COOPERATIVE LINKER FOR THE DISTRIBUTED CONTROL OF THE BARCELONA DRINKING WATER NETWORK

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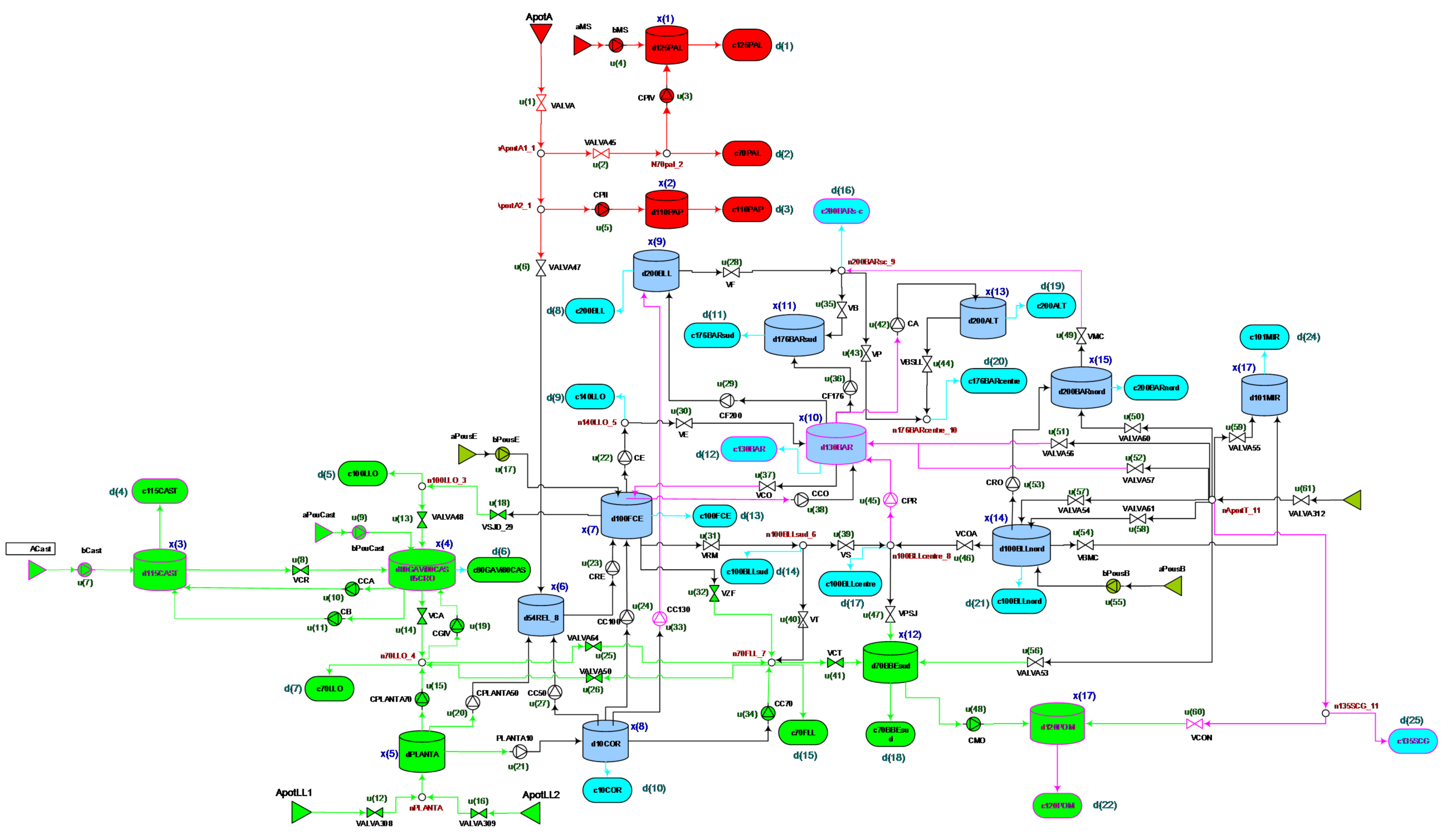
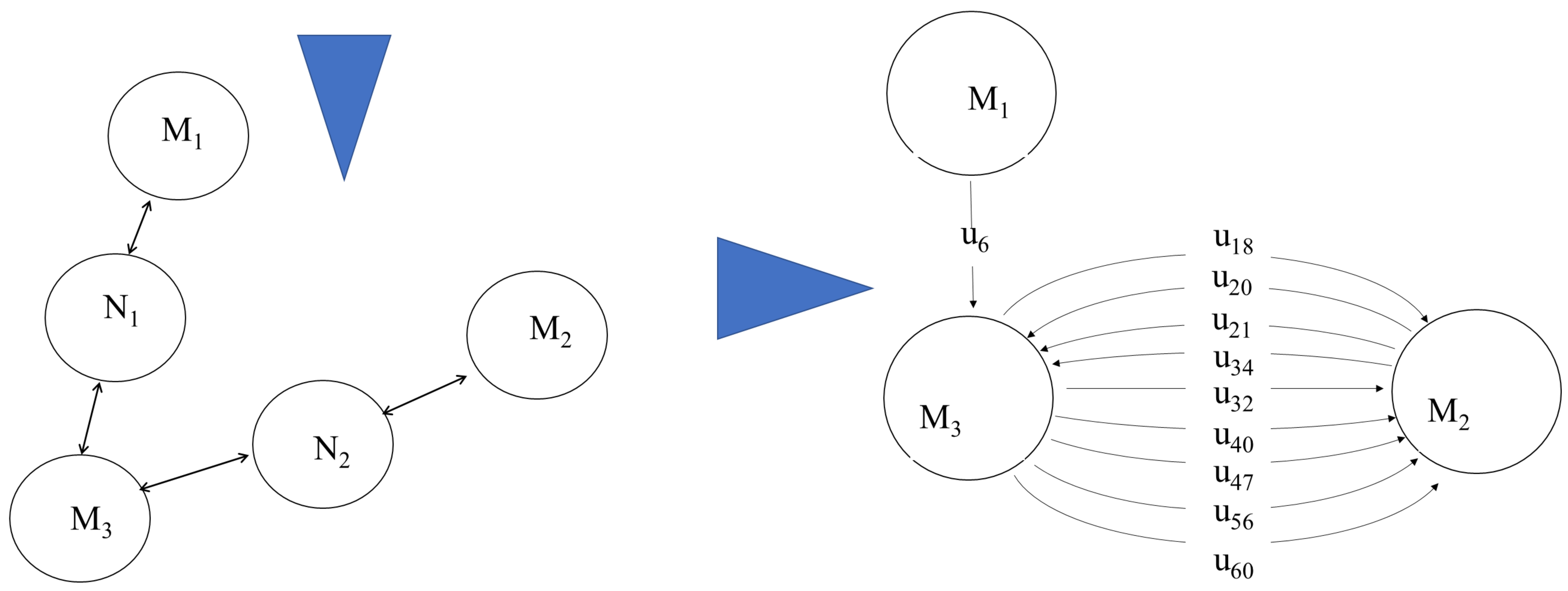
This work shows how a Linker agent coordinates a cooperative MAS environment to seek a global optimum. The approach is applied to the Barcelona Drinking Water Network (DWN) administrated by AGBAR where the main problem was to coordinate the control of three different sectors of the network. Each part has a local controller (M) to solve the local water demands, but it also has to cooperate with the other agents to satisfy the water demands of the whole network. The cooperative Linker agent (N) implemented, learns by using a Reinforcement Learning algorithm, called PlanningByExploration Behaviour with penalization (Javalera et al., 2019), to converge towards an optimal (or suboptimal) value of each of the variables that connect the local agents. For the training and simulation of the Linker agents real historical data of the Barcelona DWN provided by AGBAR were used.





