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Decision-Making Mechanisms for CyberPhysical Systems: Challenges and Opportunities for their Implementation with Low-Cost Embedded Devices

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***Abstract* – A Cyber-Physical System (CPS) is considered as one of the hottest computer applications today, while a proper design of such a system pre-assumes that a number of challenges have to be sufficiently addressed. A CPS is composed by a tight integration of cyber and physical objects, where the term *cyber objects* refers to any computing hardware/software resources that can achieve computation, communication, and control functions in a discrete, logical, and switched environment. Similarly, the *physical entities* refer to any natural or human-made systems that are governed by the laws of physics and operate in continuous time. In order to address these challenges, three complementary technologies, namely sensing, computing and communication have to be proper combined. Critical role to any cyberphysical system is the decision-making mechanism, which controls the individual entities/services in order all of them to be orchestrated and operate as a unique system. For this purpose, both the cyber and physical aspects of a CPS have to be appropriately designed, implemented and customized in order to maximize the potential gains from these platforms.**

***Keywords* – CyberPhysical System, Sensing, Decision-Making, Actuators**

I. INTRODUCTION

Recently, the convergence of emerging embedded computing, information technology, and distributed control became a key enabler for future technologies. Among others, a new generation of systems with integrated computational and physical capabilities that can interact with humans through many new modalities have been introduced. Furthermore, it is expected that computing and communication capabilities will soon be embedded in all types of objects and structures in the physical environment. Applications with enormous societal impact and economic benefit will be created by harnessing these capabilities across both space and time domains. Such systems that bridge the cyber world of computing and communications with the physical world are referred to as Cyber-Physical Systems (CPS). Specifically, a CPS is a collection of task-oriented or dedicated systems that pool their resources and capabilities together to create a new, more complex system which offers more functionality and performance than simply the sum of the constituent sub-systems. Among others, these new design paradigms have the ability to interact with, and expand the capabilities of, the physical world through monitoring, computation, communication, coordination, and decision making mechanisms. Such an emerging multidisciplinary frontier will enable revolutionary changes in the way humans live, while it is also expected to be a key enabler for future technology developments.

The integration of physical processes and computing is not new. Embedded systems have been in place for a long time and these systems often combine physical processes (e.g. through digital/analog sensors) with computing. However, the core differentiator between a CPS and either a typical control system, or an embedded system, is the communication feature among system's components, which adds (re-)configurability and scalability, allowing instrumenting the physical world with pervasive networks of sensor-rich embedded computation. The goal of CPS architecture is to get maximum value out of a large system by understanding of how each of the smaller (sub-)systems work, interface and are used. This trend is also supported by the continuation of Moore's law, which imposes that the cost of a single embedded computer equipped with sensing, processing and communication capabilities drops to-wards zero. Thus, it is economically feasible to

