WSAN QoS Driven Control Model for Building Operations

Alie El-Din Mady, Menouer Boubekeur and Gregory Provan

Abstract Currently wireless based control systems lack appropriate development methodologies and tools The control model and its underlying wireless network are typically developed separately, which can lead to unstable and suboptimal implementations. In this paper we introduce a hybrid-based design methodology that considers the performance parameters of the Wireless Sensor and Actuator Network (WSAN) in order to develop an optimized control system tailored to the specific application environment and sensor network conditions. We first identify the boundaries of the control parameters that maintain stable and optimal control model. Within these boundaries, we determine the optimal WSAN Quality of Service (QoS) parameters through a tuning process in order to reach to optimal Control/WSAN design as illustrated in the case study. The methodology has been illustrated through a distributed lighting control developed using our hybrid/multi-agent platform.

Key words: Hybrid System, Multi-agent System, Building Automation, WSAN, PPD-Controller

1 Introduction

Nowadays, networked wireless devices are widely used in many applications, such as habitat monitoring, object tracking, fire detection and modern building. In particular, buildings equipped with Building Management Systems (BMS) often use a large wireless/wired sensor network. Creating distributed sensor network applications for such systems face numerous challenges in scaling, delays associated with data collection and energy consumption, which can lead to unstable systems [1], [2] (i.e., continuously oscillating around the set points), this instability might also be

Alie El-Din Mady, Menouer Boubekeur and Gregory Provan
Cork Complex Systems Lab (CCSL), Computer Science Department, University College Cork (UCC), Cork, Ireland, e-mail: {mae1, m.boubekeur, g.provan}@cs.ucc.ie

due to the performance tradeoffs between the control and wireless networks when designing the distributed controller. Further, the different requirements of different services place many challenges on centralized control solutions; for example, in lighting control, reaction times are anticipated within fractions of a second, whereas in HVAC control, the process dynamics is much slower and the sampling/actuation time is much larger.

Control systems and communication networks are typically designed using different platforms and principles. Control theory requires accurate, timely and lossless feedback data; however, random delays and packet loss are generally accepted in communication networks, particularly in wireless networks. Therefore, the performance of the control model relies on the network performance, due to the distribution and communication-based control. From the control perspective, the more knowledge the controller has about the system, the better the control performance can be designed to tolerate communications problems. Additional knowledge about the system can be obtained by increasing the number of sensors or sending sensor measurements more frequently. However, this increases the communication burden on the network and the network may become congested. The congestion results in longer delays and more packet losses, which degrade the control performance.

As a metric for measuring relative optimality of control performance, we have used the Mean Square Error (MSE). In terms of user comfort, this metric reflects the user's dissatisfaction in relation to the preferred set point. Moreover the degradation of the QoS at the network level may reduce user comfort; for example, a communication delay may delay reaching the optimal set point (i.e. light luminance). Second, packet losses may cause false alarms or a failure to capture real alarm data.

The objective of our work is to provide a Control/WSAN design methodology that examines the tradeoffs in optimising the building control in relation to user comfort, safety and reliability. These factors are dependent on optimal control parameters and enhanced WSAN QoS [3]. As shown in Fig. 1, we start by identifying the boundaries of the control parameters that maintain stable and optimal control model. Within these boundaries, we determine the optimal WSAN QoS parameters through a tuning process to reach to optimal Control/WSAN design as illustrated in the case study.

Our research extends prior work in the area, e.g., [4], by exploring the impact of the control performance on the WSAN and vice versa. [4] provides a cross layer methodology to link the standard design layers of an Open System Interconnection (OSI). This methodology ignores the performance of the WSAN and fails to consider linking the performance evaluation of the different layers which may improve control performance but degrade that of the other layers. We have selected the Medium Access Control (MAC) protocol and the Link technique design; we do not consider the network layer because the underlying example uses a point-to-point linking technique. The impact of changing the correlated parameters on both con-

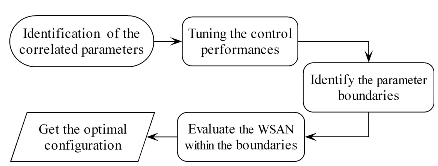


Fig. 1 Design Methodology

trol performance and the WSAN QoS has been considered, with priority given to the objectives of the application, as represented by the control requirements.

