Reinforcement Learning Approach for Cooperative Control of Multi-Agent Systems

Valeria Javalera-Rincon[1], Vicenc Puig Cayuela[2], Bernardo Morcego Seix[2] and Fernando Orduña-Cabrera[1]

[1]*Advanced Systems Analisys and Ecosystem Services and Management Programs, International Institute for Applied Systems Analysis, Schlossplatz 1, A-2361, Laxenburg, Austria*

[2]*Advanced Control Systems Group, Universitat Politècnica de Catalunya (UPC), Rambla Sant Nebridi, 10, 08222 Terrassa, Spain*

Keywords: Distributed Control, Intelligent Agents, Reinforcement Learning, Cooperative Agents.

Abstract: Reinforcement Learning (RL) systems are trial-and-error learners. This feature altogether with delayed reward, makes RL flexible, powerful and widely accepted. However, RL could not be suitable for control of critical systems where the learning of the control actions by trial and error is not an option. In the RL literature, the use of simulated experience generated by a model is called planning. In this paper, the planningByInstruction and planningByExploration techniques are introduced, implemented and compared to coordinate, a heterogeneous multi-agent architecture for distributed Large Scale Systems (LSS). This architecture was proposed by (Javalera 2016). The models used in this approach are part of a distributed architecture of agents. These models are used to simulate the behavior of the system when some coordinated actions are applied. This experience is learned by the so-called, LINKER agents, during an off-line training. An exploitation algorithm is used online, to coordinate and optimize the value of overlapping control variables of the agents in the distributed architecture in a cooperative way. This paper also presents a technique that offers a solution to the problem of the number of learning steps required to converge toward an optimal (or can be sub-optimal) policy for distributed control systems. An example is used to illustrate the proposed approach, showing exciting and promising results regarding the applicability to real systems.

1 INTRODUCTION

RL is a well-known and formally studied family of learning techniques. Moreover, depending on the formulation of the problem and the richness of experience data, the chances of convergence are high. One of the main characteristics of RL is that the agents learn by trial and error discovering which actions yield the maximum reward by trying them. However, it is also this characteristic what makes RL unsuitable for controlling critical time-varying systems where good performance is crucial all the time, and the cost of this learning curve of the agent can be too high.

Currently, some algorithms implement planning techniques such as Dyna-Q and Prioritized Sweeping. Some examples of applications of Dyna-Q algorithm are (Tateyama et al. 2007), (Hwang et al. 2015) and (Hwang et al. 2017). Moreover, for Prioritized Sweeping see (Zajdel 2018) and (Desai and Patil 2017). In these cases, the planning techniques are used to simulate experience generated by a model. Here two planning techniques are introduced aiming to work cooperatively and coordinated getting a heterogeneous multi-agent architecture for Large Scale Systems (LSS).

These planning techniques were specially developed to fit into the LINKER Architecture (LA) introduced in (Javalera 2016) as the MA-MPC architecture. First descriptions and applications of this architecture were presented in (Javalera et al. 2010), and the use of this architecture and methodology to the Barcelona Drinking Water Network is described in (Morcego et al. 2014). In all these applications the agents implement a control technique called "Model Predictive Control (MPC)," therefore the name of the architecture. However, this work is called LINKER architecture, since the algorithms and architecture can be applied to other types of agents as well, not just MPC.

Reinforcement learning (RL) works based on experience, which, in LA is used aiming to reduce the

Javalera-Rincon, V., Cayuela, V., Seix, B. and Orduña-Cabrera, F.
Reinforcement Learning Approach for Cooperative Control of Multi-Agent Systems.
DOI: 10.5220/0007349000800091
In *Proceedings of the 11th International Conference on Agents and Artificial Intelligence (ICAART 2019)*, pages 80-91
ISBN: 978-989-758-350-6

requirement of iterative methods, facilitating that the system behaves almost like a reactive system with reduced response time. Another relevant feature of RL exploited by the LINKER Architecture is that it explicitly considers the whole problem of a goal-directed agent interacting with an uncertain environment. Moreover, this is in contrast with many approaches that consider sub-problems without addressing how they might fit into a larger picture. Even more, this is important for the LINKER Architecture because it is distributed control architecture of LSS, where some of its control variables overlap between sub-systems; this issue is aboard in the next section.

This paper aims to explain how using the proposed learning techniques and the LINKER Architecture, and is possible to integrate agents of a distributed system with LINKER agents trained with the proposed planning techniques. Each LINKER agent calculates the value of shared variables between overlapping systems looking for the global optimum of the relation and coordinating its process with the other agents of the system obtaining an overall good performance. This work also proposes a solution that makes possible to achieve the benefits of RL techniques in critical systems that cannot afford to pay the learning curve of a learner agent. Even more, this is made using a meaningful reinforcement given by the distributed agents that try the actions in its internal model in offline training. Once all the functions learned are evaluated and approved, the LINKER agents use an online optimization algorithm that can also have adaptation properties.

Another contribution of this paper is to compare two learning techniques. In the first one, the actions used in training are dictated by a teacher that, in this case, is the centralized MPC (Model Predictive Control) controller. In second one a learning technique where actions are randomly selected. The LINKER agent explores actions trying and evaluating it, through the interaction with the agents that directly control the model. An illustrative example is developed using both techniques.

The structure of the paper is as follows: Section 2 introduces the problem statement. Section 3 presents the model driven control and the model driven integrated learning. Section 4 presents the planning by instruction while Section 5 presents the planning by exploration. Section 6 uses an application case study to illustrate the performance of the proposed architecture and approaches. Finally, Section 7 summarizes the main conclusions and describes the future line of research.

2 PROBLEM STATEMENT

In order to describe the learning techniques mentioned above, it is necessary to explain the underlying problem, which is the distributed control problem that the LINKER architecture addresses. This architecture is applied to a LSS.

In order to control an LSS in a distributed way, some assumptions have to be made on its dynamics, i.e. on the way the system behaves. Let us assume first that the system can be decomposed into *n* sub-systems, where each sub-system consists of a subset of the system equations and the interconnections with other sub-systems. The problem of determining the partitions of the system is not addressed in this work. The set of partitions should be complete. This means that all system states and control variables should be included at least in one of the partitions.

