

Agent-Based Control of a Municipal Water System

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Abstract. In this project, we discuss the implementation of an intelligent agent-system for controlling a municipal water system. This work presents an agent-based approach to establishing the expected water requirements, operating constraints, and evaluation criteria and the use of collaborating agents to prescribe an optimal control scheme. A distributed control strategy is implemented and evaluated in a simulation of a municipal water system.

1 Introduction

A Municipal Water System (MWS) can be defined as a combination of utility components and services that are involved in providing drinking-quality water to the local population. The system includes:

- Water: Service or product with a defined flow and quality requirement.
- Tanks: A cylindrical vessel with storage capacity.
- Pumps: Links that impart energy to a fluid thereby raising its hydraulic head.
- Pipes: Links that transport water from one point in the network to another.
- Valves: Links that limit the pressure or flow at a specific point in the network.
- Reservoirs: Large water deposit which can be natural or artificial.
- Controllers: Hardware and software components.
- Sensors: Instrumentation that extracts data from the physical system (sensors).
- Consumers: System end points or boundaries with service requirements.

Due to increased levels of urbanization and consumer demand, most water distribution systems have become increasingly complex and energy prices have continued to escalate. There is a growing need efficiently schedule pump operation to minimize energy consumption and other operating costs while insuring the reliable delivery of high quality water to meet dynamic consumer demands. The security and safety of urban water distribution system is now an extremely critical problem that must be considered in the design and operation of water systems. The control and monitoring system must allow for the implementation of different surveillance techniques to detect the presence of hazardous elements in the water to prevent their transmission to the public. These control systems must have complete and immediate knowledge and initiate an appropriate coordinated response to safely and efficiently maintain operations of the water system. We explore these dimensions by introducing agent-based control as the core monitoring and control element. The following

sections describe the implementation of autonomous agents to meet local demand for fresh water in a reliable, efficient and safe manner.

Optimizing the operation of a pump system in a municipal water-distribution system can reduce energy costs and also realize other economic and operational benefits. Theoretical and empirical studies of pump scheduling in various water supply systems suggest that 10% of the annual energy cost and related costs may be saved if by optimizing pump operation [1]. The additional benefits include more reliable delivery of water, improved water quality, and greater protection for consumer safety. However, optimal control requires a precise prediction of the short-term water demand and complete state information such as pump capacities and efficiencies. This information permits establishing minimum cost pumping schedules in advance to meet future demand. One objective of this work is to develop an intelligent agent system for monitoring and controlling a municipal water-supply system that ensures optimal control to reduce energy costs, while maintaining water quality and demand [2].

Our focus is on the operation of the pumping stations and the collaboration between the pumps and the water storage tanks. As a first step, we present the reasoning behind the creation of the agent-based rules using a simple system. Although we use a simple system, we will follow well-defined steps to scale up the solution into a multi agent system. In one way, our intention is to frame the procedure for creating agents for the water distribution system. The study of a MWS can be divided into three concepts that define the system requirements and its associated constraints: (1) Water quality, (2) Energy costs, and (3) Demand.

Water quality is affected by the time a parcel of water is retained in a storage tank. New water entering a tank from a reservoir is assumed to have age zero. The cumulative age of the water is a factor that helps define the quality of the water.

The aging of water in a tank is primarily a function of water demand, system operating strategy, and the system design or topology. As water demand increases, the amount of time a given water element is resident in the distribution system decreases. Demand is in turn related to land use patterns, commercial/industrial activity, weather (i.e., temperature and lawn watering), and water use habits by the community (i.e., conservation and reuse practices). The use of reclaimed water on-site or through separate distribution systems will tend to lead toward reduced demand and consequently greater water age when all other factors are held constant [3].

Energy costs are an important aspect affecting the operation of a MWS. An energy-efficient system should minimize cost of supplying water. This includes establishing a control strategy that keeps the water level within physical and operational constraints, minimizing the time pumps operate when energy costs are high and reducing peak energy demands and while maintaining sufficient water in storage tanks to meet the time varying demand.

Demand is another critical aspect affecting the control of a MWS. The instantaneous consumption of water in an urban system also depends on the environment, commercial and community factors. Moreover, a particular day of the week or an observed holiday will considerably influence water consumption.

It is necessary to know the current and future demand in order to define how much water is needed in the tanks and at what time. This information then provides the

basis to prescribe a time-based control strategy that meets the predicted demand while achieving cost and quality objectives.