Two tuning phases have been considered in the proposed methodology. The first considers tuning control performance to get the best correlated parameter values; for this we calculate the parameter variation boundaries. The second one deals with the WSAN QoS; for this we explore the search population within the boundaries provided previously, to determine the optimal Control/WSAN configuration.

The remainder of the paper is organized as follows: Section 2 introduces a new control strategy, called the Parameterised Predictable Distributed (PPD) control strategy, its WSAN model and the scenario specification considered. In Section 3, the hybrid/multi-agent model for the PPD-Controller is explained. The refined approach for the Control/WSAN-correlated parameters is provided in Section 4. The experimental results for our case study are provided in Section 5 and finally Section 6 highlights our conclusions and plans for future work.

2 Parameterizable/Predictable Distributed Controller

This section introduces our new Parameterizable and Predictable Distributed controller (PPD-Controller) for automated lighting systems. The PPD-Controller offers a distributed solution and aims to increase the control reliability, scalability, resource sharing and concurrency. In this section, we briefly describe the scenario specification, the control strategy and the WSAN model.

2.1 Scenario Specification

We consider an open office area with typical architecture, as shown in Fig. 2. It contains 10 controlled zones; each zone contains one artificial light, one light sensor and one Radio-Frequency Identification (RFID) receiver. There are 4 windows/bindings on the right and left boarders of the open area and a fix number of predefined person positions.

For the lighting model we consider integrating blinding and lighting controls. In order to enhance the efficiency of the resulting control model, an optimization technique has been implemented as it selects the light luminance and blind position depending on the user preferences and the power consumed due to the artificial light and the blinding actuators.

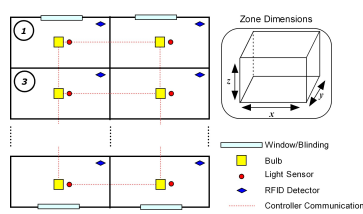


Fig. 2 Model Specification

As a summary, the lighting control scenario behaves as follows:

1. The user can switch on/off the automatic lighting system for several zones, or for all the system through a technician.

2. The users provide their preferences (light luminance and blinding position).
3. A person is tracked in each zone using for example RFID, his preferences are ignored whenever he leaves his zone.
4. A local optimization engine receives the user preferences and sends back the optimal settings.
5. The controller controls the artificial light and the blinding actuators in order to reach the user preferences considering the daylight luminance and the light interferences coming from the adjacent zones.

2.2 Control Strategy Description

Fig. 3 shows the model of a local controller and its interactions with the environments. The preference solver receives the user preferences for each zone, sends the optimal light luminance and blinding position back to the optimization engine. This latter uses Genetic Algorithm/Simulated Annealing (GASA) algorithm [5] in order to calculate the optimal actuation settings, it sends them back to the PI-Controller. The PI-Controller, is used to predict the next actuation setting for the lighting level in a close loop fashion [6] using Eq. 1. It actuates the artificial light and the blinding position according to the optimum settings. Whenever preferences change, the optimization step is updated; otherwise, the PI-Controller actuates relying on the external light and the light interference. The Light/Blinding Occlusion Preference Solver agent is used to provide the intermediate solution between several luminance/glare preferences in the same controlled zone. It applies a Low Pass Filter (LPF) in order to prevent exceeding a predefined threshold (700 Lux for luminance and 100% for the blinding position). The control equations are given by:

$$A(t+1) = A(t) + \theta \tag{1}$$
$$U(t) = A(t) + E(t) + I(t)$$

$$\theta = \begin{cases} \gamma - \dfrac{\beta}{\rho}, & \forall\, U(t) - S(t) > \varepsilon \\ \dfrac{\beta}{\rho} - \gamma, & \forall\, S(t) - U(t) > \varepsilon \\ 0, & \forall\, |S(t) - U(t)| \leq \varepsilon, \end{cases}$$

where $A(t)$ is the actuation setting for light/blinding actuators, $E(t)$ is the daylight intensity (Lux), $I(t)$ is the interference light intensity (Lux), $U(t)$ is the sensed light intensity (Lux), $S(t)$ is the optimal preference settings, ε is the luminance level produced from a single dimming level (70 Lux), β is the maximum light intensity error (700 Lux), γ is the minimal light intensity error (0 Lux) and ρ is the total number of dimming levels (10 levels).

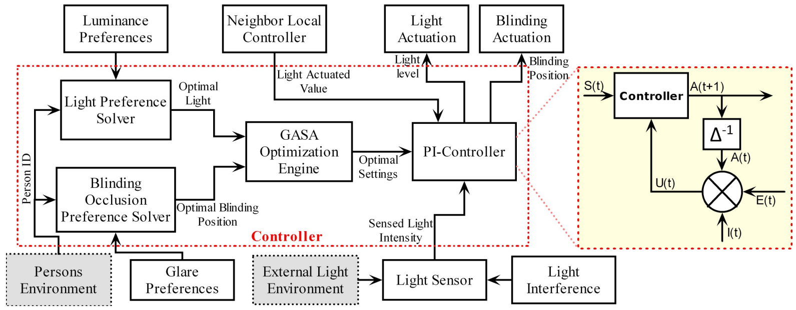


Fig. 3 Control Model

2.3 *WSAN Modelling for the PPD-Controller*

In order to evaluate the WSAN performance for the PPD-Controller, we have modelled the WSAN using the VisualSense tool [7]. We have also considered the Tyndall [8] sensor node as a reference for the model parameters. The Time Division Multiple Access (TDMA-based) MAC protocol [9] is used in the contention-free period, which leads to a free collision probability. Fig. 4(a) shows the WSAN model used for evaluating 4 zones (1, 3, 4, 5) (Fig. 2). The PPD-Controller in zone 3 has been selected to be evaluated as it constitutes the bottleneck in the model, since it is the most heavily used due to its communication with the other 3 controllers (1, 4, 5), their RFIDs and sensors. In relation to the WSAN performance, the following QoS metrics [10] have been identified: $Channel\ Throughput$, $Controller\ Duty\ Cycle$, $Buffer\ Size$, $Response\ Time(Delay)$, and $Sensorbattery\ LifeTime$.

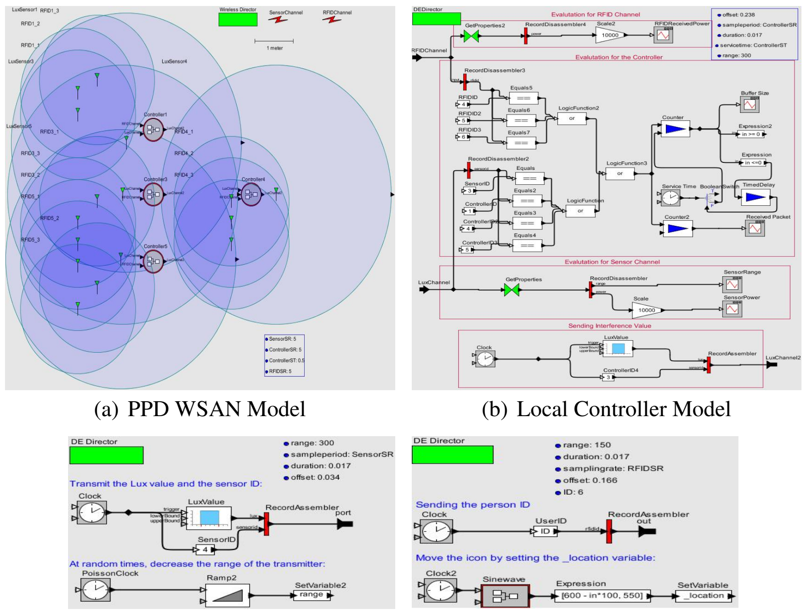
When modelling the WSAN for PPD-Controller, we distinguished four models:

Communication channels model: 2 channels are considered for the wireless communication, one channel for light sensors and the local controllers (Zigbee band, i.e. 2.4 GHz) and other for the RFIDs (RF band, i.e., 324 MHz). The power propagation factor in the communication channels is $\frac{1}{4\Pi r^2}$, where r is the distance between the transmitter and the receiver, and the loss probability in each channel is 2%.

Light sensor model: The sensor sends the Lux measured value and the sensor ID to the controller using a fixed sampling rate and frequency offset, as shown in Fig. 4(c). The sensor coverage area is 3 meters (distributed in sphere area) and its power transmission is 0.1 $watt/m^2$. In order to show the effect of the battery discharging on the sensor transmission range, we have assumed that the range is decreasing by 0.1 meter each event that follows Poisson distribution with mean time equals to 20 times the sensor sampling rate.

RFID model: The RFID detection range is 1.5 meter and its power transmission is 0.1 $watt/m^2$. As shown in Fig. 4(d), the RFID sends its ID with a fixed sampling rate and frequency offset. Moreover, the movement of the RFID is modelled as a sin wave sampled every 0.3 minute.

Controller/Receiver model: In this model, shown in Fig. 4(b), we have considered the received packets number, buffer size and the controller duty cycle. However, the controller service time is fixed per received packet. The communication between the neighbouring controllers also uses the sensor channel.



(a) PPD WSAN Model (b) Local Controller Model

(c) Light Sensor Model (d) RFID Model

Fig. 4 WSAN Model

3 Design and Model for PPD-Controller Using Hybrid Platform

In order to simulate the lighting system and evaluate its performance, the system and its environment have been modelled using the Charon toolset [11]. The Charon toolset provides a platform to create a hybrid/multi-agent system, using a hierarchy framework. Based on Charon's use of agents to specify control entities, in the PPD-Controller, we use an agent for the global controller, which sends configuration parameters to the local controllers. Two other agents model the environments (external light and presence). For each zone, 4 agents are used: RFID, light sensor, blinding controller and local controller. As mentioned earlier, the global controller sets the configuration parameters for the local controllers, e.g., it activates/deactivates some controllers (e.g. blinding controller) or some functions inside a controller (e.g. manual or automatic). The local controller contains 2 subagents, one of which is used to receive and calculate the light interferences coming from the adjacent zones. The agent also predicts light interferences using Linear Prediction Coding (LPC) algorithm [12], based on the preferences history when starting of the scheduling flow.

The other agent is used to send the actuation values and trigger the optimization engine. Each agent contains the modes describing its behaviour. There are two main environments for the lighting system, the daylight and the person movement environments. In order to verify the behaviour of the PPD-Controller, both environments have been modelled using hybrid systems, as the daylight model has continuous behaviour while the presence model has discrete behaviour. In the daylight model, five periods have been modelled as a first order differential equation with a constant slope (using linear hybrid automata [13]). During the first and last four hours of the day, the daylight slope and luminance are equal to zero, while during the second four hours the slope is equal to 100, which means that the maximum intensity in the day is 4000 Lux. In the next eight hours the slope is equal to zero and then goes to -100 in the following four hours, in order to reach zero luminance again at the end of the day. The light intensity that comes to the controlled zone is a percentage of the daylight intensity; this percentage relies on the dimensions of the window. In this model, 8% of the daylight is considered as the external light coming into the controlled zone [6].

We model occupant movements in the controlled zone using a deterministic distribution with respect to the time of day. In the first and last seven hours of the day, no one is in the zone; from 7:00 to 10:00 AM people arrive successively; during the next seven hours occupants enter or exit with a 50% probability; and finally, over the next two hours people leave individually.