Definition 1. System partitions. P is the set of system partitions and is defined by

$$P = \{p_1, p_2, \dots, p_i\} \tag{1}$$

Where each system partition (subsystem) $\mathrm{p_i}$, $\mathrm{i} = \{1 \dots \mathrm{n}\}$ is described by a model. In this example, a deterministic linear time-invariant (LTI) model is used to represent a drinking water distribution network; this type of model can also be used for other type of LSS where there is a network of connected nodes and an element that flows in the network that should be distributed to fulfill certain demands. This model is expressed in discrete-time as follows

$$\begin{aligned} x_i(k+1) &= A_i x_i(k) + B_{ui}(k) + B_{d,i} d_i(k) \\ y_i(k) &= C_i x_i(k) + D_{u,i} u_i(k) + D_{d,i} d_i(k) \end{aligned} \tag{2}$$

The model describes the topology and dynamics of the network. Variables *x*, *y*, *u*, *d* are the state, output, input and disturbance vectors (for this case, the demands) of appropriate dimensions, respectively; *A*, *B*, *C* and *D* are the state, output, input and direct matrices, respectively. Sub-indexes u and d refer to the type of inputs the matrices model, either control inputs or exogenous inputs (disturbances). Control variables are classified as internal or shared variables.

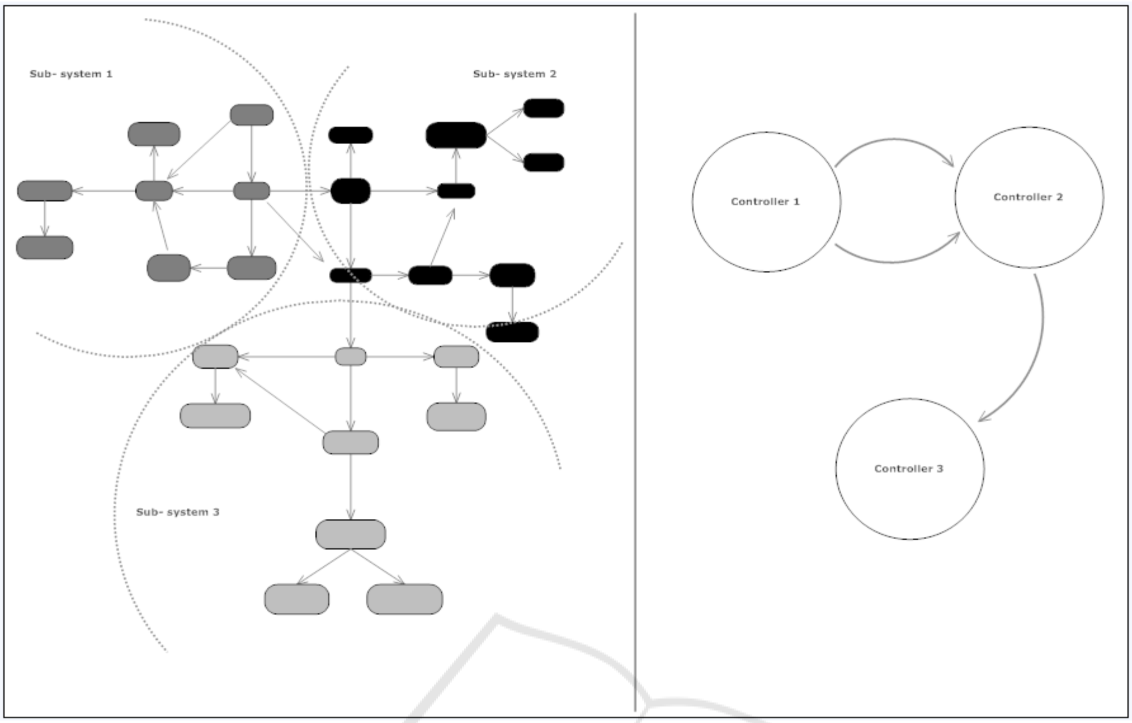


Figure 1: The problem of distributed control.

Definition 2. Internal Variables. Internal variables are control variables that appear in the model of only one subsystem in the problem. The set of internal variables of a partition *i* is defined by equation 3:

$$U_i = \{u_1, u_2, \dots, u_{ni}\} \tag{3}$$

Definition 3. Shared Variables. Shared variables are control variables that appear in the model of at least two subsystems in the problem. Their values should be consistent in the subsystems they appear. They are also called negotiated variables because their values are obtained through a negotiation process. V_{ij} is the set of negotiated variables between partitions *i* and *j*, defined by equation 4

$$V_{ij} = \{v_1, v_2, \dots, v_{nij}\} \tag{4}$$

Each subsystem i is controlled by a controller (agent) using:

- the model of the dynamics of subsystem *i* given by eq. (2);
- the measured state $x_i(k)$ of subsystem *i*;
- the exogenous inputs $d_i(k)$ of subsystem *i* over a specific horizon of time;

As a result, each agent calculates directly the internal control actions, $u_i(k)$, of subsystem i. Figure. 1 on the left shows a sample system divided into three partitions. Subsystem 1 has two shared variables with sub-system 2 and subsystem 2 has one shared variable with sub- system 3. The relations that represent those variables are shown on the right as lines. The problem consists in optimizing the manipulated variables of the global system using a distributed approach, i.e. with three local control agents that should preserve consistency in the shared variables. In order to solve the problem described above, a new framework has been developed. This framework comprises a methodology, the so called the LINKER methodology and the architecture. The methodology helps to implement the architecture

3 A MODEL DRIVEN CONTROL AND A MODEL DRIVEN INTEGRATED LEARNING

The LINKER architecture integrates a model driven control and a model driven learning process. In order to perform the negotiation of the shared variables, the Linker agent learns to think globally, by means of an offline training where negotiator and agents interact and accumulate meaningful experience. This offline training is made using a model of each sub-system environment computing value functions (*Q-tables*) whose optimality and efficiency are proved in the experimentation phase, in order to be used later in the