There are many different methods to predict the demand [4]. A simple method is to predict demand using historical data for the specific time period of interest. Based on the predicted demand it is possible to determine if water currently in the tank is adequate for the next time period or if water needs to be added or possibly refreshed. Historical demand information is needed for different times of the day, different days of the week, and for different seasons. It is useful to establish estimates of predicted demand for multiple scheduling periods beyond the current planning period. This information is used to establish more global optimum solutions and control strategies that are more stable and reliable particularly when demand is near peak capacity or upsets may impact the ability of the system to meet the expected demand.

2 General Architecture of Agents

We use a distributed control architecture based on automation controllers with an extended firmware that supports intelligent agents [7]. With these extensions, component-level intelligence is possible by associating a logical processing program with a physical device such as a pump or a valve. The physical devices can then be operated as intelligent nodes with negotiation capabilities. The intelligence of the system is distributed among multiple controllers by placing standalone or multiple agents inside the controllers. The relationship among the agents is loosely coupled but their association is cohesive and adaptable [6] and [8]. The agent architecture is organized according to the following characteristics:

1. **Autonomy:** Each agent makes its own decisions and is responsible for carrying out its decisions (i.e. performing control) to successful completion;
2. **Cooperation:** Agents combine their capabilities and simple rules of interaction into clusters to negotiate, adapt and respond to events and goals;
3. **Communication:** Agents share a common language;
4. **Fault tolerance:** Agents possess the capability to detect equipment failure and to isolate failures from propagating; and
5. **Pro-action:** Agents periodically or asynchronously propose strategies to enhance the system performance, improve reliability, or to prevent the system from entering harmful or otherwise undesirable states.

Intelligent agents possess characteristics that make them well suited to control a municipal water system. A suite of collaborating autonomous agents can reduce operating cost and provide increased control flexibility by concurrently looking at constraints, changing system economics and uncertain future demand and develop a response using negotiation scenarios. For example, a water storage tank can request water from a supplier pumping station. The pumping station can then consult with the utility company about the cheapest electricity period to schedule for inexpensive pumping. These types of agents can be programmed to evaluate control strategies based on water quality requirements that are affected by high system complexity and unpredictability. The most appropriate use of agents in a municipal water system will

be to establish an association with the plant physical devices with agent-based autonomous software elements that comprise a multi-agent system.

Agents are autonomous, problem-solving entities capable of effective operation in dynamic and open environments. Agents can follow two types of collaboration: centralized and decentralized.

The centralized approach has only one agent with knowledge about the complete system. This agent makes decisions and sends these decisions to the interested parts of the system. This kind of control may be more efficient from the agent's point of view, since only the central agent has to have substantial computing capacity. However, it is less desirable from a reliability and security point of view. For example, if the central agent breaks, the whole system stops.

Instead, decentralized control has more agents with the same capability, and each agent controls only one small part of the system. Agents communicate with each other using agent language [5] and exchange information about the system status. Furthermore, distributed agents may self-organize into clusters to insure efficient communications and coordinated operation. Central failures are avoided and parallelism is increased. However, there is a trade off between parallelism and optimality of the solutions.

This paper presents algorithms to control a MSW based only on the demand, with a distributed agent system. The aim of the control system is to guarantee enough water in the tank to satisfy consumers, avoiding empty or full tank. The framework presented is readily extended to accommodate reliability and economic considerations.

3 System Analysis

To simplify the study, we established a reduced scale model of a municipal water system. The model is comprised of: a single water reservoir, a single tank, a pump station with only one electrical pump, and pipes and valves. The model was simulated using Simulink, where we placed the simulation of the plant, the control and agent programs. After we conclude the baseline architecture we will expand the system into a complex one, with more than one tank and more than one pump. In that case, the complexity will arise for the simulation model but we will just replicate the agent behavior. We believe that this is a very important and practical observation. For example, by adding the model of a junction among the pump station and the tanks, the agent has to schedule the activity of more than one pump and it has to regulate the opening and closing of the valves of each tank. In such a case, it will make more sense to create multiple agents to handle the new scenarios and components. In particular with a more complex system the agent must be divided into multiple agents to be consistent with the distributed control approach. An idea can be to have an agent at the pumping station and an agent for each tank. In this way, the agents speak with each other to schedule the transportation of water and let the control system operate the low level devices such as valves.

