual adaptation allows devices to adjust to data received in real time. Event-driven architecture models automatically react to specific situations and adjust resources accordingly.
- **Limitations and Challenges** : Although event-based models are fast and adaptive, they pose challenges in data integration and synchronization in distributed environments.

2.3. Artificial Intelligence and Machine Learning [5][6]

- **Contributions** : The authors use artificial intelligence techniques, especially reinforcement learning, to optimize resources based on real-time forecasts and needs. For example, [Zhou et al. (2018)] and [Yang et al. (2019)] use neural networks to predict resource demand, thereby improving the efficiency of adaptation.
- **Approaches** : In their approach, AI enables proactive adaptations by learning from historical and contextual data. Machine learning algorithms can also detect patterns or anomalies in resource usage.
- **Limitations and Challenges** : Implementing AI models is resource intensive and requires high computing capabilities, often incompatible with low-energy IoT devices.

2.4. Edge Computing and Fog Computing [7] [8]

- **Contributions** : Edge computing and fog computing have become key approaches to enable decentralized dynamic adaptation. In this context, [Satyanarayanan (2017)] and [Chiang and Zhang (2016)] demonstrate the effectiveness of edge processing to minimize latency and reduce load on central servers.
- **Approaches** : These models use compute nodes close to the user to process data locally, improving speed and reducing bandwidth requirements. They thus enable near-instantaneous adaptation in the event of resource overload or failure.
- **Limitations and Challenges** : Although edge computing and fog computing improve resource scaling, they require hardware investments and raise issues of security and decentralized data management.

2.5. Blockchain for Resource Management in IoT [9]

- **Contributions** : Blockchain, as a distributed ledger, offers a solution for managing transactions and resources between IoT devices in a secure manner. Studies, such as those of [Dorri et al. (2017)], explore blockchain models to ensure reliable dynamic adaptation and resource distribution.
- **Approaches** : In their approaches the authors implemented blockchain models to enable decentralized transaction recording and secure resource management, which is crucial for complex IoT networks.
- **Limitations and Challenges** : In terms of limitations associated with their work, one can notice the greedy nature of the use of blockchain in terms of energy and computing resources, all of which pose challenges for its adoption in resource-limited IoT devices.

2.6. Multicriteria Optimization [10] [11]

- **Contributions** : Several works have explored mathematical models for multi-criteria resource optimization. Thus, [Han et al. (2018)] and [Liao et al. (2016)] present optimization models taking into account various criteria such as latency, energy consumption and quality of service (QoS).
- **Approaches** : In their approach, these models allow for optimized adaptation, meeting resource needs while minimizing tradeoffs between different factors.
- **Limitations and Challenges**: Multi-criteria optimization models require continuous evaluation and are sensitive to changes in network conditions, which can make their application complex.

Data models for dynamic resource adaptation in IoT integrate a range of approaches, from ontologies for interoperability to AI models for advanced predictions.

3. PROBLEMATIC

The literature review presented in the previous section shows that excellent works have been done. Some range from the use of knowledge-based data models and ontologies to event-based models and context related to the use of IoT devices. Also, some work illustrates the use of AI and machine learning, blockchain technologies for securing data generated by the use of IoT objects without forgetting mathematical tools to optimize the use of energy consumption. All these works have certainly presented data models but do not present a unifying model for all these works. In other words, what could be the structure of such a model and also the characteristics of its composition? It is to this question that we make our contribution through this paper.

4. CONTRIBUTION

Our contribution to resource adaptation in IOTs consists in proposing a data model that unifies all data models from the literature to our knowledge. Indeed, these different works from the literature have proposed models that do not take into account other domains. Thus, our contribution presents the model in Figure 1. This figure presents the main entities or files representing the objects, policies, resources and events at the base of a resource adaptation in IOTs. Also the relative load information of these devices is presented.

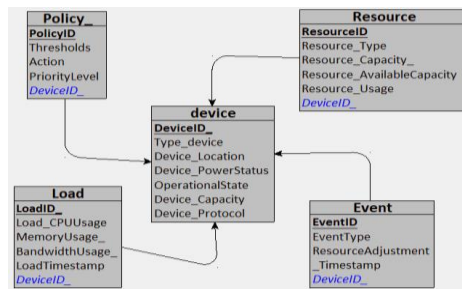


Figure 1: IOTs resource adaptation data model

For a data model of dynamic adaptation of resources in IoT networks, it is essential to structure the data to enable real-time management of resources, depending on the load and performance of IoT devices. Here is a proposal of data models that could serve as a basis for dynamic adaptation of resources in IoT.

