Automated Decision Support Framework for IoT : Towards a Cyber Physical Recommendation System

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Abstract: Among the key factors of Industry 4.0 are the intensive use of Cyber Physical Systems (CPSs). These systems can be implemented at many application levels for various application domains. Each application requires a personalized CPS architecture concerning the Physical sensors as well as the management of Cyber systems. Furthermore, it requires also the maintenance of the communications among these different sub-systems. However, researchers and engineers may lack the essential knowledge to design and build an autonomous CPS. In this paper, we propose the concept of a novel Cyber Physical Recommendation System (CPRS) in order to address this open challenge. The proposed approach is subjected to assist the competencies of researchers and engineers to design and build more efficient CPS according to the given objective, domain, and input application scenarios. In this regard, CPRS recommend the components of the desired CPS, based on a novel architecture model of the components, connections, and tasks of the CPSs. The proposed system is eventually intended to aide the progress in leading factories towards the maturity of fourth industrial revolution.

1 INTRODUCTION

The practices and massive data in Industry 4.0 have significantly proven their utility for the transformation phase of manufacturing processes. The current literature in this domain prominently demonstrates the research work towards the tuning of machine learning algorithms and parameters to transform factories into smart industrial components (Garouani. et al., 2021). The main concept is to deal with the major challenges faced by the companies, especially the evolution of big data, arbitration of decision-making, real-time monitoring and control of integration of novel technologies such as Cyber Physical Systems (CPS) or enabling Internet of Things (IoT). It is principally intended to better manage the interconnections between the Cyber systems and Physical systems.

The CPSs are generally described as physical and engineered systems whose operations are monitored, coordinated, controlled, and integrated by a communication and computing core (Rajkumar et al., 2010). A CPS is recognized as a networked collection of cyber systems and physical systems that are monitored and controlled by user-specified semantic laws. For this purpose, a network connects the cyber and physical systems to construct a real-time system on a large scale (Chung, 2017). In this respect, a CPS can be viewed as a real-time feedback system where the cyber sub-systems and physical sub-systems are inter-connected with multiple means of communication. The recent structures of CPS are often implemented with the increasing use of smart sensors and embedded systems in addition to the practices involving the cloud computing, data storage, and artificial intelligence techniques (Garouani et al., 2022c). The major objective is to mainly pursue the idea of transformation of industry towards the rise of more smarter factories that can further enhance the maturity of the fourth industrial revolution. It can also help, among others, in the advancement of predictive maintenance, real-time monitoring systems, and improved self-optimization capabilities (Garouani et al., 2022a).

The CPSs have been widely used in the real-time systems. Most of these systems have customised configuration according to the application domains and

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their architecture and connection system. In this context, each application needs its own physical components, communication network, and computational primacy. These could change according to the objective, type of physical entities being measured, type of generated output data and parameters,etc. The system stakeholders usually lack the essential knowledge to identify and choose suitable components that match their requirements (Garouani et al., 2022d). Thereby, the automated assistance for the required human expertise can allow the engineers and researchers of smart factories to rapidly build, validate, and deploy CPS solutions. It may also improve their quality of service, productivity, and more importantly, reduce the need of the interventions from human experts (Garouani et al., 2022b).

Motivated by this goal, in this paper, we discuss the architecture, concept and application domain of the CPSs. Later on, we present the architecture and connection of a personalized CPS that serve as a base for the CPRS (Cyber Physical Recommendation system). The proposed system mainly attempts to provide necessary recommendations for building a CPS according to the presented set of objectives and application scenarios. In this regard, CPRS recommends the components of the desired CPS, based on a novel architecture of the components, connections, and achievable tasks. This system is intended to help in leading the smart factories toward the fourth industrial revolution. It might enable the identification of CPS parts and components to save time and effort avoiding unintended accidents.

The rest of the paper is organized as follows : The section 2 discusses the architecture, concept and domain of application of CPS. The section 2.3 presents our own CPS architecture and connection to be a basis for the proposed CPRS. The section 3 introduces the main components of the proposed recommendation system and discusses how these components collaborate to achieve the pursued goals. We later on show, how to implement the framework for representative application scenarios, in the section 4, and we discuss the prototypical implementation. Finally, the section 5 concludes the paper and outlines future perspectives.