The pumping station takes water from the reservoir and moves it into the tank through a main trunk line (distribution pipe). In between the tank and the pump station, there is an electrically operated valve. The tank is assumed of cylindrical

shape. For each of these components, there are intelligent behaviors to control and monitor in the simulation. These intelligent behaviors are defined as controller and agent behaviors, as shown in Figure 1.

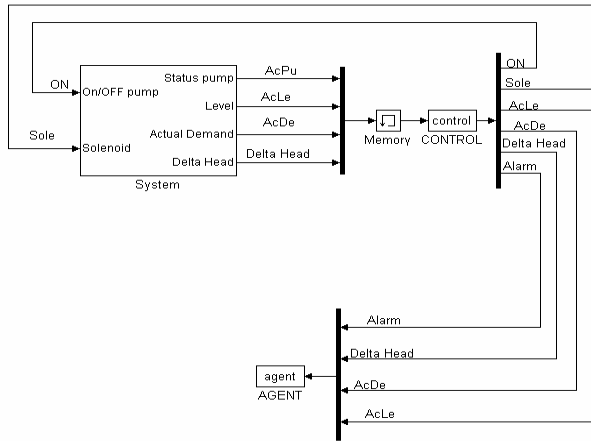


Fig. 1. Simple water system simulation with controller and agent

Both the control and agents were implemented as S-functions in Simulink. The algorithms will be converted into formal languages to build agents and control charts for implementation in a hardware automation controller. The approach used is that the simulation will act as test bed to validate the behavior of the algorithms. In addition, the same algorithms may be directly employed for operating the real equipment. In fact the simulation model of the plant may also be employed in the control of the actual MWS to analyze what-if scenarios and to assist in isolating faults or analyzing unusual disturbances. A training system is also an option.

The agents collaboratively evaluate the condition or state of the system, make decisions about the operation of the system, establish execution plans, and initiate the prescribed change in operation. In this simulation study, an agent establishes the operating schedule of the pump such as when to turn it on or off. The agent generates the schedule. The control function reads the schedule to control the pump. The schedule’s structure is shown in Table 1.

Table 1. Schedule generated by agent

T_{start_1}	T_{end_1}	Pump activity	Predicted_level _{start_1}	Predicted_level _{end_1}
...
T_{start_n}	T_{end_n}	Pump activity	Predicted_level _{start_n}	Predicted_level _{end_n}

Where,

- T_{start_i} is the beginning of the *ith* interval;
- T_{end_i} is the end of the *ith* interval;

- Pump activity is the binary variable that indicates if pump is on (1) or off (0);
- Predicted_level_{start_i} is the predicted level at the beginning of the *i*th interval; and
- Predicted_level_{end_i} is the predicted level at the end of the *i*th interval.

Time is expressed in seconds and because of the continuity of the schedule, $T_{end_i} = T_{start_{(i+1)}}$. The same applies for the predicted level, a value that denotes the expected water level in the tank in feet. The pump activity is expressed as a binary value indicating the state of the pump.

The control module reads this file and stores the data in memory. It commands the simulation to carry out the actions affecting the different simulation subsystems. Later, the same control signals will be emitted by a control program from a hardware-based controller(s) to affect the real equipment. The control signals correspond to Inputs and Outputs (I/O) of the control system which are associated with the devices.

3.1 Agent Function

The agent is being created to generate schedules using the demand. The problem is that the future demand is not known accurately because it is a dynamic, probabilistic factor (independent variable). An altered version of the historical demand is used to estimate the actual demand inside the simulation and to establish a difference between the actual and historical demands and for calculating the expected demand schedule. The historical demand trend is shown in Figure 2.

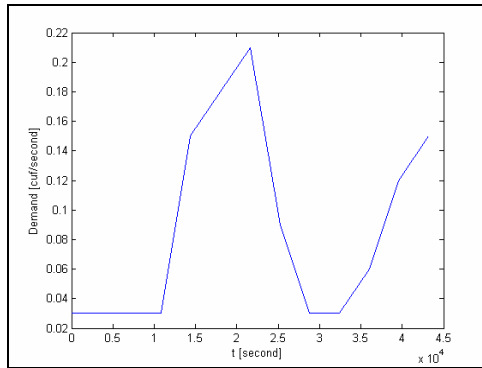


Fig. 2. Historical demand

With this information, we calculate the predicted level after fixed intervals (e.g., 30 minutes and 60 minutes, as shown in Equation 1).

