Reinforcement learning (RL) is a technique that mimics the human process of learning through interaction. Performing an action in a certain situation will produce a feedback that reinforces or punishes the specific action in that state. This dissertation, a RL technique is used to control industrial setups. One of the big problems in industrial control is the fact that traditional control techniques are hard to use when a mathematical model of that system is not available. For instance, when the behavior of the system is impossible to track during the whole process, it is very hard to model the system. To control such systems there is a need for other control designs.

Reinforcement learning has been proven to be very successful in environments where limited or no knowledge is present. Learning through interaction is very effective to gradually learn or approximate the behavior to control the system. Several industrial applications were experimented with while each of these applications tackles a certain limitation in control, e.g. a system with limited feedback or systems with non-linear behavior.

Limited feedback creates a challenging problem where RL algorithms need to learn the control action to take, e.g. making a cart stop in front of a discrete sensor on a rail while the system can only send feedback when the cart passes in front on the sensor.

On other experiments, where the control signal is multi-dimensional and the systems behavior is difficult to correctly model, a basic software model was developed that simulates a (part of) the industrial setup. On the wet clutch setup and the hydrostat, the learning time is reduced by deploying the RL algorithm on the limited software model and use this control strategy as prior knowledge for the industrial system.

We present reinforcement learning as an intelligent controller that learns how to control industrial setups using a direct approach, RL determines the control action, or indirect control, RL learns the control signal to aid a low-level controller.