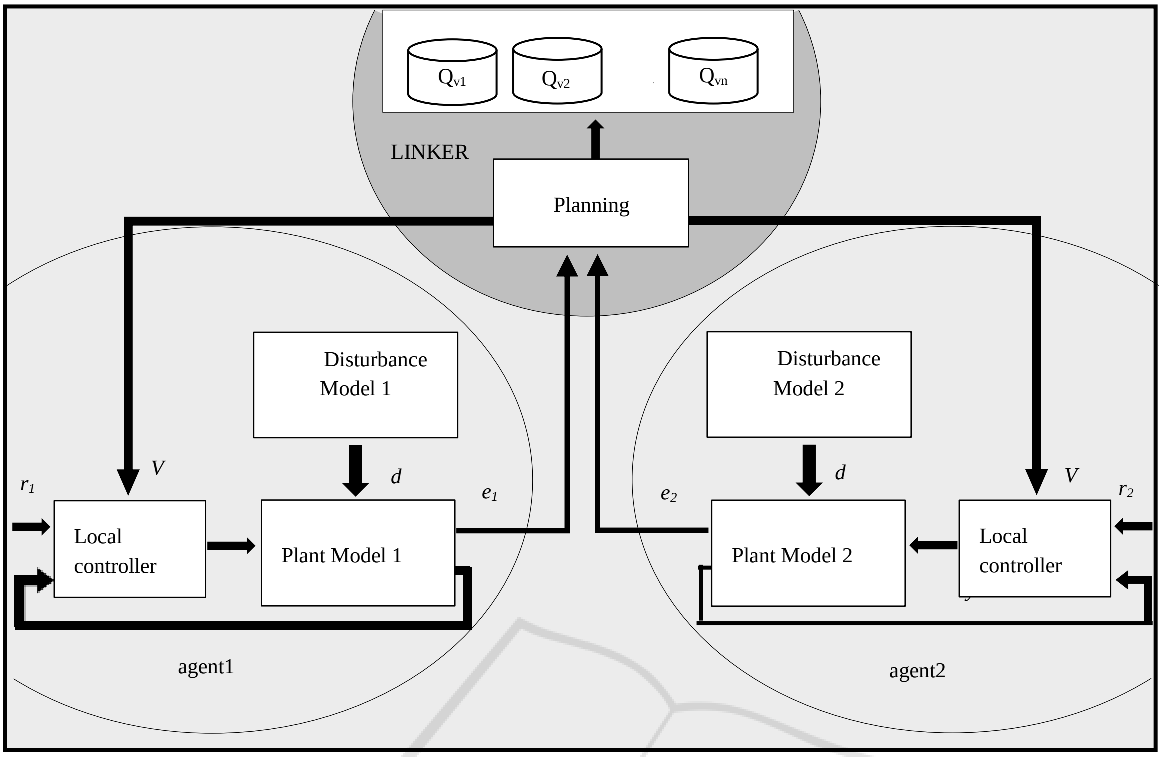


Figure 2: Integration of the models of agents in the planning process.

negotiation process. This allows eliminating iterative communication between agents in the negotiation process, increasing efficiency, decreasing time of response and making it safe to implement.

Figure 2 shows the integration of the models in the agents in the planning process. The Linker agent assigns the values of *V* to the related agents. Each related agent has its own reference, disturbance model and plant model according to Eq. 2. The local controller takes *V* as constraints, computes vector c and applies the control action to the plant model producing y and e. e is an error vector that indicates to the Linker how good the actions (*V*) were. In order to evaluate that, it is necessary to calculate the state of both agents. This is made based in the cost function of the agents, as for example,

$$s1=\Sigma\ Hpi=0J(i)=\Sigma\ Hpi=0Jx\ (i)+\Sigma\ Hpi=0\ J\Delta u(i) \quad (5)$$

$$s2=\Sigma\ Hpi=0J(i)=\Sigma\ Hpi=0Jx\ (i)+\Sigma\ Hpi=0\ J\Delta u(i) \quad (6)$$

where

$$J_x(i) = \vec{e}^T(i)\ w_x\ \vec{e}(i) \quad \text{and}$$
$$J_{\Delta u}(i) = \overrightarrow{\Delta u}^T(i) w_{\Delta x} \overrightarrow{\Delta u}(i) \quad (7)$$

The reward (r), is calculated using the states of both MPC agents with the equation:

$$\sigma = \rho - s_1 - s_2 \quad (8)$$

where σ represents the reward r and ρ is a constant that satisfies:

$$s_1 + s_2 < \rho \quad (9)$$

Given that s_1 and s_2 represents a sum of quadratic errors (5), (6), the reward will be always positive. With a smaller sum of errors the reward will be larger and vice versa. s_1 and s_2 have to be discretized in order to be use in

$$Q(s'_1, a', s'_2) \leftarrow r + \propto Q(s_1, a, s_2) \quad (10)$$

that is the function that updates each Q-table where the parameters ∝ rates past experience.

The purpose of this three-dimensional matrix is to map the state agent 1 (s_1) and the state of agent 2 (s_2) to a single action. The coordination feature of the Linker agent lies on the fact that, in exploitation, the Linker agent will map to an optimal (or sub-optimal) action every s_1 and s_2 eliminating with this conflicts between agents assigning the value of shared variables.

The Linker uses this simulated experience and updates the Q-values in the Q-tables, one for each shared variable of the vector V in order to improve its policy. All this process is implemented through the PlannigByInstruction and PlanningByExploration behaviors of the Linker that will be explained in further detail in next section.

The integration of RL with the LTI model in this approach offers high cohesion to the system. The support that the LTI model (2) offers is deterministic, descriptive and highly trusted. So, the integration of these techniques coupled by the implementation of the methodology makes the planning process efficient and reliable.

The policy obtained is evaluated in the experimentation phase. The fact that the policy is obtained offline is a very important characteristic of this approach due to the critical nature of LSS. The use of a standard trial-and-error technique of RL would make the implementation of this approach unfeasible. If the learning process is driven from real experience in the plant, the system will be unfeasible most of the time at the beginning of the process and the actuators can be damaged. That is why, in this framework, in order to arrive to the implementation phase, the optimality of the obtained policy has to be tested beforehand.