$$\begin{aligned}
 \text{Predicted_Level}_{30'} &= \text{Level}_{\text{now}} - \text{Demand}_{30'} \\
 \text{Predicted_Level}_{60'} &= \text{Level}_{30'} - \text{Demand}_{60'} \\
 &\vdots \\
 \text{Predicted_Level}_n &= \text{Level}_{(n-\text{Delta}T)} - \text{Demand}_n
 \end{aligned}$$

Equation 1. Equations to calculate the predicted level

The minimum level of water in the tank is chosen be to one foot. The trigger level was another important value that was also arbitrarily chosen. This variable indicates the level at which the pump needs to be on. However, if due to a fault or inaccurate forecast, the level reaches the minimum level, an alarm signal is generated into the agent by the control module. Knowing the predicted level, a set of rules can be generated to control the level in the tank, as shown in Equation 2.

$$\begin{aligned}
 (\text{Pr edicted_Level}_n - \text{Level_Trigger}) > 0 &\Rightarrow \text{PumpOn} = 0 \\
 (\text{Pr edicted_Level}_n - \text{Level_Trigger}) = 0 &\Rightarrow \text{PumpOn} = 1 \\
 (\text{Pr edicted_Level}_n - \text{Level_Trigger}) > 0 &\Rightarrow \text{PumpOn} = 1
 \end{aligned}$$

Equation 2. Rules for the pump

- Rule 1: PumpOn = 0. This rule indicates that the tank contains enough water and that there is no need for additional pumping;
- Rule 2: PumpOn = 1 (a). This rule says that the level of water is low and that pumping is needed to recover the safety buffer; and
- Rule 3: PumpOn = 1 (b). This rule tells that the demand was more than the previous prediction and that water is needed now.

The needed water was calculated to reach the level trigger value plus an error:

$$\text{HowMuchWaterToPump} = \text{level_trigger} * (1 + \text{Percentage}) - \text{prediceted_level}$$

Knowing the suction head (head at the pump station location) and the discharge head (head at the water in the tank location), it is possible to calculate the “Delta_Head”, as follows:

$$\text{Delta_Head} = \text{Discharge_Head} - \text{Suction_Head}$$

With this information, it is possible to calculate the flow out to the pump, knowing the pump curves (Figure 3). From Figure 3, it is clear that more water in the tank means a higher discharge head and less flow out to the pump. Knowing the pump curves (from OEM), it is possible to calculate the pumping time, i.e. t_{ON} .

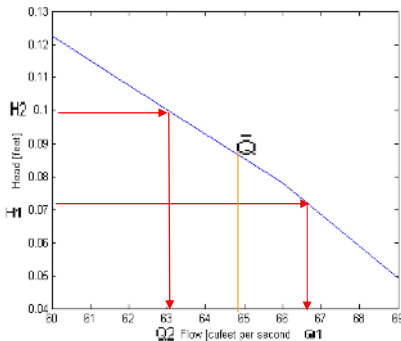


Fig. 3. Head versus flow

The actual flow leaving the pump is calculated as the average between the flow at the beginning of the pumping interval and the flow at the end of the interval based on the variable discharge head, which is affected by the level in the tank. With these assumptions, we can formulate the next set of rules:

- Rule 1: Let $Level_1$ be the level of water at the beginning of the pumping interval. The agent decides the value of “*HowMuchWaterToPump*” (the amount of water that will be needed in 30 minutes). And so after 30 minutes $\Delta Head$ is changed because the level in the tank will be $Level_2 = Level_1 + HowMuchWaterToPump$;
- Rule 2: Let Q_1 be flow out of the pump associated with $Level_1$ and Q_2 flow associated with $Level_2$. The average flow \bar{Q} used to calculate t_{ON} is obtained as the average between the boundary flows: $\bar{Q} = \frac{Q_1 + Q_2}{2}$. t_{ON} is calculated as follows:

$$t_{ON} = HowMuchWaterToPump * AreaTank / \bar{Q};$$

- Rule 3: In this way, we calculate the average time that the pump has to be on and so it is possible to fill out the schedule table for the next period. Hence, the predicted level in the tank can be approximated as follows:

$$Predicted_Level_i = Predicted_Level_{i-1} + HowMuchWaterToPump; \text{ and}$$

- Rule 4: At the end of the scheduled period, a new plan for the pump is created using the predicted level. Practically, the schedule can be done more often. The control actuates the commands decided by the agent, but it always monitors the condition of the system to prevent harmful conditions from happening (e.g., excessive or lack of pumping into the tank).