4.1. Proposed Data Model

In this part of our contribution, we will present the different entities, their attributes and the roles associated with these attributes during the adaptation activity.

Device (Figure 2): Represents each IoT device in the network (**Figure 2**) and has the following attributes:

- **Attributes :**
 - DeviceID: It represents the unique identifier of the device in the IOTs environment. This identifier could be a MAC address, an EMEI, an IP address.

- Device_Type: It represents the type of device, i.e. a sensor, an actuator, a gateway etc.
- Device_Location: This attribute represents the geographical position of the IOT device or in the network.
- Device_PowerStatus: IOT devices, in their operation need a power source. In these conditions this attribute "powerstatus" will allow to have an idea of the level of the battery associated with the device or the energy consumption.
- Device_OperationalState: This attribute represents the current operational state (active, standby, out of service) of IoT devices.
- Device_Capacity: This attribute allows to know the capacity and storage level of an IOT device. This capacity could allow to initiate an adaptation activity according to the processing and the available storage space
- Device_Protocol: This attribute allows to store and determine the communication protocols used by IoT devices during their collaboration with other members of their neighborhood. In terms of communication protocols used, it could be (MQTT, CoAP, HTTP).

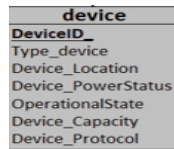


Figure 2: DEVICE entity

Resource (Figure 3): This entity represents the different resources (CPU, memory, bandwidth) required for the proper functioning of each device. These attributes are:

• **Attributes :**

- ResourceID: Unique identifier of the resource.
- DeviceID: Identifier of the device with which the resource is associated.
- Type: Resource type (CPU, memory, bandwidth).
- Capacity: Maximum capacity of the resource.
- AvailableCapacity: Available capacity of the resource.
- Usage: Real-time resource usage rate.

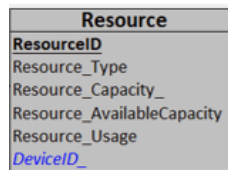


Figure 3: Resource entity for R IOT

- **Load (Charge) (figure 4):** this entity is used for the management (capture and storage) of the load in real time of the device.

○ **Attributes :**

- LoadID: Unique identifier of the load.
- DeviceID: Identifier of the device with which the load is associated.
- CPUUsage: It represents the current CPU usage.
- MemoryUsage: It represents Current memory usage.
- BandwidthUsage: It represents Current bandwidth usage.

- LoadTimestamp: It represents the timestamp of the load measurement.

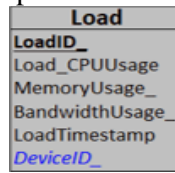


Figure 4: Load entity

- **Event (Figure 5)** : This entity records significant events related to resource adaptation. It has the following attributes:

- **Attributes :**

- EventID: Unique identifier of the event.
- DeviceID: Identifier of the device affected by the event.
- EventType: Event type (scaling up, scaling down, sleep mode).
- ResourceAdjustment: Details of resource adjustments made.
- Timestamp: Timestamp (start and end time) of the event.



Figure 5: Event entity

- **Policy (Figure 6)**: Defines the rules and policies for adapting resources.

- **Attributes :**

- PolicyID: Unique identifier of the policy.
- DeviceType: Type of device to which the policy applies.
- Thresholds: Trigger threshold values (eg: CPU > 80%).
- Action: Action to take if threshold is exceeded (e.g.: increase capacity).
- PriorityLevel: Priority level of the policy.

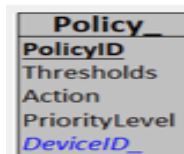


Figure 6: political entity

4.2. Relationships or link between entities

To adapt IOT devices based on the occurrence of events, we proposelinks between devices and other entities such as resources, load, policy.

- **Device - Resource** : A device can have multiple resources, for example, a sensor can have CPU and bandwidth capabilities. Relation: DeviceID -> ResourceID.

