# Methods for Machine Learning Assisted Reliable Control Design

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**Abstract**

In recent years, with the rapid development of machine learning techniques, especially deep learning, the application of these techniques to model-based control design has attracted much attention. Machine learning is expected to be able to obtain mathematical models directly from data and achieve high prediction accuracy even for complex subjects that are difficult to model from first principles. From its strong learning ability, machine learning is expected to model not only the behavior of physical systems but also complex control laws or algorithms. However, there are few examples of practical evaluations of such techniques on complex real systems, and machine learning models are difficult to guarantee *reliability* in practical applications because their structures are black boxes.

The objective of this dissertation is to address the above issues by (1) experimentally verifying the applicability of machine learning assisted control design methods by applying them to real systems, and by (2) proposing novel methods that can theoretically guarantee reliability requirements assumed for real applications. Throughout the dissertation, the methods are applied to an engine system, employed as a representative of complex real systems, and are verified through numerical simulations and experiments of the system.

In approach (1), we attempt to learn not only the physical dynamics of the control subject but also the control law of model predictive control (MPC), which is a typical control method applicable to nonlinear systems. Although learning of the target dynamics has long been studied as system identification and many efforts have been made, there are relatively few cases where learning of control laws has been studied and its experimental verification has been reported. The control law of MPC is so complex that it could not be approximated well by learning models with simple structures, but we have demonstrated that deep learning can approximate it with high accuracy. In addition, good control performance has been confirmed in experiments using real engines.

As for approach (2), since there is a wide range of requirements for *reliability*, this dissertation considers representative requirements for models, controllers, and control systems. As a requirement for models, we consider that the learned model should satisfy some dynamical properties such as stability, if there is prior knowledge about the target. To realize this requirement, we proposed a model structure that can guarantee that the state trajectories obtained by the model have certain topological properties (asymptotic stability, existence of stable limit cycles, etc.), and demonstrated that the proposed model can guarantee such properties even for targets which are difficult to guarantee those properties by naive learning models. As a requirement for controllers, we consider that the control problem defining the controller should be always solved correctly. We proposed model structures, in which the target system is attributed to a linear dynamics through bijective mappings, and control design methods that can guarantee the uniqueness and continuity of the optimal solution. As a requirement for control systems, we aim to achieve short computation time and the stability of the feedback system implemented as a sampled-data system. Instead of directly solving the control problem, we employed a continuous-time dynamical controller that can determine near-optimal input quickly by relaxing the problem over time, and derived a sufficient condition that can guarantee the stability of the resulting sampled-data system.