3.2 Control Function

The task of the control module is to activate the pump based on the schedule done by the agent. So the first job of the control module is to check the pumping intervals. The control module sets the pump start and end times in the control table by indicating the corresponding times. Because the schedule is created using a prediction, there is a need to monitor the system to periodically correct the predicted demand, if required.

The second task of the control module is to change the pump activity before an anomalous state occurs. It generates alarms to notify the agent that something is deviating from a desired trend. Given this condition, the agent re-schedules the activity to compensate for the dynamic changes. An alarm signal is generated under the following states:

- State 1: When the predicted level value is different than the actual level and greater than an acceptance threshold;
- State 2: When the level in the tank is near less than a fixed percentage of the maximum level admissible;
- State 3: When the predicted level value is very different from the actual level and the actual level is very close to the level trigger; and
- State 4: When the actual level is very close to the minimum level.

We have observed that usually the last state doesn't occur because preceding states change the pump activity before the level can reach the minimum level.

4 Simulation Results

In this section, preliminary simulation results are reported. The duration of each simulation trail is 43200 seconds (12 hours).

The predicted level is calculated looking at the historical demand after 30 minutes from the actual simulation time. So, the agent calculates a new schedule every four hours using 30 minutes intervals. The agent also creates a new schedule if an alarm occurs. This interval of time is chosen to guarantee an accurate prediction. In fact, the time interval does not have to be too long to avoid missing sudden changes in the demand. But it does not have to be too short either to know the demand in advance. Figure 4 illustrates the demand curves, actual (green) and historical (blue).

The curves in Figure 4 represent a typical morning demand. During the first hours of the morning, the demand is not very high, but about 3 a.m. until 8 a.m. the demand increases, people are getting up. Then about 11 a.m., the demand increases again.

Figure 5 represents the simulation results for the actual demand with correction actions. The real level in the tank is the green line. The predicted level is the blue line. The trigger level is the red line and the minimum level is the cyan color line.

In particular, we can see that at time 14400 sec (4 hours), the predicted level changes instantly because the first schedule is finished and the agent has scheduled the next four hours of water consumption. The agent adjusts the predicted value with the real value, as shown in Figure 6.

Another case corresponds to the schedule at time 36645 sec (about 10 hours), as shown in Figure 7. This change is due to the difference between the two levels. The difference in the levels was more than the 30% of the maximum level (10 ft) allowed in the tank, and so the control module sent an alarm signal to the agent to re-schedule the pumping.

From Figure 5, it can be established that there is no need to pump water because the levels are higher than the trigger level. But the pump, instead, is turned on anyway. The agent decides that to have enough water in the future, when the demand is high, the pump has to be on very soon. This behavior is proactive, purely autonomous and emergent. It was triggered by the agent itself with no explicit rules, just looking at the future trying to have always the water requested.