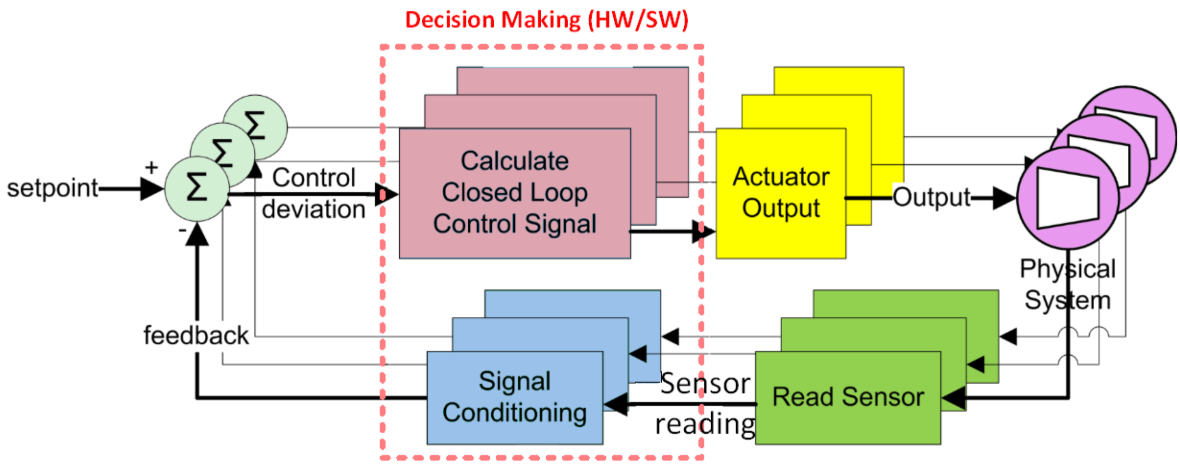

Fig. 1. The block diagram of a typical cyber-physical system

denselydeploy networks with very large quantities of sensor readings from the physical world, compute quantities andtake decisions out of them. Such a very dense network offer a better resolution of the physical world and therefore a better capability of detecting the occurrence of an event; this is of paramount importance for a number of foreseeable applications. Apart from their efficiency to deploy complex systems, CPS exhibits also substantially stricter performance constraints. This problem becomes far more challenging when (i) real-time constraints have to be met, (ii) entities comprising a CPS run over heterogeneous environments and (iii) these entities interact with each other in a very complex manner. To make matters worse, existing approaches for CPS usually impose components with increased processing power, which is not always the case especially at the embedded domain. Moreover, as the physical world is not entirely predictable, it is not expected the CPS to be operating in a controlled environment; thus, it must be robust enough to unexpected conditions and adaptable to subsystem failures. Finally, it is also expected that the derived products should be highly extensible for new functionalities that enable flexible adaption especially under run-time, or real-time constraints.

A critical challenge for designing an efficient CPS relies on the decision-making mechanism. The majority of existing control mechanisms exhibit increased computational and/or storage complexity, which in turn makes their implementation as part of an embedded system a challenging issue. The importance of this problem was also considered by research institutions and industry as a big challenge for upcoming large-scale CPS platforms. Note that the absence of developing lightweight solutions (able to be executed onto embedded platforms) for supporting large-scale system's decision making is not due to neglect, but rather due to its difficulty. Also, as we have already highlighted, this problem becomes far more challenging in case the decision making has to be made under run-time (or real-time) constraints. In such a case, usually a compromise between the desired accuracy and the processing overhead is performed. Existing approaches for supporting the system's decision making rely mainly on ad-hoc methods: After all the components, have been designed and manufactured, the control mechanisms aim at making the system to work somehow. However, as the complexity of engineered systems continues to increase, the lack of a systematic theory for system's decision making introduces additional problems.

In this paper we will study the case of Air Conditioner (A/C) control. Through this use-case, all aspects and stages of designingdecision making mechanisms for Cyber-Physical Systems will be considered. This is a crucial case because non-optical manual configuration usually leads to increased energy consumption and poor thermal conditions. Considering that the buildings energy consumption constitutes arround 40-45% of the total European Union's energy consumption [1], designing cyberphysical control systems for controlling energy demanding facilities, like Air Conditioners, becomes a very important task.

There are many different approaches for solving this problem, such as building smart thermostats that control the heating/cooling of the whole building. These systems are usually based on non linear control techniques, neural networks [2], fuzzy rules [3], PID controllers [4] or combinations of techniques [5]. The introduced approach faces the problem of making a smart controller embedded in every A/C device.

This paper presents the main concepts for designing decision-making mechanisms targeting Cyber-Physical Systems, especially the controlling of Air Conditioners will be studied, which is a very indicative and important case. Emphasis for this task is given to the implementation of those systems in low-cost embedded devices, therefore the work targets to low-complexity mechanisms.

II. DESCRIPTION OF THE METHOD

This section provides information for each stage of designing decision-making for CPS. Detailed information about implementation and testing techniques is also given. To support all this tasks clearly, they will described through the use-case of A/C control. Fig. 2 depicts the proposed framework for this use-case.

A. *Crucial metrics*

Each Cyber-Physical system depending on its type requires the computation of specific metrics in order to make decisions and achieve a targeted control. Especially for the use-case of A/C control, a key component of the whole approach is the thermal comfort.