2 RESEARCH BACKGROUND AND RELATED WORK

Nowadays, CPSs are termed as one of the key factors of the fourth industrial revolution, as they help in achieving the goal of intelligent, resilient, and self-adaptable machines required by the industry 4.0 (Lee et al., 2015). As a result of their ability to integrate into a wide range of domains and applications, they are considered to be one of the fastest growing technologies in the world (Raisin et al., 2020).

2.1 Application Domains

This section presents an overlapped overview of some of the advanced CPSs used in different domains and application levels. We attempt to assess the internal mechanisms of CPSs for various domains; healthcare, manufacturing, and transportation are the most significant but neither limited nor exhausted to be applied across different contexts in order to better understand the nature of machine states and anomalies. These are briefly reviewed in the following sections.

2.1.1 Healthcare Domain

Healthcare domain broadly encompass the applications used in hospital management systems, intensive care units, assisted living, and/or monitoring the health condition of elderly patients. Healthcare is a very delicate and sensitive domain to work with since it depends on accurate decision-making in real-time analysis. Among them, the CPS with the implication of cloud computing and big data can play a major role in the development and improvement of the medical science applications. These may use the stored data either structured or unstructured e.g the doctors input and feedback, in addition to the data collected from medical instruments, biosensors and wearable devices for high-performance modeling and accurate decision making. In (Banerjee et al., 2011) the authors present a framework for modeling and analyzing Cyber Physical Medical frameworks, with two major applications. The first, is an infusion pump system for future prediction of drug concentration while the second is a multi-infusion pump for chemotherapy. Healthcare domain is a diverse field of research that has been performed with the help of numerous CPSs architectural designs and implemented applications (Haque et al., 2014).

2.1.2 Manufacturing Domain

For the last decade, most of the research literature has been focused towards the development of smart factories for more reliable and efficient results. The market needs have shown continuous demand of new requirements in contexts of optimal cost, quality, flexibility, and real-time execution. In this regard, the recent CPSs are integrated as a technological evolution that has mainly resulted, in response to achieve these demands. Furthermore, the CPSs are embedded in various manufacturing applications like automation (Garouani et al., 2022c), shop floor, etc. For example a systematic approach for predictive production systems is proposed by (Lee et al., 2017) using CPSs to inject resilience and interoperability so that the productivity of manufacturing can be optimized. We believe that data generated by these systems can be used to further improve the equipment intelligence and reduce energy consumption to benefit environmental constraints. It require to take advantage of big data analytic and data enabled predictive collaborative decision making for the real time control systems, hence, increase the production efficiency (Wan et al., 2018).

2.1.3 Transportation Domain

The transportation domains often involve the np-complex combinatorial problems. Many of the problems, such as traffic congestion, have arisen due to the increase in the number of transportation vehicles and actors. Traffic bottle-necks, air pollution, and safety issues require to address a carefully focused attention on each individual elements of a transportation system. The transportation systems can reach a new smart solution for different applications with the integration of smart sensors, embedded systems, and CPSs computing capabilities. The cooperative vehicle safety systems (Fallah et al., 2010), intelligent intersection management systems (Zheng et al., 2017), intelligent charging systems for electric vehicles (Ge et al., 2012), and different application in other transportation fields (aviation, automotive aerospace, intelligent transportation, traffic control, etc.) are some of the examples in this domain.

2.2 CPS Architectures

Although the main concept of the CPS remains the same, the state of the art literature shows a variety of different architectures. For example, Jamwal *et al.* present a CPS architecture for Intelligence Manufacturing Systems (IMS) spanned over three layers, as given below (Jamwal et al., 2020) :

Physical Connection Layer: The concerned industrial components at this layer embed the equipment such as sensors and various types of measurement devices in the manufacturing resources. Different communication means are used to connect the involved set of machines in order to establish a proper, robust, and uniform connection among the actuators, manufacturing resources, measurement instruments, and sensors.