- **Device - Load** : A device has an associated load that varies in real time and is measured and stored periodically. Relation: DeviceID -> LoadID.
- **Device - Event** : A device can be involved in multiple resource adaptation events. Relation: DeviceID -> EventID.
- **Policy - Device** : A policy is applied to devices based on their type. Relation: DeviceType -> PolicyID.

4.3. Dynamic adaptation process (Example)

In this section, we present an adaptation process. This process goes from data collection to the actual adaptation activity.

4.3.1. Load collection : In this step, load data (CPU, memory, bandwidth) are recorded periodically for each IoT device. This collection involves and involves the entities “device” and “resource”

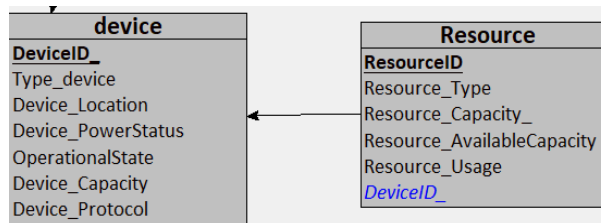


Figure 7: Load collection

4.3.2. Threshold Analysis: Once the load is collected, the thresholds defined in the policies are compared to the real-time load data. This step involves the “policy” entity in addition to the one in step 1 (load collection)

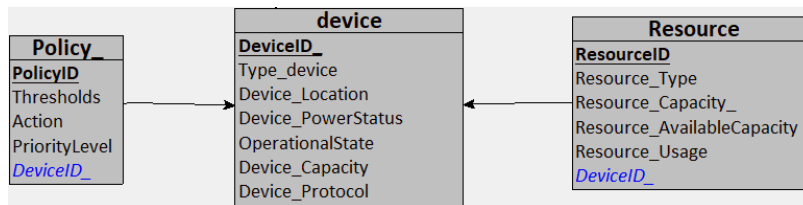


Figure 8: Threshold analysis

4.3.3. Event Triggering : If a load exceeds a policy threshold, an event is created, and resource adjustments are recorded. This event triggering step involves the model in Figure 8. It associates this model with the “event” entity to obtain Figure 9

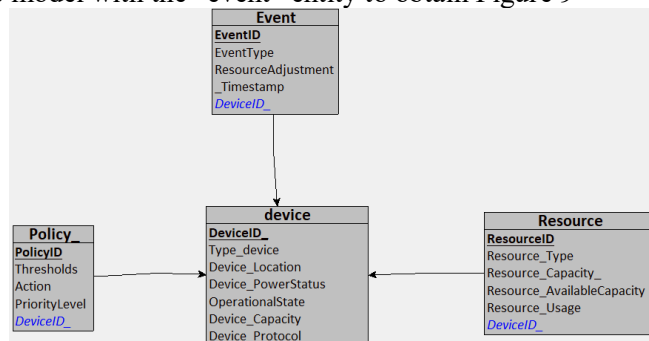


Figure 9: Event triggering

4.3.4. Resource adaptation: Depending on the triggered event, the device resources (e.g. CPU allocation or bandwidth limitation) are adjusted according to the adaptation policies. The final resource adaptation involves (or combines) the model of Figure 9 and the “load” entity to give the starting model (Figure 1)

4.4. Mathematical Modeling

For dynamic resource adaptation in IoT (Internet of Things) networks, resources must be allocated flexibly and efficiently according to changing network conditions, connected devices' needs, and energy constraints. Thus, in this part of our paper we propose a mathematical model that can formalize this adaptation by taking into account several parameters such as: bandwidth, latency, energy, and specific user needs.

4.4.1. Modeling Resources and Demands

Suppose we model an IoT network with the following parameters:

- $\mathbf{R} = \{\mathbf{r}_1, \mathbf{r}_2, \dots, \mathbf{r}_n\}$ represents the set of available resources. (With n = maximum number of resources)
- $\mathbf{D} = \{\mathbf{d}_1, \mathbf{d}_2, \dots, \mathbf{d}_m\}$ represents requests from users or IoT devices (with m = maximum number of requests)
- Each resource \mathbf{r}_i has a maximum capacity C_i (for example, the amount of bandwidth, processing power, or available energy).
- Each request \mathbf{d}_j has a specific resource requirement, denoted \mathbf{E}_{ij} ,

where \mathbf{E}_{ij} is the quantity of resource \mathbf{r}_i required to satisfy the demand **already**

4.4.2. Objective Function: Minimizing the Cost of Adaptation

The goal is to minimize the total cost of resource allocation, while satisfying the demands of connected devices. The cost may include factors such as power consumption, latency, or bandwidth used.