4 PLANNING BY INSTRUCTION

In contrast to some IA learning methods, like supervised learning, in this work, the term *instruction* refers to the way in which the action is selected in the learning process, and not to the type of the feedback used. So, *PlannigByInstruction behavior* (PBIB) is a learning behavior that implements a specific combination of choosing actions and providing feedback.

4.1 Description of the Approach

The purpose of this learning behavior is to obtain an *optimal policy (Q), constructing a knowledge base* based on the evaluation of actions given by a teacher. This teacher has to be a trustable controller, like a centralized MPC or the actions taken by a human expert. These actions are simulated in the model system and the result (states s_{a1} and s_{a2}, (5), (6)) is evaluated obtaining a *reward (r)* (8) that is used to obtain the new *Q-value (10).* n_{it} iterations are made for the complete control horizon with random initial conditions. This behavior is performed offline in the *training phase* of the LINKER methodology. Assuming that there is a single negotiation variable, the *PlanningByInstruction behavior algorithm* describes the training algorithm that the NA executes in order to update its Q-table by this learning behavior

In this algorithm, s_{a1} and s_{a2} represents the *states* (5), (6) of *agent1* and *agent2* (the two agents that share that particular negotiation variable). V_{a1} and V_{a2} are the internal representations of the shared variable in *Agent1* and *Agent2* (sub-indices *a1* and *a2* respectively) for *k* instant. *teacherAction* is the action dictated by the teacher.

```
Define ρ, n,   sa1 ← random, sa2 ← random,
controlHorizon, teacherAction (1-control horizon), k=1
loop while iterations ≤ n
  loop while k ≤ controlHorizon
      Va1 (k) ← teacherAction (k)
      Va2 (k) ← teacherAction (k)
      sa1 ← send Va1 (k) to agent1, agent1 set the
      action Va1 (k) and calculates its internal variables,
      apply all the controls (actions) obtained (and
      given) for step k to its LTI model of its partition
      and calculates sa using (5).
      sa2 ← send Va2 (k) to agent2, agent2 set the
      action Va2 (k) and calculates its internal variables,
      apply all the controls (actions) obtained (and
      given) for step k to its LTI model of its partition
      and calculates sa2 using (6).
      r ← ρ- sa1 - sa2
      Q (sa1', teacherAction (k)', sa2' )← r +α Q(sa1,
      teacherAction (k), sa2)
         sa1'← sa1
         sa2'← sa2
         k=k+1
     end loop
     iterations=iterations+1
   end loop
```

5 PLANNING BY EXPLORATION

Learning by exploration is the main type of learning technique used in RL. It is based on trying random actions from a deterministic and finite set, in order to obtain a feedback that represents how good the taken action was. Learning by exploration in LSS can be a difficult task because of the size and complexity of these systems. The *PlanningByExploration* behavior (PBEB) implements learning by exploration combined with selective feedback. The use of selective feedback reduces drastically the time of training needed in order to obtain an optimal policy (Q) and the difficulty to find a good parameterization of the learning process in the experimentation phase. The purpose of this learning behavior is to obtain an *optimal policy (Q), constructing a knowledge base* based on the exploration of a deterministic and finite

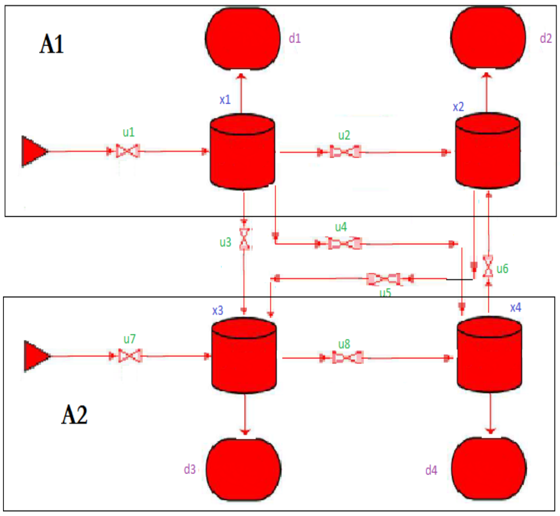


Figure 3: Water network considered as case study.

set of actions. These actions are simulated in the model system and the result (states s_{a1} and s_{a2}) is evaluated and only in case a feasible solution for both agents (*agent1* and *Agent2*) is found, the feedback is selected for leaning. For those cases, a *reward (r)* is obtained and used to calculate the new *Q-value (10)*. n_{it} iterations are made for the complete control horizon with random initial conditions. This behavior is performed offline in the *training phase* of the LINKER methodology. Assuming that there is a single negotiation variable, the *PlanningByExploration behavior algorithm* describes the training algorithm that the LINKER executes in order to update its *Q-table* by this learning behavior:

```
Define ρ, n, sa1 ← random, sa2 ← random,
controlHorizon, k=1
loop while iterations ≤ n
  loop while k ≤ controlHorizon
     a ← random (a) ∈ A  Q (s1',a, s2')
     Va1 (k) ← a
     Va2 (k) ← a
     sa1 ← send Va1 (k) to agent1, agent1set the action
     Va1 (k) and calculates its internal variables, apply
     all the controls (actions) obtained (and given) for
     step k to its LTI model of its partition and
     calculates sa1 using (5).
     sa2 ← send Va2 (k) to agent2, agent2set the action
     Va2 (k) and calculates its internal variables, apply
     all the controls (actions) obtained (and given) for
     step k to its LTI model of its partition and
     calculates sa2 using (6).
     if agent1 and agent2 have a feasible solution
            r ← ρ- sa1 - sa2
            Q (sa1', a', sa2' )← r +α Q(sa1, a, sa2)
            sa1'← sa1
            sa2'← sa2
     else
            sa1'← random
            sa2'← random
     end if
     k=k+1
  end loop
  iterations=iterations+1
end loop
```

6 ILLUSTRATIVE APPLICATION

This section shows an example of the optimization of a water distribution network using the proposed architecture. The partitioning of the network obeys a geographical criterion, so it has been divided in two partitions, north and south (see Figure 3). The tanks x_1 and x_2 will belong to the north sector where a local control is required. The tanks x_3 and x_4 will belong to the south sector, with its corresponding local controller.