Middle Layer: This layer is aimed at data transfer, data management, and device management. It is also used to allow the interconnection between the external applications, the elements of the physical layer and the computation layer.

Computation Layer: This layer is of utmost importance to carry the decision-making with the help of analysis and processing of stored data. The major objective is to render the autonomous capabilities for the machine functions in order to make them self-aware and self-dependent.

Some authors, in (Yan et al., 2019) present a four-level framework for CPS that is partitioned into sensors and control, connection, cognition, and application & services. Although we can also witness in (Lee et al., 2015) a five-layer architecture where the authors present the CPS system as composed of a smart connection level, data-to-information conversion level, cyber level, cognition level, and configuration level.
(Djouad et al., 2018),also present an architecture encompassed at five major parts, as discussed below :

1. The Physical sphere contains physical process (e.g. Temperature) and Physical entities (cars, humans, animals, etc.)
2. The Cyber-Physical sphere contains sensors, actuators, and a user interface for control.
3. The Cybernetic sphere contains computational elements, storage elements, and a CPS application (which consists of computational services designed to assist the user by interacting with other cyber components).
4. The Data and Information sphere contains the data collected by sensors and the output information generated by the computational elements.
5. The Deployment sphere contains hardware and software components that can offer information and data; it may provide actuating capabilities.

2.3 Proposed CPS Architectures and Connections

The flexibility and multi-dimensional capabilities of using the CPSs allow them to be incorporated across a vast range of application domains. These are may include predictive maintenance, monitoring and control for the applications in agriculture, electric smart grid, instrumentation, infrastructure and communications systems, etc. Inspired by the CPS design concept given by (Djouad et al., 2018), we propose a novel CPS concept which is intended to be more simple and more convenient to be used as a base concept for the proposed recommendation system in our approach. This architecture is intended to be used as a conceptualization of the Cyber Physical Systems. This means that it will be used as a sphere of CPS ontology. We eventually intend to develop a recommendation system concerning the design of CPS. The proposed architecture play a central role in the definition of the knowledge-base that may constitute the core of the recommendation system.

The proposed architecture is depicted in the figure 1 which divides the CPS into three main parts :

Physical Sphere: The physical sphere contains components responsible on interacting with the real world systems to measure and collect information or to perform a given task.

1. **Sensing Sphere** is responsible to collect data and information from the physical entities by using smart components and smart sensors.
2. **Execution Sphere** is responsible to perform and execute commands given by the output data after being analyzed and processed. For example, these orders can be performed by actuators, machines or even using alarms.
3. **Human in The Loop** use the HCI (Human Computer Interaction) strategies such as the user can trigger an actuator by giving command whenever it is needed.
4. **Control Unit** controls the module by receiving and modifying data to be processed on cyber level, followed by the execution of produced commands.
5. **Micro-Controllers** contains the devices which are used to read and store measured data that shall be scheduled later on for further analysis and processing.

Network Sphere is subjected to the communication means and establishment of connection among the devices of physical sphere. This part must consider the following aspects :

1. **Security:** The development of CPS involves the various interconnected systems. It also involves the progress of networking, computing, and integration of novel smart technologies that most domains nowadays requires. Among other, these include the quality factors like the efficiency, accuracy, and authenticity. So due to vast interconnection and the use of IoT, CPSs can be widely contingent on various malicious uninvited access through cyber-attacks, polluting input data, or the manipulation of physical entities. So, security measures regarding the system limitations and background must be prioritized during the building of a CPS.
2. **Data Transport Sphere:** This part is responsible for the interconnection between the physical and the cyber layer where data transmission is done using communication technologies such as BLT, 4G, 5G, LANs, IR, RFID, Wi-Fi, and Zigbee along with other technologies. Due to the increasing number of devices which are interconnected through the communication protocols over the internet (TCP/IP, IPv4, IPv6). These must ensure data routing and transmission either through cloud computing, or internet gateways. The communicated data can also be subjected to the encryption in order to ensure enhanced security to prevent malicious attacks.