Formula for the cost function:

$$\text{Minimiser } \sum_{i=1}^n \sum_{j=1}^m x_{ij} \cdot c_{ij} \quad (1)$$

With $x_{ij} = \begin{cases} 1 & \text{if } r_i \text{ resource is allocated on request } d_j \\ 0 & \text{otherwise} \end{cases}$

C_{ij} = represents the cost of using the resource \mathbf{r}_i to satisfy the request \mathbf{d}_j .

4.4.3. Constraints Associated with the Model

In this section, we present 3 constraints related to the resource adaptation activity.

1. **Maximum resource capacity:** The sum of allocations for each resource must not exceed its maximum capacity.

$$\sum_{j=1}^m x_{ij} \cdot E_{ij} \leq C_i, \quad \forall i \in \{1, \dots, n\} \quad (2)$$

2. Satisfaction of requests : Each request must be satisfied by one or more resources.

$$\sum_{i=1}^n x_{ij} \geq 1, \quad \forall j \in \{1, \dots, m\} \quad (3)$$

3. Energy constraint (if applicable) : In IoT, devices are often limited in energy. We can therefore add an energy constraint so that the sum of energy consumptions does not exceed a given threshold E_{\max} .

$$\sum_{i=1}^n \sum_{j=1}^m x_{ij} \cdot e_{ij} \leq E_{\max} \quad (4)$$

With e_{ij} representing, the energy consumption associated with the allocation of r_i for d_j

4.5. Example of Dynamic Adaptation by Resource Allocation in IoTs

In this example, we present adaptation by resource allocation. This allocation could include managing limited resources, such as network bandwidth, memory, and device energy, to adapt resource usage in real time.

Since the goal is to ensure efficient resource utilization in a dense IoT network, by dynamically adapting resources based on the needs of these devices and the availability of resources, we define the variable and notation of the Resource Allocation Function (5) as follows:

$$R_i = \frac{\delta_i \cdot r_i}{\sum_{j=1}^N (\delta_j \cdot r_j)} \cdot R_{\text{total}} \quad (5)$$

- With R_{total} : Total resources available (e.g. bandwidth, memory, energy).
- N : Number of active IoT devices.
- r_i : Resources requested by device i .
- R_i : Resources allocated to device i .
- δ_i : Priority coefficient of device i (expressing the importance or criticality of resource allocation).
- α : Allocation threshold to decide whether a device should receive a minimum allocation to avoid overloading.

Formula 5 allows resources to be distributed based on demands weighted by device priorities. Thus a device with high demand and high priority will obtain a larger share of total R .

4.5.1. Real-Time Adaptation

For each new request, the algorithm evaluates whether resources can be allocated without exceeding R_{total} . If the total demand exceeds the available resources, the algorithm reduces the allocations proportionally so as not to saturate the network:

$$R_i = \min \left(r_i, \frac{R_{\text{total}}}{N} \cdot \delta_i \right) \quad (6)$$

4.5.2. Result and Interpretations

For simulation, assume an IoT network with 10 devices. Each device has a random resource demand and a priority coefficient. The total available resource is fixed (e.g., 100 units).

4.5.2.1. The Results of the Simulation in Python Environment are Shown in Table 1

Table 1: IOT resource allocation result

Device No.	Resource Demand	Priority Coefficient	Allocated Resources
1	17	0.884381707	14.82165788
2	10	0.797534607	7.862445518
3	5	0.556712977	2,744160201
4	8	0.772656295	6.093747376
5	16	0.977665117	15,4212016
6	8	1.312168729	8
7	12	0.979977172	11.5932531
8	14	0.892784796	12,32204906
9	8	1.336078764	8
10	10	0.83739616	8.255418177

