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Shaping the dynamics of interconnected cycles – optimal control using fuzzy logic based models

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Introduction

Innovation in companies is a key factor for competitiveness in many business areas. Managing and planning innovation is thus an important task, and continuous adaptation and improvement of the process is required. Cycle management is approaching this task by subdividing it into the management of certain reoccurring patterns inside the companies, called cycles. There are many of those reoccurring patterns which influence each other. The aggregation of the cycles with their interconnections is called the cycle network [1]. As a consequence of the interconnections, it is not enough to look at only one cycle, but all the relevant cycles and their interconnections must be considered and managed. To facilitate this task, project A7 is unifying operations research with cycle management. The goal is to find methods to model the cycles and their interconnections, as well as methods for a subsequent analysis and derivation of actions.

Modeling cycle networks using difference equations

Operations research is dealing with quantitative modelling and analysis of problems in management. For the mathematical modelling of cycles, simple static functions were used in the past [2]. There functions might show a typical development of the cycles, but fail at capturing interconnections and don't reflect any quantitative information for a derivation of action. A more common way to model time varying quantities is to derive a dynamical model in the form of a difference equation. This derivation can be done using the laws of physics for some technical systems, but it is more difficult for non-physical systems.

In the recent past, fuzzy logic has been used intensively in order to make expert knowledge available. Fuzzy logic can translate a bunch of linguistic rules into a mathematical model. The rules should be of the form: If A and B, then C. The resulting model is in the form of a difference equation

$$x_{t+1} = f(x_t, u_t)$$

which is suitable for simulation and analysis. The variable x_t describes the state of one or multiple cycles at time step t and u_t represents optional inputs into the cycle network. Methods for the analysis of this kind of systems have been intensively developed in the past, some of them will be mentioned in the next section. The model resulting from the linguistic rules is often of unsatisfying accuracy and should be used with care. However, fuzzy logic is only one possible method to derive difference equations for non-physical systems. A second promising approach is to fit a model to data. This procedure is called systems identification and reduces to solving an optimization problem conditioned on the data. The general problem with this approach is a general lack of data, even in times of industry 4.0.

Optimal control for cycle networks

The dynamical model serves as a basis for both analysis and derivation of action. We leave out the analysis part in this place, interested people can refer to [3, 4]. The following will deal with ways of generating an optimal feedback or feedforward control for generic systems described by difference equations.

A first method of deriving a feedforward optimal control is to directly optimize the model inputs $U = [u_t, u_{t+1}, \dots, u_{t+N}]$ for a given start state $\hat{x}_0$. The goal of the optimization needs to be clarified in a cost function $c(x, u)$. A simple form of the optimization problem could be written down as

$$
\begin{aligned}
U^* = \underset{U}{\operatorname{argmin}} \sum c(x_t, u_t) \\
s.t. x_{t+1} = f(x_t, u_t) \\
x_0 = \hat{x}_0
\end{aligned}
$$

Constraints can be added if necessary, and the optimization problem can be solved e.g. using interior point methods. The resulting sequence is locally optimal can be used as feedforward control. The same method can be sued to create a feedback control, by repeatedly solving the optimization problem in each time step. The starting state for the optimization has to be updated with the observed state in that case. This approach is called model predictive control and is used widely in industrial applications. A main drawback is the potentially high computation costs during operation and lack of guarantees.

As an alternative, optimal control can be solved for a parametrized controller. The controller is a function $u_t = g(x_t; \Theta)$ where Θ defines the parameters to be optimized. The problem, in its simplest form is thus

$$
\begin{aligned}
\Theta^* = \underset{\Theta}{\operatorname{argmin}} \sum c(x_t, u_t) \\
s.t. x_{t+1} = f(x_t, u_t) \\
u_t = g(x_t; \Theta) \\
x_0 = \hat{x}_0
\end{aligned}
$$

The methods used to solve this problem use are called policy gradient methods and have their origins in the machine learning and game theory communities. The optimization is computational expensive, but the evaluation of the controller during operation is not. The policy gradient methods are still object of current research, and the application in operations research and cycle management is promising.

To conclude, cycle management as it is treated by subproject A7 is part of classical operations research, with the focus on finding suited methods for modelling, analysis and control. The methods have to be very generic, as the cycle network models are different for each company.

References

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