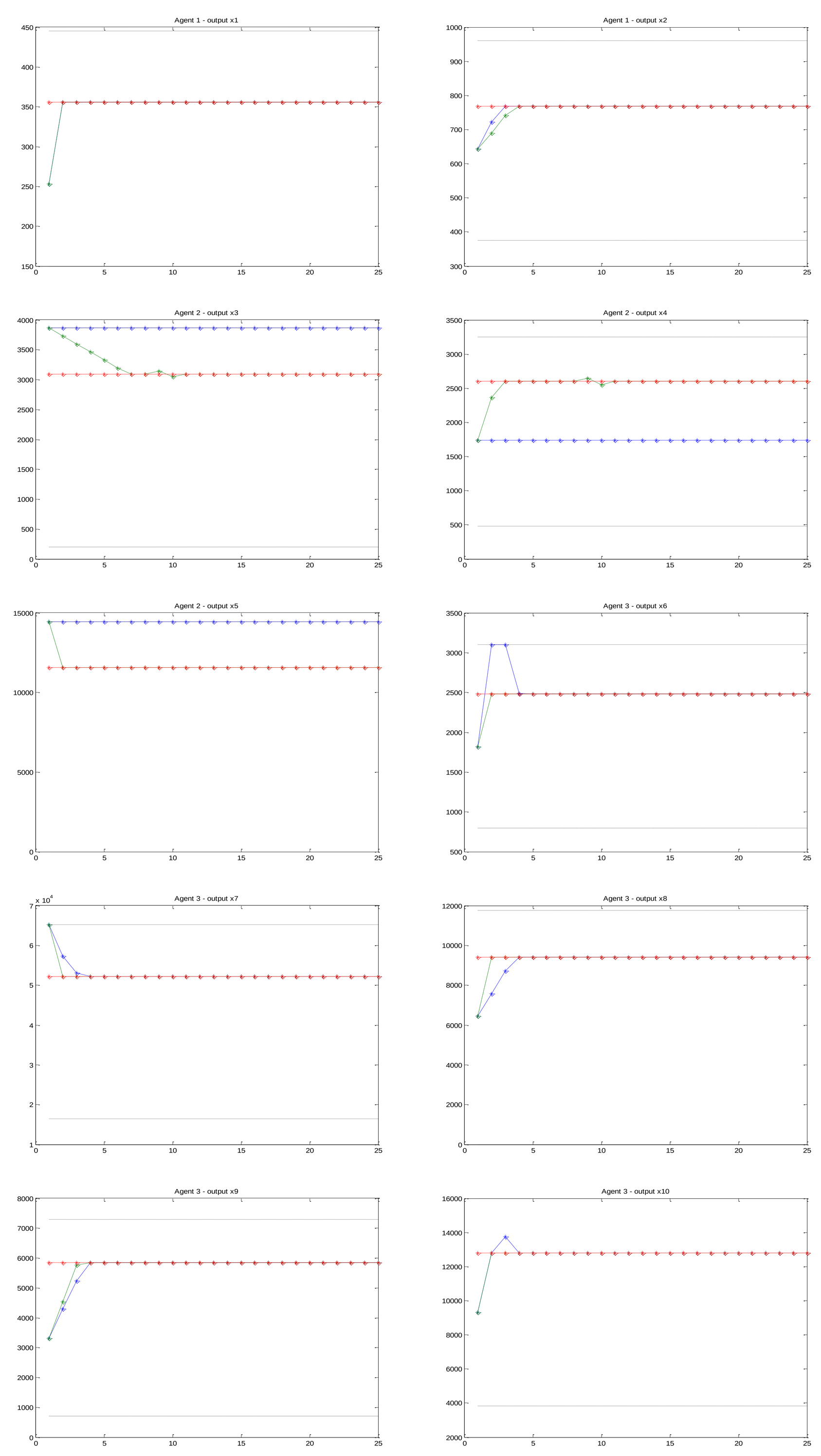
The Barcelona (DWN) divided in to tree sectors (red, green and blue), then the Relation diagram shows two linker agents (N1 and N2) related to MPC agents M1.M2 and M3, one for each sector.

