Popular Science Summary of Master Thesis

Nonlinear Model Predictive Control for Combined Cycle Power Plants

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This master's thesis project [1] was carried out in cooperation with Siemens AG Energy sector in Erlangen Germany [5] and Modelon AB in Lund Sweden [6]. It served to investigate the possibilities to apply Nonlinear Model Predictive Control (NMPC) for control of the steam enthalpy at the outlet of a BENSON HRSG (Heat Recovery Steam Generator) of a Combine Cycle Power Plant (CCPP).

Figure 1 displays the basic setup of a CCPP, it consists of two cycles for power generation; a gas turbine cycle and a steam turbine cycle, where the waste heat generated by the gas turbine is used to produce steam in the HRSG. [2]

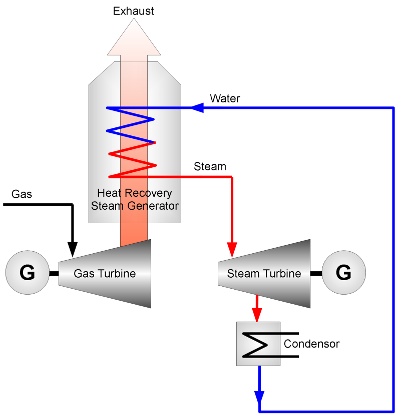

Figure 1: A combined cycle power plant.

The currently implemented controller for this purpose (used in Siemens plants today) is quite complex, and it is desired to, in the future, replace this controller with one that is more accurate and at the same time easier to understand, analyze and modify.

The CCPP and the HRSG are well known processes which are possible to represent with algebraic equations, and it is therefore interesting to investigate the possibility of applying NMPC.

Model predictive control (MPC, NMPC in the nonlinear case) is an advanced control strategy where the known system dynamics are exploited for control of the process. The next control action is determined by solving a finite time optimization problem which considers both the future behavior of the plant (according to the model) and the control objectives (keeping/reaching specified enthalpy).

A great advantage is that the optimization problem also considers constraints, e.g known physical limitations such as negative temperatures and pressures, and it can be applied on nonlinear processes. Another feature is that it isn't necessary to define an explicit control law. The optimization problem is solved at every sampling step, with the current state of the process as starting point. The starting point is updated at the next sampling instant and this is how the feedback property is introduced. [3]

The control strategy was implemented in the Python interface of the Modelica-based platform JModelica.org. Modelica is a programming language used to describe physical systems. JModelica.org also supports the Modelica extension Optimica which enables the possibility to solve optimization problems based on Modelica model objects. For more information about Modelica and JModelica.org, see [7] and [8] respectively.

For the implementation purpose, two model objects were central, one representing the actual real plant and one used by the controller. These two models are in reality different, but they were considered to be the same as a starting point for the project.

For basic MPC, one might assume that the process is modeled perfectly, but this is however never the case. First of all, it is impossible, and second, it is not always beneficial to include everything related to the process, some simplifications and limitations are necessary in order to obtain a optimization problem which is reasonable to solve. It is therefore necessary to introduce some sort of state estimation, to consider modeling errors and noise. The extended Kalman filter (EKF) was included in the implementation, because of its simplicity and its reputation of being "good enough". The big drawback with EKF is that it is an approximation, it is necessary to linearize the equations at every sampling step, and the EKF cannot consider constraints, this needs to be considered and handled separately. [4]

The performance of the state estimator is so far to satisfying levels, but remember: the plant model object and the controller model object used were quite similar.

The results for this setup were quite satisfying, there are many interesting aspects to consider when continuing with the work. For example:

- To use a more accurate and elaborate model object as real plant.
- To reevaluate the strategy for state estimation, look into Moving Horizon Estimation, which considers constraints.
- To use time-varying parameters, and introduce parameter estimation.
- To make the implementation real time compatible.

To conclude, NMPC is still an interesting possibility for this application, but it requires further investigation and more evaluation. Another important part to remember when talking about optimization is that the actual optimality depends on how the problem is defined, if it is an ill-defined problem, then the optimal solution to this problem probably isn't very optimal in reality.

References

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