4 Control/WSAN Refinement Approach

As stated earlier, in modern buildings, distributed controllers over large wireless/wired sensor/actuator network face the challenge of achieving good WSAN performances while designing the control application. The case where both control and WSAN models are designed separately may lead to unstable and suboptimal implementations. In this research work we assume a high correlation between the performance parameters of both control and WSAN models. For example, if the WSAN has received many requests at a certain moment, this will lead to either delay in responding to the next request (in order to serve all the buffered requests) or dropping some requests which will create unexpected behaviour in the environment. In this section we explain our approach for an integrated design of both control and WSAN.

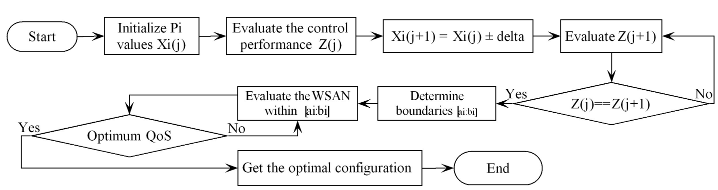


Fig. 5 WSAN/Control Evaluation Algorithm

Fig. 5 shows the flowchart of the approach:

1. We start by identifying the correlated parameters P_i which mutually affect both WSAN QoS and the control performance.
2. Initialize the P_i with acceptable values $P_i(0)$.
3. With the assumption that the control performance has higher priority, evaluate the control performance (MSE) according to the initial parameters.
4. Increase/decrease P_i with a (delta) step using Gradient Descent algorithm and remove the inconsistent solutions, as will be explained later.
5. Evaluate the MSE according to $P_i(j)$, which indicates the value for P_i at instance j.
6. Repeat step 5 untill getting the acceptable control performance, and hence identify the boundaries $[a_i, b_i]$ for each parameter P_i.
7. Evaluate the QoS of the WSAN within the identified boundaries $[a_i, b_i]$.
8. Repeat step 7 untill the QoS equals a predefined criteria for WSAN.

Through studying the correlated parameter space of the PPD-Controller/WSAN, we have identified that the Sensor Sampling Period (*SSP*), Controller Sampling Period (*CSP*) and Controller Service Time (*CST*) are the correlated parameters $P_i \subseteq \{SSP, CSP, CST\}$. However, other parameters may affect the WSAN or the control separately; for example, the sampling period for the RFID affects the WSAN QoS but it does not affect the controller. As it is handled by the controller in an event-based model, the controller considers only the occupant presence and not the frequency of the sampling period. Relying on the aforementioned P_i, we can conclude that $P_i(j)$ depends mainly on the control strategy, as in the centralized control model, $P_i(j)$ will have different values than the PPD control model (i.e high *SSP* and *CSP*, and low *CST*).

5 Experimental Results

The proposed methodology has been used to design the PPD-Controller presented in Section 2 and its underlying WSAN model for the zones 1, 3, 4 and 5. We used a Gradient Descent algorithm to identify the direction for improvement. In order to optimize the solution space, we defined two design constraints to determine $P_i(j)$ and eliminate the inconsistent combinations that do not match these constraints. The first constraint considers that *CSP* is used to exchange the actuation values, the controller can then detect the interference coming from other zones. In this case, the controller changes its actuation value only when it receives a new sensed value from the sensor, i.e., $CSP \geq SSP$. The other constraint expresses the fact that the controller should be the fastest component in the design, this means that $CST < \min\{CSP, SSP\}$.

Table 1 Controller Performance

$P_i(j)$	MSE (Lux)
{20, 20, 0.5}	52.53
{15, 15, 0.5}	40.13
{10, 10, 0.5}	39.17
{5, 5, 0.5}	36.48
{0.6, 0.6, 0.5}	35.64
{0.6, 5, 0.5}	34.32
{0.6, 10, 0.5}	45.89

5.1 Control Refinement

The main metric used for evaluating the control performance is the MSE, calculated using Eq. 2. The MSE indicates user dissatisfaction, i.e., it indicates how the actuated values deviate from the preferred ones. As a starting configuration, for P_i we have chosen $P_i(0) = \{15min, 15min, 0.5min\}$, which corresponds to a typical system settings. The Gradient Descent algorithm is then used in order to identify the next values for P_i.

