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Title

Experimental and Simulative Evaluation of a Reinforcement Leaning Based Cold Gas Thrust Chamber Pressure Controller

Authors

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Abstract

In Europe, only open loop control of rocket engines is available. For the reuse of engines and propulsive landing with the requirement of deep throttling, closed loop control of several engine variables is necessary.
However classical control approaches like PI, PID or MPC cannot be easily applied for control of the full operation envelope of a deep throttleable engine, as they need a linearized state space model of the system.
At DLR neural networks, as potential future controllers for rocket engines, are studied. Currently different simplified applications are investigated as a first step towards the control a full engine. Reinforcement Learning is used to train the neural networks in EcosimPro simulations. Neural network-based controllers can also incorporate secondary control goals like temperature limitations, maximum efficiency or life expansion control.
In the full paper a neural network-based chamber pressure controller for a simplified cold gas thruster is presented and analyzed in simulation and experiment. The goal of the controller is twofold: It can track a control sequence with different changes of setpoints and it allows to set and control a wide variety of steady state operation points. Therefore, the neural network gets measurement data as input and calculates valve positions as output values.
The training phase of the controller is done in an EcosimPro simulation, that is validated with data from the corresponding experimental set up. To increase the robustness and to allow a transfer from the simulation directly to the test bench domain randomization and curriculum learning is applied. The robustness and stability of the controller is evaluated by simulative-investigations of the full state space and Monte-Carlo simulations. The simulative control quality is analyzed by metrices like: reward, overshoot, settling time, standard deviation and root mean squared error for the full operational envelope. Figure 1 shows an exemplary evaluation of the achieved reward for different pre-pressures and desired chamber pressures. It can be seen that - in the range of physically possible operation points - the controller achieves a constantly high reward which corresponds to a low error and a good control performance. In the simulation the controller was able to adjust all required setpoints with a steady state error of less than 0.1 bar while keeping a small overshoot and an optimal settling time.
At the test bench experiments corresponding to the simulations are conducted and the results are compared with the simulations. It is found that the controller is able to regulate all desired set points in the real experiment and also allows to follow different trajectories in the chamber pressure, an example thereof can be seen in Figure 2. The experiments are analyzed according: settling time, root mean squared error, max. deviation from setpoint, overshoot and reward.
Interestingly, the evaluation of the experiments show that the controllable operation-area is not only restricted to the state space that occurs during the training process. Nevertheless, it is not predicable in which extend the controller works outside the pre-trained borders. This phenomenon is described in detail in the full paper.

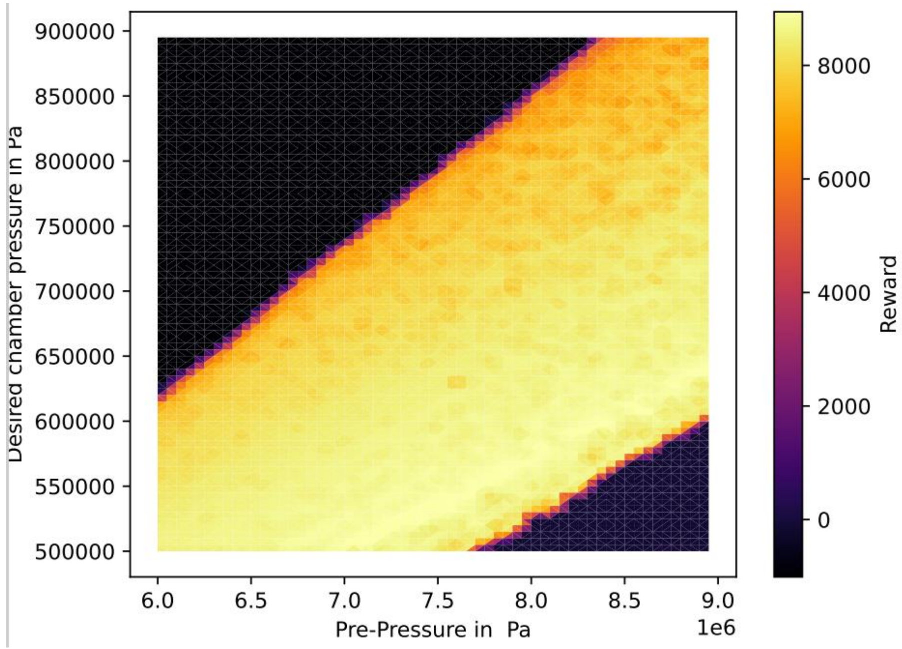

Figure 1 Evaluation of the calculated reward for simulations with different operating points.

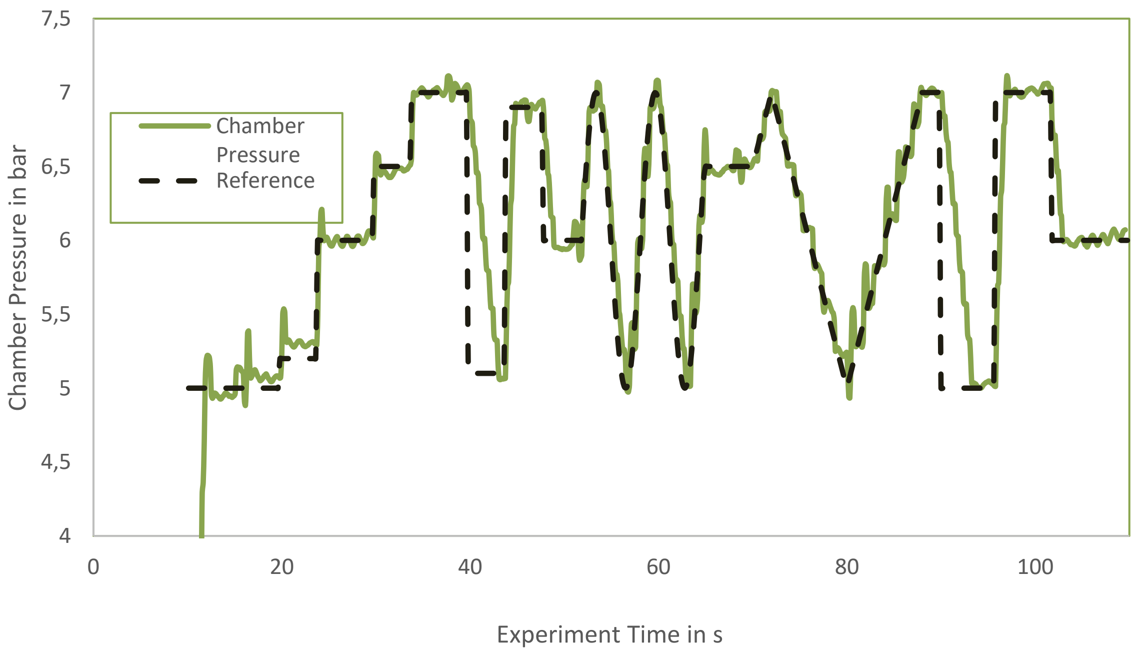

Figure 2 Measured and predetermined chamber pressure. The neural network-based controller follows a predefined trajectory.