Elements	Subsyst (Red)	Subsyst 2 (Green)	Subsyst 3 (Blue)	Whole Model
Tanks (x)	2	5	10	17
Actuators (u)	5	22	34	61
Demands (d)	3	7	15	25
Nodes (E)	2	3	6	11

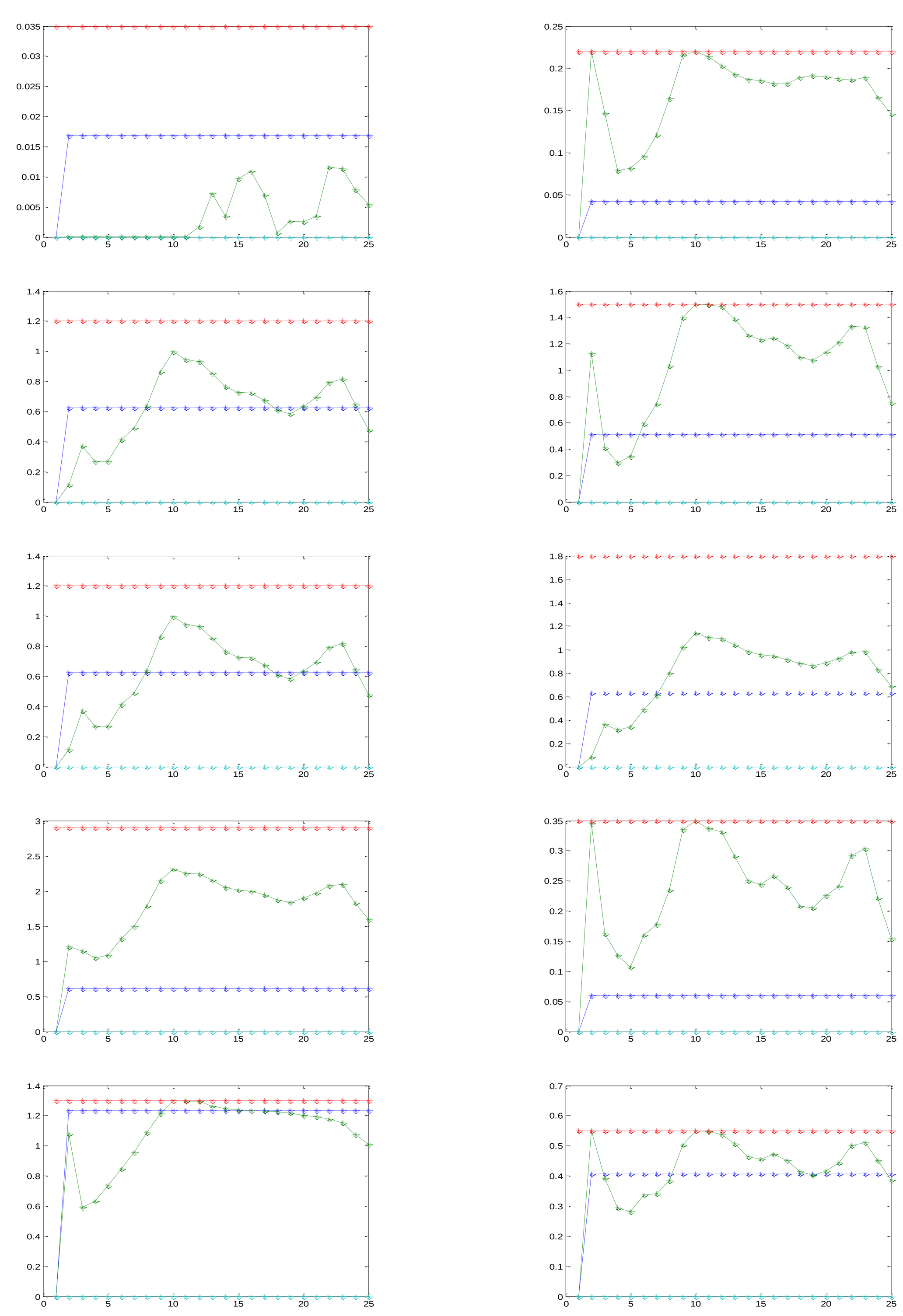
The Linker agents (N) coordinates and optimizes a cooperative MAS environment to seek for a global optimum.

Results and conclusions

The implementation of the LINKER Architecture and the PBEB in the case of the Barcelona DWN leads to a good solution where all the states are kept within limits with a cost $J_{\Delta u}$ of almost half (53.55%) of the centralized solution. Ten of seventeen (the 58.8%) tanks of the entire system could even follow the desirable reference (that was not mandatory). That means that the system accomplishes the objectives of keeping within the security levels and maintaining a smooth control better than to track the reference. It seems that with a more balanced partitioning the DWN performance could still improve.



Examples of simulations results of tank volume evolutions. From tank x1 to x10. Blue line represents LINKER solution and green line centralized MPC. Doted lines are min and max volumes of tanks and red line is a desired volume (not mandatory).



Evolution of some of the control actions applied by The LINKER (blue) and the centralized MPC (green) during simulation of figure 4. Max value (Red) and min value (Cyan)

For a detailed explanation of the algorithm applied for this case, please see the PanningByExploration behavior (PBEB) at :
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