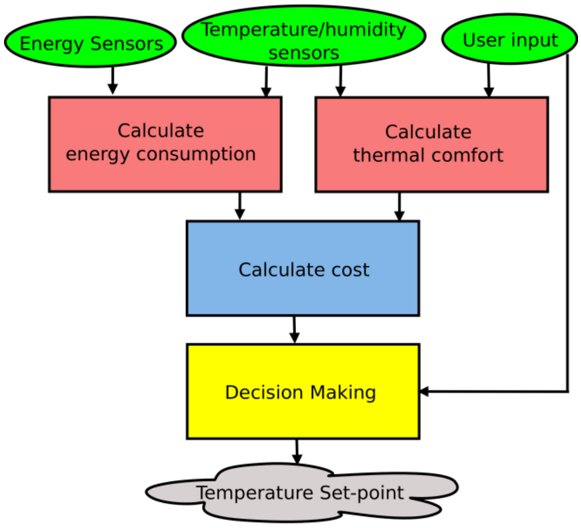

Fig. 1. Proposed Use-Case Framework

The improvement of this value is the main goal of Air Conditioners. The most well-known methods for measuring this abstract quantity are the Predicted Mean Vote (PMV) and the Predicted Percentage of Dissatisfied (PPD). The first is scaled from-3 to +3, values around 0 are considered as optimal. The second is a percentage that represents the percentage of dissatisfied occupants in a thermal zone, or generally a dissatisfaction measurement. In this approach we will use the PPD value, estimated by the model designed by P.O Fanger. The Fanger's model was published in 1967 [6]. Fanger used empirical studies and heat balance equations about skin temperature to define the thermal comfort. This model is adopted by ASHRAE Standards [7]. Fanger's thermal comfort model needs the following inputs:

- Air Temperature
- Mean Radiant Temperature
- Relative Humidity
- Relative Air Velocity
- Metabolic Rate
- Clothing Insulation

The second key component is the energy consumption reporting. In order to achieve energy saving, the measurement of energy consumption for each configuration is necessary.

B. *Sensoring / system - human interraction*

The system in order to calculate the crucial quantities, to be able to make decisions and to evaluate these decisions needs feedback from the environment. This can achieved through sensors. In some cases the system may need also feedback from users. Especially for this type of CPS, as the one presented in this paper, that interact directly with humans. For the computation of thermal comfort, described in the previous paragraph we need a number of values. The air temperature and the relative humidity which are the most important factors will be measured and reported by sensors. These sensors are common and usually are included in A/C systems and thermostats. Mean radiant temperature refers to radiant heat from surfaces. This value can be captured by sensors but usually some default or approximated numbers are given, because in the ordinary way it is close to air temperature. The air velocity is definitely affected by the A/C for closed spaces (for example the fan speed) and this means that A/C can control this value. Metabolic rate depends on the activity of the occupants. Metabolic rate is measured in met units, which is equal to 58.2 W/m^2. This is chosen according to the building's usage, for example in offices, where people are seated and are typing the value is 1.1 met. A/C can have an option so as users can select the activity, for example if they are sleeping, seating or exercising. Clothing insulation depends on season and also on activity. For example common values for offices are 0.8 – 1 for winter (suit-shirt-trousers) and 0.4 - 0.6 in summer (shirt-trousers). A/C can also have an option for selecting between some typical clothing ensembles. Finally, the required energy consumption can easily be measured by sensors in the A/C for capturing electric power (wattmeters).

C. *Problem formulation (cost calculation)*

Every CPS controller targets to solve a problem, for example to minimize a cost. The formulation of the problem that the decision-making mechanism targets to solve is very important and some-times not trivial. In this paragraph the problem formulation for A/C control use-case is presented. A/C controller will set the configuration (temperature set-points) for each operation time, in order to decrease energy consumption while achieving a simultaneous reduction of the thermal dissatisfaction (PPD). The problem of finding these optimal temperature set-points is not simple. It constitutes a multi-objective problem, because energy saving and dissatisfaction reduction are conflicting tasks. Equation 1 shows the problem that the proposed method solves.The system, on every time-step *t* tries to find the setpoint *stp* that minimizes a total *cost* which associates energy and thermal comfort using afactor *a*, a trade-off between energy saving and thermal comfort optimizing.

$$\min\{a * PPD(stp,t) + (1-a) * Energy(stp,t)\} \quad (1)$$

This model lets the system operate in different modes, depending on the trade-off. For example user can select the *high satisfaction* mode (*a=1*), or the *energy savings* mode (*a=0*). The second one does not mean that the A/C is off because according to ASHRAE standards PPD has to be lower than 10-15%. Therefore *a=0* option leads to the maximum possible energy saving keeping the thermal comfort within the permissible limits. The thermal comfort categories according ISO7730 [8] standards are:

- Category A: PPD < 6%, -0.2 < PMV < +0.2
- Category B: PPD < 10%, -0.5 < PMV < +0.5
- Category C: PPD < 15%, -0.7 < PMV < +0.7

D. *Decision - making*

Decision-making is the basic part of the CPS controller. In the case of A/C control that is examined in this paper we are going to compare 2 different techniques: the first is a very simple controller that finds a local minimum for the cost described in equation 1, it does this very quickly and without a large number of computations, and the second is a machine learning based mechanism (using regression models).