There are two supply sources and four demand points, one for each tank. Typically the demands have a sinusoidal behavior throughout the day that try to emulate the actual demand behavior. The system shall operate in a distributed way but looking for global optimum in the controlled tank levels, satisfying the demand points of both subsystems, and avoiding collisions or conflicts among them.

It is expected that the performance of the tank levels follow a reference variable in time, but without performing drastic actions in the actuators. The target control is defined as follows: For each tank ($\underline{x_1}$, x_2, x_3, x_4) there is a given reference that describes the desirable behavior of the levels of these tanks. These levels will be achieved through the manipulation of the control variables (u_1, u_2,…,u_8) with minor variations over time.

6.1 Using PBIB

6.1.1 Training

Figure 4 shows a representation of the *Q-values* calculated in different phases of the training of the variable u_5. The *Q-table* contrast the error of M_1 and M_2 (or the discretize state of each agent) with the action taken.

In order to use only positive errors, in Fig. 4, errors range from 0 to 200. Negative errors range from 0 to 99, 100 corresponds 0 and from 101 to 200 are range the positive errors. Actions are ranging from 0 to 100. As it can be appreciated in the figure, the states visited in this training tend to be denser near the optimum state (100). This is because all the actions were dictated by the teacher, the centralized system. Making a comparison between sub-figures (a), (b), (c) and (d) it can be seen that the *Q-values* cloud is spreading on the axis of the actions and becomes denser as the training progresses. It is important to notice that the only random factor in this training (using PBIB) are the initial states of A_1 and A_2. The fact that in this training *instructed learning* is used makes it fast and efficient. The *Q-values* stored in these *Q-tables* represents meaningful and evaluated experience (because of the accumulation of the rewards).

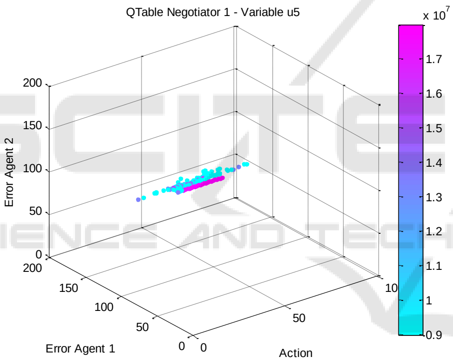
It can be noticed that between section c and d of the Fig. 4 there is not much difference. This is one of the factors that can show that no more iterations are needed. Additionally, the results of the exploitation phase are necessary in order to determinate that the training phase is finished. Similar results are obtained for the rest of the *Q-tables.* A training based on PBIB can be also used as a good start (or seed) before a *non-instructed learning* technique.

6.1.2 Simulation

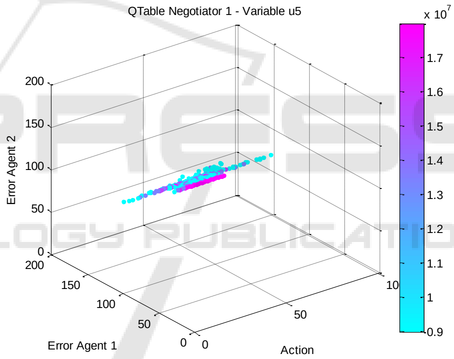
As it was mentioned before, in order to know if the training phase is finished it is necessary to evaluate the *Q-tables* making test and exploiting. In order to do that, the *greedy behavior* has to be implemented. The algorithm of greedy behavior is shown below.

$Q\,(s_1, a, s_2)\ \forall\, s \in S,\ a \in A$
observe initial state, s_1, s_2
loop
    a ←max $a' \in A\ \ Q\,(s_1', a, s_2')$
    s_1 ← send V_{a1} (k) to agent 1
    s_2 ← send V_{a2} (k) to agent 2
    $s_1 \leftarrow s_1'$
    $s_2 \leftarrow s_2'$
end loop

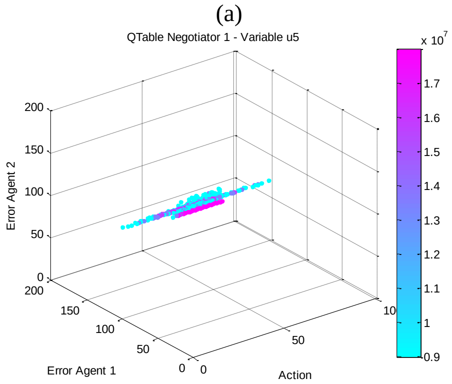
This algorithm observes the state of the agents s_1 and s_2 (in a discretized way) and maps it to the action



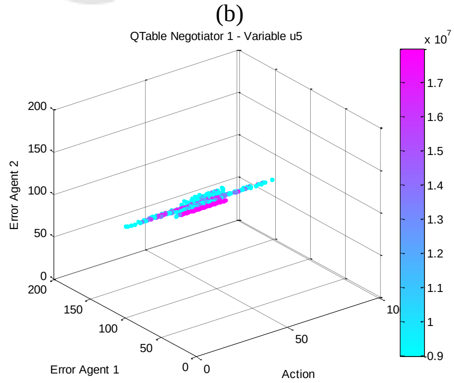
Q-table Negotiation variable u_5 training of 50 iterations
(a)



Q-table Negotiation variable u_5 training of 100 iterations
(b)



Q-table Negotiation variable u_5 training of 200 iterations
(c)



Q-table Negotiation variable u_5 training of 300 iterations
(d)

Figure 4: Different phases of the training using PBIB of the variable u5.

that maximizes the accumulated Q-value. Figure 6 shows the resulting actions of the shared variables applied in the simulations shown above. It can be notice that the ones calculated by the Linker (blue) vary les over time than the ones calculated with a centralized MPC (green). This is archived without sacrificing performance.