Cyber Sphere is finally responsible for analyzing, processing, and storage of data and information which have been subsequently measured in the physical layer that may produce more data. It might be subjected to control instructions for the computational elements or to execute specific tasks. Some of the sub-system modules in this part are as follows :

1. **Front-End Module:** This module implements the interactive platform which are used to visualize data (Input or output) to present the desired information on usable user interfaces.
2. **Back-End Module:** This module is a part of the middle layer between the data and the front-end module. Since the back-end processes manipulate the stored data by some defined algorithms to generate an output decision, that can be used to control or exploit the database to eventually develop an application subject to the user groups.
3. **Storage Module:** This module gives an easy access to store and manage data that may be used to analyze the physical entity conditions. Examples of storage systems are DB, Cloud, Excel, MongoDB, oracle, MySQL, etc.
4. **Server Module:** The servers offer numerous services to varied network objectives. Even though they come in different forms (Computer software programs, or hard drives) they mostly carry out the same function of receiving, storing, and sharing data. The servers also play a crucial role in a company's ability to collaborate, since these provide the ability to communicate the essential data components for the clients and the dependency services that the other applications may need.

(Oks et al., 2019) propose a reference architecture for the design of the demonstrators for industrial cyber-physical systems. It displays the components

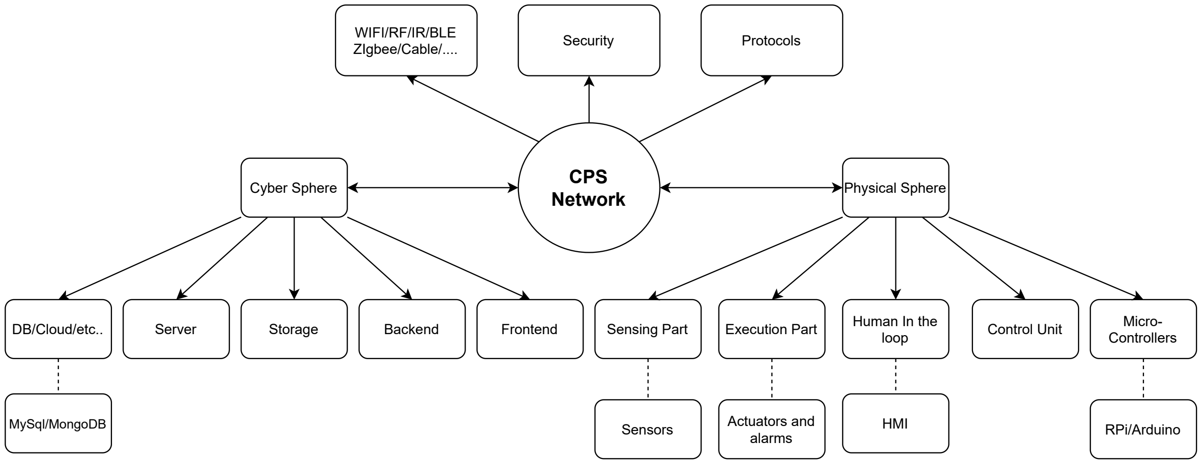

Figure 1: General overview of the proposed CPS architecture.

of the CPS from the physical sphere to communication and cyber spheres. It also include the objectives, scenarios, configurations for better demonstration of the connections among these components.

We eventually intend to develop a general connection concept that can be applied in most of the applications domains and that can serve as a base for the recommendation system. The illustrated concept in figure 2 serves as a framework to build a CPS according to the user's objective. This architecture is composed of two major parts; the first part is the physical sphere which contains the HMI for human interference, along with the sensing and actuating components. Additionally, it has the control unit and the micro-controllers to store data and carry out commands. While the second part, which is the cyber sphere consists of the front-end and back-end for the data processing and presentation. It also involves the database and the server components to communicate and transfer data.