The first method's controller is based on an algorithm inspired by the *"bang-bang" control* theory (known as bang-bang controller or hysteresis controller) [9].Usually this type of controllers are used when the system has binary input or for optimization problems that a really fast response is needed (for example the brakes of a vehicle). The basic idea of the controller is that it switches the system between two states (usually extreme states like on – off) according to a condition. The whole controller's algorithm for the case of A/C control is presented in Algorithm 1. Every time-step of the operation the PPD value is calculated using the Fanger's model and the energy consumption is reported by the sensors. Then the normalized cost that was described in the previous paragraph is calculated. In each time-step the controller switches between two states: adding or subtracting a value step from previous set-point to create the next one. If the cost decreases then the controller continues applying the same operation. Elsewhere the controller changes the operation/state. In each case the controller keeps the acceptable PPD limits (or if PPD is above the limits, tries to reduce it).

***Algorithm* 1**: *Proposed Simple Controller*

```
operation = +1
Each timestep:
 E = energy from sensors
 PPD = Fanger_PPD(temp,rad,hum,vel,met,clo)
   cost = a*PPD + (1-a)*E
  if((cost > prev_cost)
   operation = operation*(-1)
  end
   setpoint = setpoint + operation*step
end
```

The purpose of this paper is to present the challenge for implementing decision-making for CPS in low cost devices. The first proposed algorithm for the problem that we chose to face is very light-weight. The complexity is proportionate to *O(1)*because it includes only a small number of numerical operations. However there are a number of disadvantages. This method can produce good results but is not stable and sometimes can lead to very wrong choices. This happens because for some periods even a series of bad actions can lead to decrement of the cost due to, for example, the energy consumption decreases for all the setpoints. But the setpoint that the controller sets will be worse than all the other setpoints. This happens in periods with rapid climate changes. A way to mitigate this problem is needed.

The second technique will use a machine learning model such as a neural network or a Support Vector Machine (SVM) [10] to estimate the energy consumption and the thermal comfort. The model requires a number of data to be trained in order to be able to estimate the required values. Here we have to face two challenges according the way that the system is trained. There can be a pre-training on simulation or production process level. This means that the dataset will be produced using a simulation software or during the production of an A/C making a large number of experiments. In this way of training the model can't be very accurate because it is difficult to approach all the real conditions and building/zone dynamics of the place where the A/C will be placed. The second and more usual way is to build a "plug-and-play" A/C that is able to learn on-line the dynamics of the room, to collect data and be re-trained. This way will produce a more accurate system but needs considerable computational complexity to train the machine learning model and constantly growing storage requirements to save the dataset that comes from the sensor values. A way to optimize this technique and design an efficient low-complexity mechanism is needed. Algorithm 2 presents this type of decision making.

***Algorithm* 2**: *Proposed Quality Controller*

```
initialize dataset
Each timestep:
update dataset (from sensors)
  if estimation errors> limit
     train model1 , model2
  end
  fori in [18 – 25]
PPD = predict(model1, sensors + setpoint)
  E = predict(model2, sensors + setpoint)
cost = a*PPD + (1-a)*E
  if cost<min_cost
        setpoint = i
     min_cost = cost
  end
end
```

The aforementioned techniques are just a representative example of the challenges that have to be encountered when decision-making for CPS is designed. The first method is very simple, ideal for low-cost devices but not accurate and sometimes can lead to very bad results in contrary with the second method, which is more accurate but it is difficult to implement in low cost devices due to high computer and storage requirements.

E. *Designing and testing framework*

To design and test CPS performance, simulation programs are used on the first level. On the second level, the physical implementation takes place. In this subsection the implementation and the testing of the proposed control system is presented.

For testing the proposed design and for making experiments a well-known simulation tool, namely the *EnergyPlus* [11], is used. EnergyPlus provides a complete simulation solution with building modelling and a large number of reporting results. All the results presented in Section III were produced using this software. To implement and test the controller a co-simulation is needed. This is achieved through *Building Controls Virtual Test Bed (bcvtb)*[12]. This software allows the combination of different programs and the exchange of information between them. In our case we used bcvtb to connect EnergyPlus with *Matlab*. This means that EnergyPlus will simulate the performance of an A/C system in a zone of a building model and the control of the set-points will be accomplished through Matlab. Similar simulation systems are used in the literature [13-14]. At the last step Matlab will communicate through *Serial USB port* with a single board computer (for example Raspberry Pi), or a microcontroller (for example Arduino UNO) where the proposed controller is implemented. Every time step of the simulation EnergyPlus sends information to Matlab through bcvtb, Matlab send this information to the microcontroller, where decision-making is applied to calculate the set-point. Then the responsed A/C action is sent to Matlab and from there (through bcvtb) back to EnergyPlus. Fig. 3 depicts the described system.