6.1.3 Performance Analysis and Validation

Table 1 shows the average absolute error of the output of 30 simulations. The first column was calculated with a training of 50 iterations, next ones with 100 iterations, 200 and 300 iterations. The sum of the error A_1 and error A_2 provides the total error. It can be seen how the error in the LINKER system (the first three) decreases as the iterations of the training progresses. Also it can be noticed that between 200 and 300 iterations there is not much difference in the error. The analysis of this table and the differences between the resulting *Q-tables* is useful to establish when the training is completed. The results shown in Figure 5 show, that the LINKER system using Instructed learning by implementing the *PlanningByInstruction* behavior (PBIB) has a better performance than the centralized MPC solution from iteration 200.

Table 1: Accumulative Δu between trainings.

$J_{\Delta u}$	50 it	100 it	200 it	300 it
Centralized MPC	4,666e-05	6,333e-05	5,000e-05	6,333e-05
LINKER	0,0140833	0,0153533	0,0116933	0,0155466

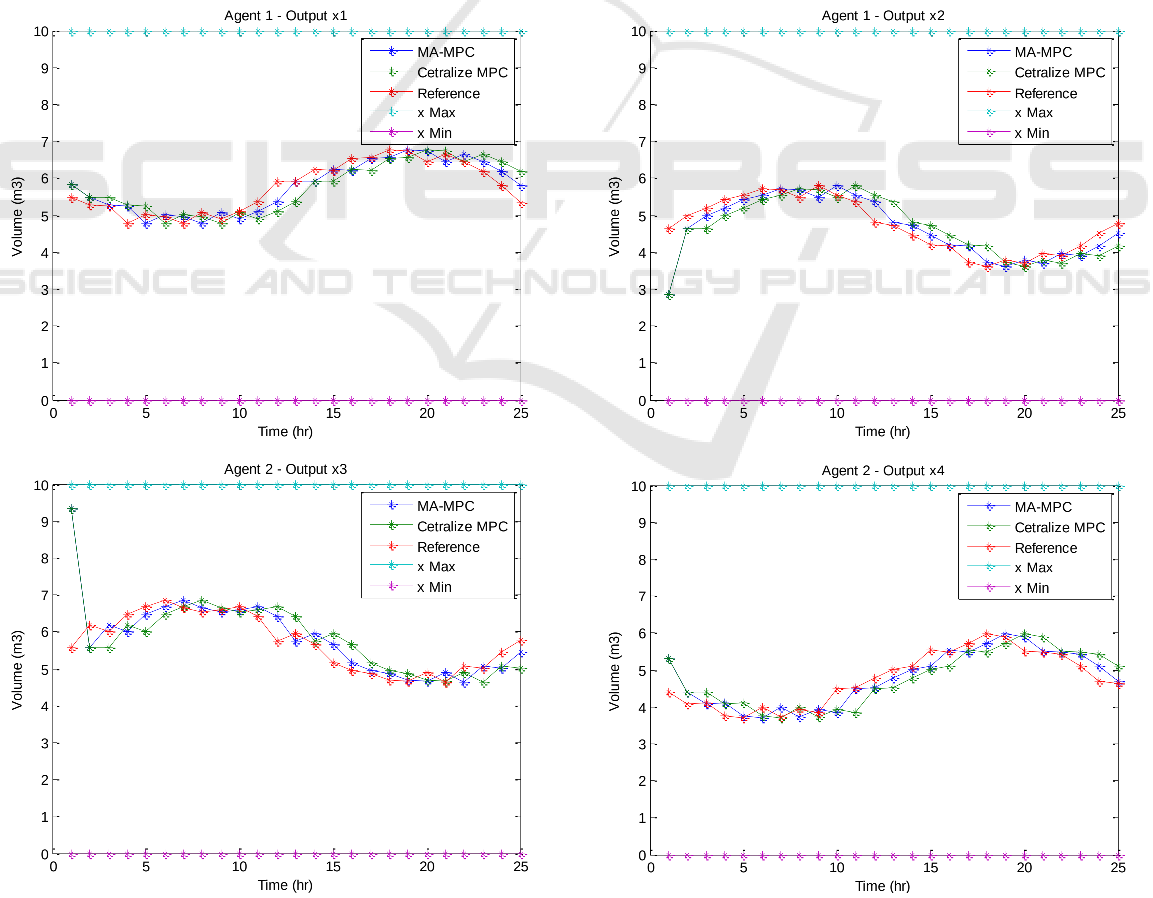


Figure 5: Results of the Linker agents (blue) compared with the centralized MPC (green) solution. The red line is the reference, purple x min, cyan x max.

Table 2: Average of absolute error between increasing iterations during training with PBIB.

J_e	**50 it**	**100 it**	**200 it**	**300 it**
A_1	62,36	24,04	18,07	17,14
A_2	60,11	24,23	17,20	17,37
LINKER (PBIB)	122,47	48,27	35,27	34,49
Centralized MPC	45,91	44,08	45,04	44,71

Table 2 shows the accumulative Δu objective applied by the LINKER and the centralized MPC solution in 30 simulations. The first column was calculated with a training of 50 iterations, next ones with 100, 200 and 300 iterations.

The results of this example shows that a system with multiples dependences between its components can be governed efficiently using distributed agents and, even more, it can increase its performance using the LINKER architecture implementing instructed learning by the PBIB behavior.

It can also be observed that the actions calculated by the LINKER (the shared variables) vary less over time without sacrificing performance. But the accumulative control effort is minor compared with the centralized MPC.

Other experiments have been carried varying the weights of the parameters $w_{\Delta x}$ and w_x of Eq. (7). Making the same changes in the teacher (the centralized MPC) and performing a new training, the Linker adapts to the new parameterization providing similar results than ones obtained with the ones used.

6.2 Using PBEB

6.2.1 Training

The training implements the *PlanningByExploration* behavior. Many experiments were made in this phase. First experiments were made using just explorative learning. Then, the *PlanningByExploration* behavior (PBEB) was implemented varying the number of the iterations in the training. Then, PBEB with selective penalization of reward was implemented. All training was made for the complete control horizon (24 hrs.) for each shared variable. Random initial conditions were set for each complete horizon. During training, the *Q-table* for each shared variable was filled with the *Q-values* calculated for all states visited.