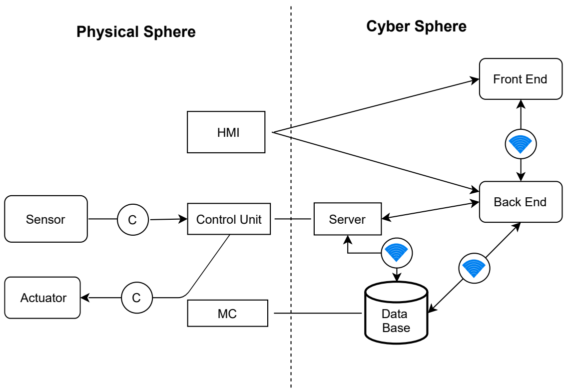

Figure 2: Proposed CPS Connection.

The communication network mainly establishes link between the physical sphere and cyber sphere. It also deals with the communication links among the different sub-components of the physical and cyber spheres. According to the given scenario, these components (sensors, actuators, DB, etc.) shall be recommended as deemed fit to the user needs to achieve ultimate objective.

3 THE RECOMMENDATION SYSTEM

Every application requires its own physical components, communication network, and computational part. The stakeholders of the system usually lack the required knowledge to identify the suitable components that are susceptible to match their requirements. Thus, it may require a decision support system that can help stakeholders to identify the CPS parts and components, which can save time and effort along with avoiding the mistakes and accidents. The generated output is further maintained with the help of the suggestion engine through the use of a Knowledge-Base (KB). The knowledge-base contains the collection of meta-features that describe the sensors, their specifications, concerned domains and any descriptions. The global architecture of the proposed framework is illustrated in Figure 3.

The system receives the user input (such as product features, domain, case, price range, etc.) through the interactions with the chatbot. In case of the introduction of a fresh problem the system retrieves the information regarding the user's objective, application scenario completed by the properties, details and any other information regarding the new input project. This input is mainly achieved by the *frontend*. As a

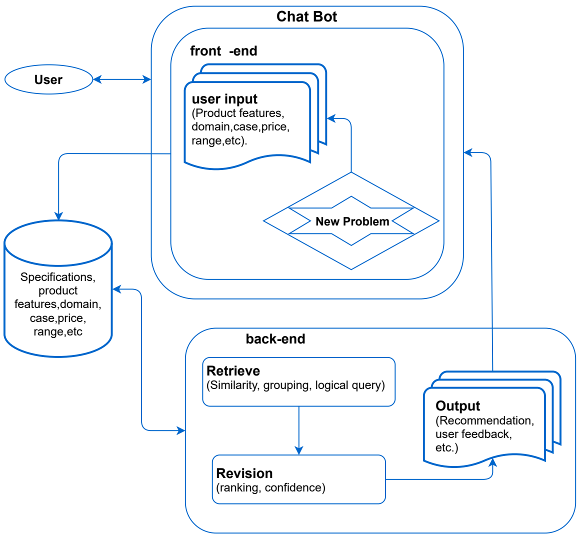

Figure 3: The global architecture of the Recommendation System.

result, a new problem is generated and stored in the KB which shall be analysed later on. In this respect, when the system receives a new unseen problem, it first extracts the meta-features that describes the problem then these are analyzed and processed using Natural Language Processing (NLP) techniques in order to extract the keywords that describe the domain of the application. The steps in this order are executed to make use of the stored data in the KB (specification, description, and domain) to produce a sorted list, after a fetch and return. It contains the candidate which refers to particular sensors in the KB. Retrieval of data is made according to similarity, grouping, and logical queries. Then, the output is revised according to the obtained ranking and confidence, before its recommendation to the user. Feedback questions are presented to take the opinion of users according to the compatibility of the result to his/her objective and needs. In this respect, the feedback allows the knowledge base to be upgraded with the results of the each new problem.

The Meta-knowledge base provides the means to store and search the knowledge issued from offline phase (the training of the recommendation system). Broadly, it can be divided into the following two major categories :

- Storing the knowledge (description, specifications, meta-features) in a structured way.
- Searching and acquiring information while driving explanations acquisition process.