As shown in Table 1, when $P_i(1) = \{20min, 20min, 0.5min\}$, which indicates an increase in *SSP* and *CSP*, the controller performance degraded. However when *SSP* and *CSP* are decreased, $P_i(1) = \{10min, 10min, 0.5min\}$, the control performance improved. Therefore, the improvement is achieved by decreasing the initial value. Accordingly, the search population considered for control performance evaluation is $P_1(j) = P_2(j) = \{15min, 10min, 5min, 0.6min\}$ and $P_3(j) = \{0.5min\}$. Note that $P_1(j)$ and $P_2(j)$ are stopped at 0.6 min according to the pre-defined constraint stipulating that the controller is the fastest system component ($P_3(j)$). At the start *SSP* is equal to *CSP* according to the pre-defined constraint, $CSP \geq SSP$, we explore then the search space while evaluating the MSE to identify the optimal point corresponding to the Minimum MSE (MMSE).

After evaluating the control performance for all the search population identified previously, we found out that the MMSE is at $P_i(j) = \{0.6min, 5min, 0.5min\}$; however, when $P_i(j) = \{0.6min, 10min, 0.5min\}$, the performance is improved over the previous evaluated point, and hence the controller's optimal point is $P_i(j) = \{0.6min, 5min, 0.5min\}$. Accordingly, the boundaries for *SSP* is $[a_1, b_1] =]0.5, 0.6]$, *CSP* is $[a_2, b_2] = [0.6, 5]$ and *CST* is $[a_3, b_3] = [0, 0.5]$.

$$MSE = \frac{\sum_{a=1}^{N} \frac{\sum_{k=1}^{M}(U_a(k) - S_a(k))^2}{M}}{N}, \tag{2}$$

where N is the total number of zones, M is the total number of samples.

Table 2 WSAN QoS

$P_i(j)$	Channel Throughput	Controller Duty Cycle	Buffer Size	Response Time	Battery Life Time
{5, 5, 0.5}	1.4 packet/min	70%	7 packets	1 min	79.64 days
{0.6, 5, 0.5}	5.67 packet/min	100%	367 packets	183.5 min	76.47 days
{0.6, 5, 0.4}	5.69 packet/min	100%	319 packets	127.6 min	76.47 days
{0.6, 5, 0.3}	4.63 packet/min	100%	148 packets	39 min	76.47 days
{0.6, 5, 0.2}	5.5 packet/min	100%	65 packets	9.4 min	76.47 days
{0.6, 5, 0.1}	5.73 packet/min	57.3%	5 packets	0.1 min	76.47 days

5.2 WSAN Refinement

When studying the WSAN, assuming that *SSP* and *CSP* are fast enough, the most effective QoS metric for the user comfort is *Response Time*, as it reflects how much time is needed to serve an update detected by the light sensor or the neighbourhood controller. It appears that the *CST* is not affected by the WSAN QoS, since it is linked with the MAC layer switching, which implies timing constraints. In exploring the impact of the *CST* on the WSAN QoS, we selected the stopping WSAN criteria based on the *Response Time* metric. Assuming that the required criterion for the WSAN evaluation is $Response\ Time = CST$, we modify the *CST* within the boundaries obtained at the control refinement stage, as shown in Table 2. The table shows the search space and the corresponding WSAN QoS metrics, including Channel Throughput, Controller Duty Cycle, Buffer Size, Response Time and Battery Life Time.