The learning behavior *PlanningByExploration*, selects the actions that leads to a feasible solution of the related MPC agents. In this experiment, PBEB with selective penalization of reward was implemented applying a penalization in the opposite case, this means that if there is no feasible solution for the local agents, a negative reward was assigned (-1000). This negative reward ensures that the *Q-value* of state-action-state that leads to critical states stays low and accelerates drastically the training process allowing the LINKER system to improve the centralized MPC solution from the iteration 20 (see Table 3).

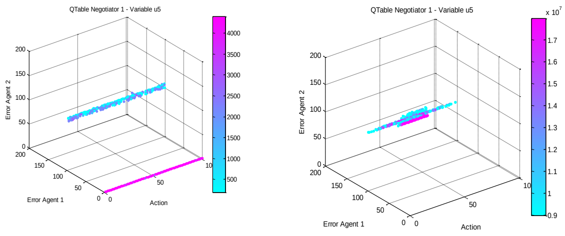
Table 3: Comparison of the average absolute error between local agents, LINKER system and centralized MPC solution with trainings of 20, 50 and 100 iterations.

J_e	**20 it**	**50 it**	**100 it**
A1	17,2429	15,8219	16,3230
A2	18,3069	17,5714	16,3808
LINKER	35,5499	33,3932	32,7038
Centralized MPC	45,3116	43,7657	42,8805

The experimentation made on this example shows that using just using exploration, the system cannot recover from states related to unfeasible solutions. In addition, these states have high frequency of visits because it is more likely that the random action selected were not the good one. This affects negatively the learning process because the accumulation of many small rewards becomes in larges *Q-values*.

In order to solve that issue, selective feedback was applied. This reduces drastically the iterations needed using just exploration and the *Q-values* result more reliable. Moreover, the use of a negative reward in the selected actions that lead to unfeasible states also provide a huge improvement. After assigning the negative reward, s'1 and s'_2 are set to random in order to continue the learning process effectively.

With these conditions a training of 100 iterations was carried out. Figure 6 (a) shows a color representation of the *Q-values* calculated in the learning process. The *Q-table* allows to present the error of A_1 and A_2 (or the discretize state of each agent) with the action taken. In order to use only positive errors, the errors are scaled from 0 to 200. Negative errors are scaled from 0 to 99, 100 is 0 while values from 101 to 200 correspond to positive errors. Actions are ranging from 0 to 100. The figure compares the *Q-tables* obtained using PBEB (a) and (PBIB) (b). From Figure 6 (a), it can be noticed that the cloud of data spreads all over the action axis, meaning that all actions were explored. Fig. 6 (b) shows the Q-table of shared variable u_5 with a training of 300 iterations using PBIB. In this *Q-table*, the cloud of *Q-values* is more compact because its training only tried the actions dictated by the teacher (in this case, centralized MPC).



(a) (b)

Figure 6: Comparison of the resulting Q-Tables of the variable u5 using PBEB (a) and PBIB(b).

6.2.2 Simulation

In other to know if the training phase is finished it is necessary to evaluate the elements of the *Q-table* by means of testing and exploiting. The simulation process implements the *greedy behavior (described above).*

The simulation results presented in Figure 7 allow to compare the LINKER using PBEB (blue line) and the centralized solution (green line) with the same random initial conditions and references (red line), obtained after a training of 100 iterations using PBEB with selective penalization of reward explained above. Notice that the reference is variable in time. The parameters of MPC agents and the centralized MPC system are the same.

From Figure 7, it can be noticed that both approach force the system to track the reference.