The proposed system intends to make considerable use of ontologies in form of knowledge graphs, both for improved information gathering and query understanding by the suggestion engine as well as for facilitating the acquisition of explanations.

Below is an example of the data stored in the KB where sensors are presented by means of name, type, specification, description, and domain.


```
<Sensor>
    <Name>FHI</Name>
    <Type> Humidity sensor </Type>
    <Specification>
        <Powermax> 5 </Powermax>
        <RangeminC> -60 </RangeminC>
        <RangemaxC> 140 </RangemaxC>
        <RangeminRH> 0 </RangeminRH>
        <RangemaxRH> 100 </RangemaxRH>
        <Accuracymin> -1 </Accuracymin>
        <Accuracymax> 1 </Accuracymax%>
        <Price> 5.8$ </Price>
    </Specification>
    <Description>
      <Use> Designed for high volume, cost sensitive
          applications </Use>
      <Manufacturer> TE Connectivity </Manufacturer>
      <Data Type> Analog </Data Type>
      <Programmable> True </Programmable>
      <Communication> Cable </Communication>
    </Description>
    <Domain>
      <Historical App>
          1-automotive cabin air control
          2-home appliances
          3-industrial process control systems
          4-Meteorology
      </Historical App>
      <Domain of App> Industry </Domain of App>
    </Domain>
</Sensor>
```


Figure 4: Xml file that describe a humidity sensor.

4 CASE STUDY : REAL TIME SURVEILLANCE SYSTEM

To illustrate our approach, we consider the construction of a Patient Surveillance System (PSS) for elderly people. In this context, the main purpose is to help the users in achieving their objective by analyzing the needs. For instance, concerning the PSS problem, the objective is to build a system that support in the day-to-day living tasks and assure the patient safety. For this purpose, the recommendation system provides the information on sensors/actuators related to the different application levels and tasks. The eventual goal is to choose the most convenient set of sensor(s)/actuator(s) among the recommendations made by the system.

In the proposed system, the eventual recommendation is chosen interactively, based on the details provided by the user with the help of the chatbot. These are presented in form of the textual keywords (such as reason, objective, budget, etc.), as illustrated in Figure 5. The details may be clear or somehow vague according to the user's knowledge of the domain. The user's description can range from ex-

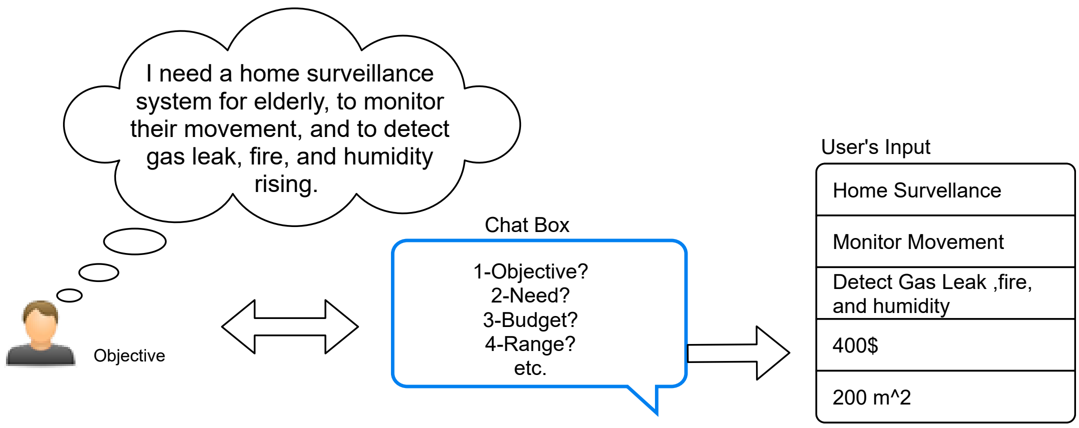

Figure 5: Example:Home Surveillance for Elder Patients (Data Input).

plaining the exact need with details (such as explaining the need for monitoring the patient's movement, pill-taking times, or other stuff. It may also include configuration of material regarding his safety e.g a gas leakage, fire detection, extreme humidity, etc.) or otherwise it can include the general parameters (such as describing the need for patients monitoring system or home safety surveillance system). Regardless the issue, the system must be able to analyze and recommend either a precise recommendation (a specific type of sensors like pressure sensor) or a general one (a set of multiple sensors concerning the same application such that gas, fire detection or humidity sensors). Still, in both cases, it must respond according to the user's needs.