In relation to the sampling period (*SSP*, *CSP*), it is obvious that the slower the period, the better is WSAN QoS. We have thus chosen the higher values from the control (*SSP*, *CSP*) boundaries (*SSP* = 0.6, *CSP* = 5). We can conclude that the optimal point matching the Control/WSAN requirements is $P_i(j) = \{0.6, 5, 0.1\}$ and moreover it shows a good improvement in the *Control Duty Cycle* and the *Buffer Size* metrics. However the *Battery Life Time* and *Channel Throughput* have almost the same effect. It is obvious that the selection of the design points presents a tradeoff between battery life and user comfort (reflected by sampling period). If we consider increasing the *SSP* to 5 min, we should expect $Response\ Time = 2 \times CST$ and a slightly worse control performance, as depicted in Table 1.

6 Conclusion

In this article, we have provided within our hybrid/multi-agent platform a refinement methodology for improving the Control/WSAN performance within the building automation domain. Such an improvement plays a key role in guaranteeing properties such as safety, accuracy, stability and reactiveness, which greatly impact user comfort. The developed methodology can configure the Control/WSAN-correlated parameters, and thereby reach an efficient configuration. The approach has been tested on an PPD-Controller used for lighting systems and the impact of changing the correlated parameters on both control performance and the WSAN QoS has been considered. At this stage, we prioritise the objectives of the application, as represented in the control requirements.

As future work, we intend to apply our methodology to Heating, Ventilating, and Air Conditioning (HVAC) system, as this presents more interesting challenges in relation to user comfort and control stability. We also aim to deploy a demonstration of the developed system in the Environmental Research Institute (ERI) building, which is the ITOBO Living Laboratory [14]. The benefit of cross-layer modelling for distributed control constitutes an important research topic that we also intend to pursue in future work.

Acknowledgment

This work was funded by Science Foundation Ireland (SFI) grant 06-SRC-I1091.

References

1. Nakamura, M., Sakurai, A., Furubo, S., Ban, H.: Collaborative processing in Mote-based sensor/actuator networks for environment control application. In: Signal Processing, Elsevier (2008)
2. Lin, Y., Megerian, S.: Low cost distributed actuation in largescale Ad hoc sensor-actuator networks. In: International Conference on Wireless Networks, Communications and Mobile Computing, pp. 975-980 (2005)
3. Akyildiz, IF., Kasimoglu, IH.: Wireless sensor and actor networks: research challenges. In: Ad hoc networks, Elsevier (2004)
4. Liu, X., Goldsmith, A.: Cross-layer Design of Distributed Control over Wireless Networks. In: Advances in Control, Communications Networks (2005)
5. El-Hosseini, M.A., Hassanien, A.E., Abraham, A., Al-Qaheri, H.: Genetic Annealing Optimization: Design and Real World Applications. In: Proc. of Eighth International Conference on Intelligent Systems Design and Applications (ISDA'08) (2008)
6. Kolokotsa, D., Pouliezos, A., Stavrakakis, G., Lazos, C.: Predictive control techniques for energy and indoor environmental quality management in buildings. In: Building and Environment (2008)
7. The Ptolemy Project.http://ptolemy.eecs.berkeley.edu/
8. Tyndall National Institute.http://www.tyndall.ie/
9. Liu, A., Yu, H., Li, L.: An energy-efficiency and collision-free MAC protocol for wireless sensor networks. In: 61st IEEE Vehicular Technology Conference (2005)
10. Demirkol, I., Ersoy, C., Alagoz, F.: MAC protocols for wireless sensor networks: a survey. In: IEEE Communications Magazine (2006)
11. Charon: Modular Specification of Hybrid Systems.http://rtg.cis.upenn.edu/mobies/charon/
12. Garg, M.: Linear Prediction Algorithms. In: Indian Institute of technology, Bombay, India (2003)
13. Henzinger, TA.: The theory of hybrid automata. In: Proc. 11th Annual IEEE Symposium on Logic in Computer Science (LICS 96), pp. 278-292 (1996)
14. Environmental Research Institute.http://www.ucc.ie/en/ERI/