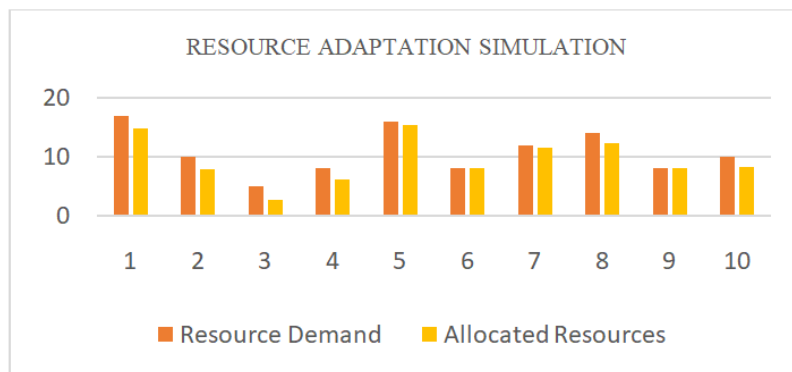


Figure 10: Graphical presentation of resource allocations in IOTs

In Table 1, we have:

Resource Demand

- This column shows the amount of resources requested by each device. High demand may indicate a device that needs more processing power, memory, or bandwidth.

Priority Coefficient

- This coefficient indicates the criticality or importance of each device. A high priority coefficient means that the device is crucial to the system, such as a security sensor or a monitoring device.
- Devices with higher priority coefficients should receive a higher proportion of resources, even when resource demand is similar.

Allocated Resources

- This column shows the resources actually allocated to each device after taking into account demand and priority coefficient.
- If the allocated resources are close to the actual demand, it means that the system is efficiently meeting the needs of the devices.

4.5.2.2. Interpretation

On the Evaluation of Equity and Efficiency of Allocation

The results produced by our resource allocation adaptation method allow us to notice that high priority and high demand devices have had resource reallocations close to or equal to their needs (device 6.9 in Table 1). Also, for low priority devices, they have had proportionally lower allocations. We can also notice that for priority devices having received less resources than their demand would mean that these devices need an increase in total available resources or a stricter adaptation of priorities.

On the Identification of Under- or Over-Allocated Devices

If demand is consistently higher than the allocation for some devices, this may cause the device to operate in a restricted mode and may not optimally meet needs. Adjustments may be necessary to redirect more resources to these devices.

For over-allocated devices (if allocated resources exceed request), the model could readjust allocations to avoid waste.

If a critical device with a high priority receives an allocation close to or equal to its demand, this would mean that the model is managing resources efficiently. On the other hand, if several low priority devices have received as many resources as critical devices, this could signal a necessary adjustment of the model so that priority is taken into account more. Furthermore, it could be recommended to monitor these indicators over time to optimize allocations and respond to variations in demand as well as device priorities.

5. DISCUSSION

In this work, we proposed a data model for dynamic resource adaptation in an IOT environment. Indeed, this work could find an application in the field of:

- **smart cities** for intelligent lighting and traffic management (road, territory surveillance, etc.). In this area, our proposed model could adapt to the variable density of urban flows and to real-time events.
- **Industry 4.0** : in this area, the use of our proposal could find application in smart factories where the dynamic adaptation of resources allows to optimize processes according to production conditions and demand in real time.
- **Connected health** : here the use of our model in the health framework by connected medical devices would create a real-time adaptation of resources to ensure constant monitoring of vital parameters, particularly in the event of an emergency.

Also, the benefits that our model could generate in the fields of application cited above could be:

- Real-time monitoring of the load of IoT devices,

- adapting resources based on request, ensuring the efficiency of the IoT network.
- Application of intelligent management policies based on usage conditions, thus optimizing device availability and performance.
- Ensuring traceability of adaptation events for continuous monitoring, analysis and optimization of resources in the IoT network.

Additionally, key challenges remain optimizing resource utilization, data security, interoperability between heterogeneous devices, and reducing energy consumption.

6. CONCLUSION AND PERSPECTIVES

The objective of this work was to contribute to the adaptation of resources in an IoT environment in a dynamic way. To do this, we proposed a structured data model including the entities that are: devices, resources associated with these devices, policies and events triggering the adaptation activity of said resources. Also, a mathematical modeling as well as an adaptation process were proposed.

Future work of our proposal could focus on machine learning tools to automate adaptation decisions and provide advanced predictions on resource requirements. Also, new approaches, such as hybrid architectures combining multiple techniques (e.g., AI and edge computing), could be explored to address the specific constraints of IoT environments.

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