For the sake of simplicity, we take the PSS application as a case study as it can correspond to a large number of public such as the elderly people. In this case, the system can be considered at two consecutive levels, as explained in the following :

- Data Input: In this part, the users can interact with the system using the chatbot through a series of questions where the user can express his objective, need, use case, budget, range, etc. According to the users preferences the input data can be generated as shown in figure 5. This data can be used by the system, later on for the analysis in order to generate more accurate recommendation.
- Data Analysis: In this part, the input text can be pre-processed using e.g segmentation technique which is used to split the text into meaningful segments that can be composed into words, sentences or topics, or the tokenization technique that can be used as a way for separating a piece of text into smaller units called tokens. These can be broadly classified into three types: word, character, and sub-word. For the sake of clarity, let us consider the word *monitoring*, it can be tokenized as characters: *m-o-n-i-t-o-r-i-n-g*. Similarly, we may use Stemming technique, which in fact is a process of removing a part of a word, or reducing a word to its stem or root for example *monitor* is the root of the word *monitoring*.

As a result of pre-processing keywords we formulate the data preparations that can be generated, as shown in figure 6. The processed data can be analyzed using semantic analysis based on RNN/LSTM. The choice of RNN/LSTM is justified by the fact that RNN are an important variant of neural networks that are heavily used in Natural Language Processing. It can be further observed in the literature that it provides flexibility in the network to work with varying lengths of sentences. The Recurrent Neural Network (RNN) has a major advantage, in comparison to the standard neural networks, as it gives the back propagation technique that may enlarge the training data set for the recurrent learning. In addition, it also manifest the advantage of sharing features that are learned across different positions of text which in both cases can't be achieved with standard neural network. The Long Short-Term Memory (LSTM) algorithm is a type of a popular RNN for learning sequential data prediction problems. Like any other neural network, LSTM comprises a few layers that aid in pattern recognition and learning for improved performance. The fundamental function of an LSTM can be viewed as holding the necessary data while discarding the data that is neither necessary nor helpful for subsequent prediction. All this analysis can be stored in the Knowledge-Base that is built using Neo4j (Vágner, 2018). Neo4j is an open-source graph oriented database management system. It allows data to be represented as nodes connected by a set of arcs whereas each object (either node or an arc) can have their own properties.