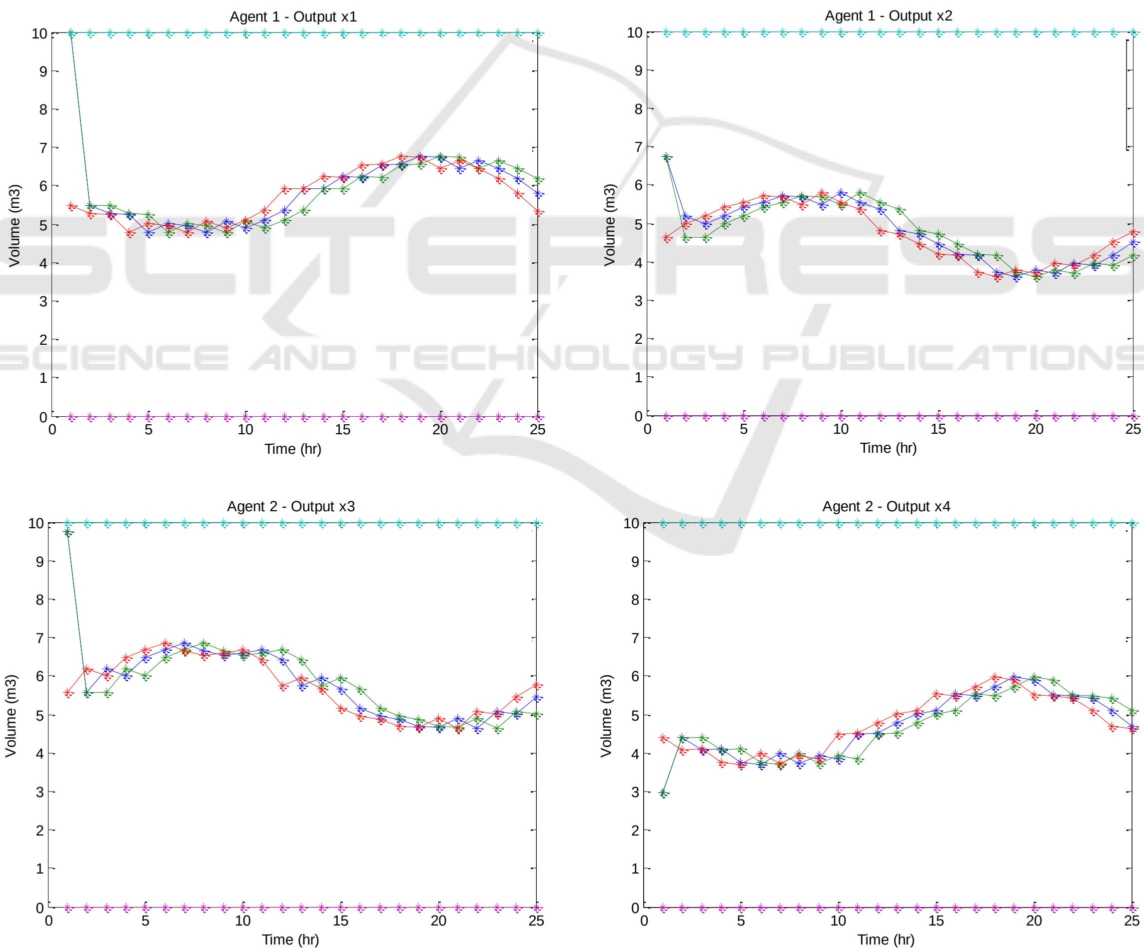


Figure 7: Results of the MPC agents (blue) compared with the centralized MPC (green) solution. The red line is the reference, purple x min, cyan x max.

6.2.3 Performance Analysis and Validation

Many simulations were made to assess the performance of the extended proposed approach. Table III shows the comparison of the average absolute error (with respect to the reference) of 30 simulations in the training process of the best Q-tables found, the ones obtained using PBEB with selective penalization of reward. Columns show the results of a training of 20, 50 and 100 iterations with random reference and initial conditions. From this table, it can be noticed that the LINKER solution improves the centralized solution since the first 20 iterations of the training and keeps improving slightly as iterations increase.

It was observed that the actions calculated by the Linker (the shared variables) vary less over time without sacrificing performance. But, the accumulative control effort is grater compared with the centralized MPC. Other experiments were made increasing or decreasing the negative reward but for this problem the best negative reward was -1000.

7 CONCLUSION

This article describes three behaviors that implemented in the LINKER architecture, they manage to separate the learning process of the optimization process, eliminating with this the cost of the number of learning steps necessary to converge towards an optimal (or can be sub - optimal) policy.

Explorative training is usually exhaustive. In this work this complexity is reduced applying selective feedback (using PBEB) but the combination of the use of negative reward for the selected feedbacks not just improves the results compared to the centralized MPC but also the *PlanningByInstruction Behavior* (PBIB) and decrease drastically the iterations needed in the training phase. Table 4 shows the average absolute error with respect to the reference of 30 simulations of the PBEB with selective penalization of reward and the PBIB. Random initial conditions and random references were use. The random cases calculated for PBEB with selective penalization of reward were different than the ones calculated for PBIB. The training of the PBEB with selective penalization of reward, involves 100 iterations while in the case of the PBIB uses 300 iterations.

Table 4: Errors between PBEB with selective penalization of reward and PBIB.

	PBEB selective reward	**PBIB**
A_1	16,3230	24,04
A_2	16,3808	24,23
LINKER	32,7038	48,27
Centralized MPC	42,8805	44,08

Table 5 shows the average $J_{\Delta u}$ obtained using the LINKER and the centralized MPC solution in the same experimentation conditions that those used to obtain the results presented in Table 4.

Table 5: Comparison of the J_Δu between the PBEB with selective penalization of reward and PBIB.

	PBEB	**PBIB**
Centralized MPC	0,0001	6,333e-05
LINKER	0,0107	0,0153533

Thus, the experimentation results obtained in this example show that PBEB with selective penalization of reward is a more efficient learning technique than PBIB due to the reduction of the error and the iterations needed in training.

The training of the PBEB with selective penalization of reward and the LINKER framework was successfully applied into a more realistic case of study, the Barcelona drinking water network (DWN) case study (Morcego et al. 2014) and (Javalera et al. 2019). This DWN in managed by Aguas de Barcelona, S.A. (AGBAR).

ACKNOWLEDGEMENTS

This work was financed by the National Council of Science and Technology (CONACyT) and PRODEP of Mexico.

REFERENCES

Desai, R. M. and Patil, B. P., 2017. Prioritized Sweeping Reinforcement Learning Based Routing for MANETs. *Indonesian Journal of Electrical Engineering and Computer Science*, 5(2), pp.383–390.

Hwang, K., Jiang, W. and Chen, Y., 2017. Pheromone-Based Planning Strategies in Dyna-Q Learning. *IEEE Transactions on Industrial Informatics*, 13(2), pp.424–435.

Hwang, K.-S., Jiang, W.-C. and Chen, Y.-J., 2015. Model learning and knowledge sharing for a multiagent system

with Dyna-Q learning. *IEEE transactions on cybernetics*, 45(5), pp.964–976.
Javalera, V., 2016. Distributed large scale systems: a multi-agent RL-MPC architecture. Universidad Politécnica de Cataluña. Available at: http://digital.csic.es/handle/10261/155199.
Javalera, V., Morcego, B. and Puig, V., 2010. Negotiation and Learning in distributed MPC of Large Scale Systems. In *Proceedings of the 2010 American Control Conference*. pp. 3168–3173.
Javalera, V., et al. Cooperative Linker for the distributed control of the Barcelona Drinking Water Network *Proceedings of the International Conference of Agents and Artificial Intelligence. 2019*.
Morcego, B. et al., 2014. Distributed MPC Using Reinforcement Learning Based Negotiation: Application to Large Scale Systems. In *J. M. Maestre & R. R. Negenborn, eds. Distributed Model Predictive Control Made Easy. Dordrecht: Springer Netherlands*, pp. 517–533.
Tateyama, T., Kawata, S. and Shimomura, T., 2007. Parallel Reinforcement Learning Systems Using Exploration Agents and Dyna-Q Algorithm. In *SICE Annual Conference 2007*. pp. 2774–2778.
Zajdel, R., 2018. Epoch-incremental Dyna-learning and prioritized sweeping algorithms. *Neurocomputing, 319*, pp.13–20