III. RESULTS AND DISCUSSIONS

In this Section the results of the use-case Cyber-Physical system decision making which is described in the previous section will be presented not only to inform about the final results for this example, but also in order to demonstrate the importance and the challenges of such designs.

A. *Experimental Setup*

Before presenting the results of a decision making method for CPS, the description of the experimental setup and the way that these results were measured is required. For the use-case of the A/C controller that is proposed in this paper the results were calculated using the EnergyPlus software. The simulation setup is an office in an office building, while using the weather of Athens Greece at a representative winter week (18 – 24 January), with a time-step of 20 minutes. The A/C operates from 6am to 9pm.

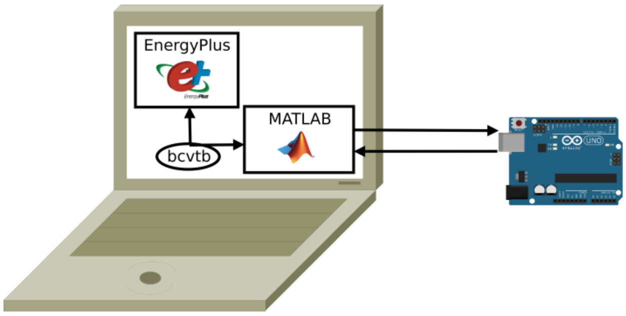

Fig. 2. Designing and Testing Framework

B. *Results*

Fig.4 demonstrates the results of the two proposed controller methods against typical fixed set-points for A/Cs (winter). Only the active time steps (6am – 9pm) are presented. This comparison helps to show that the controller achieves a good performance, no matter what set point occupants could have set. Usually occupants change the set point many times during the day. We chose *a=0.5*, which is the balanced configuration just for demonstrating purposes because the system takes into account energy and thermal comfort equally.

We might observe that for the presented first days the simple light-weight controller achieves similar performance with the learning (based on SVM) controller. However after the 3rd day the simple controller starts to diverge from the optimal solution.

The complexity and the storage requirements are negligible for the Simple controller. However the Learning decision-making has some problems. It is lightweight if the model is pre-trained at simulation level, but this technique may lead to bad performance for the real operation of the Air Conditioner. For achieving better results an on-line learning technique should be used but this creates challenges with regard to meet the process and storage resources of low-cost embedded devices.

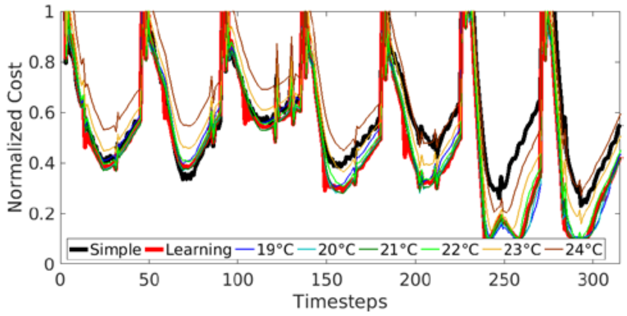

Fig. 3. Comparison among different decision-making techniques and typical fixed setpoints

IV. CONCLUSIONS

The challenges and opportunities for decision-making mechanisms for Cyber-Physical Systems and their implementation with low-cost embedded devices were presented through a typical and representative use-case: the problem of controlling Air Conditioners. The purpose of this type of controllers is to achieve both minimum energy consumption and best thermal comfort conditions. This problem is not trivial and the design of a simple decision making controller was introduced step by step. All the important stages on designing decision making mechanisms for Cyber-Physical Systems were presented through this use-case and plenty solutions as well as different options were given clearly and with sufficient details. Finally some results that highlight the importance of the controller and the performance compared to manual control and fixed configuration options were presented thoroughly. Different approaches are compared revealing the challenges and the conflicts between quality of the results and possibility of implementing in low-cost embedded devices.

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