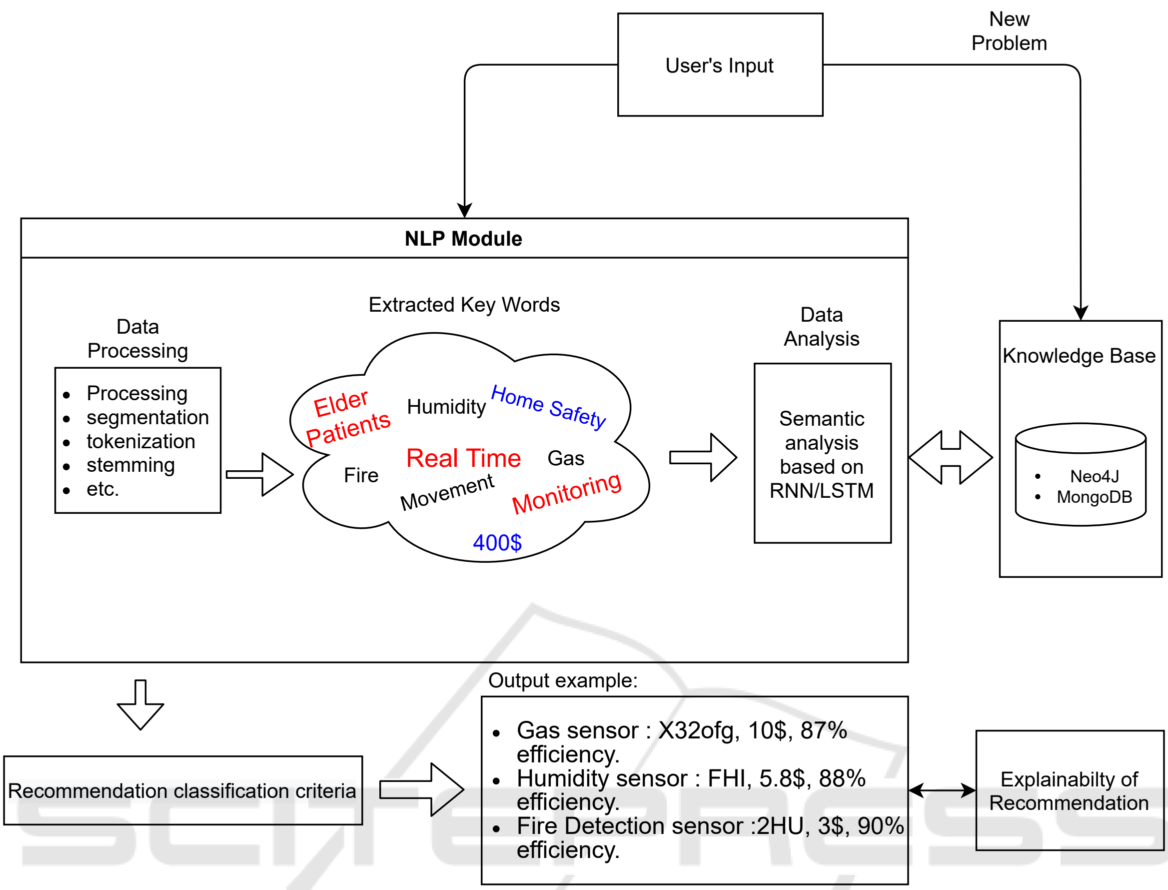

Figure 6: Example:Home Surveillance for Elder Patients (Data Analysis).

The Output recommendation can be classified on the basis of some criteria, as chosen by the user with the help of the communication via the chatbot. These criteria can include the classification on the basis of budget, efficiency, range, etc. The output can be presented to the user on the chatbot including the explainability factors of the generated recommendation. The explainability part render the capability to justify the recommendation in a transparent manner, as it provides the explanations of the recommendation system on multiple levels. For instance, let us consider the recommendation of a temperature sensor. This sensor is recommended because it fits the objective of the user, since a similar application was found that has used this sensor in the historical traces (like Room Temperature Measurement applications). The knowledge-base provides the means to query the trances in the Historical App component, as shown in the listing 4. We can also observe that the specification fits well the criteria from the budget constraints (5 euros), temperature range (0°C,100°C) and accuracy (-1,1) as were given by the user. Similarly, the specifications from the knowledge-base can give the supplementary information (power range, data type, ability to be programmable or not, and communication types, etc.) related to the sensors.

5 CONCLUSION AND PROSPECTIVE

The Cyber Physical Systems are usually complex amalgamation of hardware and software components. These are applied on various application levels for the different domains. Hence, the CPS configurations may differ from domain to domain and at multiple application levels. Furthermore, according to the technological evolution, the CPS are required to be maintained at both the layers of hardware components and their articulating software components; which presents a major research challenge. In this paper, we attempt to briefly encompass the architecture, concept and domains of different applications of CPS. In this respect, we present a novel CPS design and modeling approach that may allow the maintenance and management of its configurations to be stored in a knowledge-base. The facts in the knowledge-base are further exploited with the help of a Cyber Physical Recommendation System (CPRS). In this context, the CPRS presents a model architecture that may provide necessary recommendations for building a CPS according to the presented objective, details, and application scenario. In the future work, we plan the to improve the knowledge-base using the training and testing phase with the help of natural language processing algorithms and techniques. While this must also provide means to explore the explainabilty aspects of such a supporting system.

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