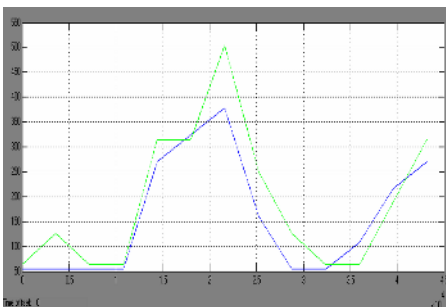


Fig. 4. Historical and actual demands

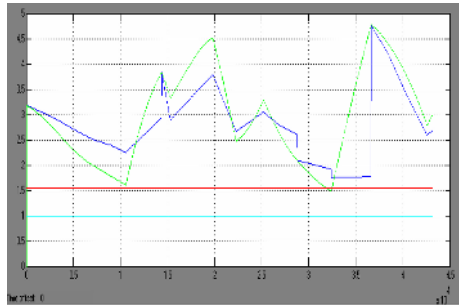


Fig. 5. Levels

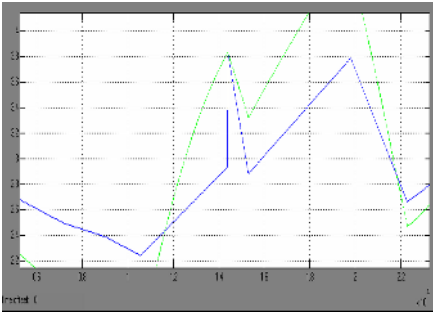


Fig. 6. Particular at time 14400 sec

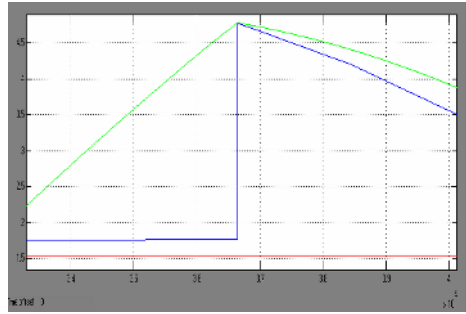


Fig. 7. Particular at time 36645 sec

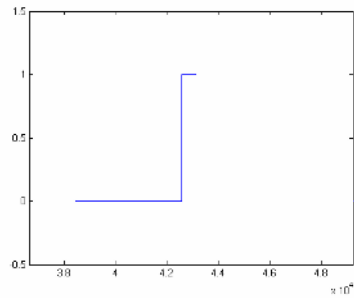
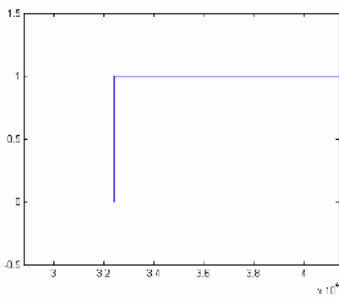


Fig. 8. a) First hypothesis b) Correction and second hypothesis

In Figure 8, there is an example of the correction of pump activity. For the last four hours of simulation, the agent made another hypothesis for the schedule and it was like shown in Figure 8(a). But as seen at time 36645 sec in Figure 7, the levels were too different from each other, and so after the correction of the predicted level, the agent generated a new hypothesis for the schedule to pump less, as shown in Figure 8(b). The agent assumed that because of a prediction error, there is enough water in the tank, and so the pump must be turned off earlier.

5 Conclusion

In this paper, a method to schedule pump activity in a municipal water system was presented. Preliminary results were obtained using simulation, a single agent, and a control program written as S-functions. The algorithms proposed looked at only the control of the water level in the tank. Water in the tank was kept at a level enough to satisfy the demand, but also it was always away from saturating the tank. The algorithms proposed were able to change the schedule when unforeseen situations happened in the actual demand.

The system proposed is the bases for a larger system. The behavior of the agent will need to be split to isolate the pump behavior from the tank behavior, so to create pump agents and tank agents. These agents will serve as the template behaviors for

building any size municipal water system using real equipment. The results presented here may be readily expanded to accommodate a variable rate structure for energy costs, machinery prognostics, objectives for optimizing life cycle cost or optimizing asset utilization, or to establish an operating mode that is less brittle or more secure from externally induced disruption.

References

1. G.Mackle, D.A.Savic, G.A.Walters “*Application of genetic algorithms to pump scheduling for water supply*”. Genetic Algorithms in Engineering Systems: Innovations and Applications 12-14 September 1995, Conference Publication No. 414, © IEEE, 1995.
2. “*Effects of water age on distribution system water quality*”. By AWWA with assistance from Economic and Engineering Services, Inc.
3. An, C.Chan et al. “*Applying knowledge discovery to predict water-supply consumption*”. Knowledge discovery IEEE, 1997.
4. G.McCormick, R.S.Powell “*Optimal pump scheduling in water supply systems with maximum demand charges*”. Journal of water resources planning and management © ASCE. September/October 2003
5. FIPA: *The Foundation for Intelligent Physical Agents, Geneva, Switzerland, 1997.*
6. Mařík, V., Pěchouček, M., Štěpánková, O.: *Social Knowledge in Multi-Agent Systems. In Multi-Agent Systems and Applications, LNAI 2086, Springer, Berlin (2001) 211-245*
7. Maturana F.P., Staron R., Hall K.: “*Methodologies and Tools for Agents in Distributed Control*”. In IEEE Intelligent Systems Magazine, pp. 42-49, January/February 2005.
8. Shen W., Norrie D., and Barthès J.P.: “*Multi-Agent Systems for Concurrent Intelligent Design and Manufacturing*”. Taylor & Francis, London, 2001.