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HIERARCHICAL INTELLIGENT REAL-TIME OPTIMAL CONTROL FOR LLRF USING TIME SERIES MACHINE LEARNING METHODS AND TRANSFER LEARNING

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Abstract

Machine learning (ML) is under study for Low-level RF (LLRF) control systems to keep the voltage and phase of superconducting radio-frequency (SRF) cavities stable within 0.01 degree in phase and 0.01% amplitude as constraints. Model predictive control (MPC) uses an optimization algorithm offline to minimize a cost function with constraints on the states and control input. The surrogate model optimally controls the cavities online. Time series deep ML structures including recurrent neural network (RNN) and long short-term memory (LSTM) can model the control input of MPC and dynamics of LLRF as a surrogate model. When the predicted states diverge from the measured states more than a threshold at each time step, the states' measurements from the cavity fine-tune the surrogate model with transfer learning (TL). MPC does the optimization offline again with the updated surrogate model, and transfer learning fine-tunes the surrogate model with the new data from the optimal control inputs. The surrogate model provides us with a computationally faster and accurate modeling of MPC and LLRF, which in turn results in a more stable control system.

INTRODUCTION

ML with optimization provides the system and control with constraints and optimum objective functions. Nonlinear optimization takes long to perform, and recent advances have been solving this problem by applied surrogate model during optimization including Bayesian optimization [1], surrogate modeling for data-driven optimization [2], and surrogate modelling on the data from the optimization [3]. These ML methods have been implemented in the attitude control of spacecraft, where a ML based surrogate model can learn the entire optimal attitude control system with the optimal configuration of spacecraft [4], the entire optimal control of spacecraft for the landing problem [5], the optimal controllers' parameters of spacecraft [6–8]. In a similar way, ML based controllers including surrogate models have been implemented in particle accelerators [3, 9–12].

MPC is used for both linear and nonlinear systems. The optimization in MPC satisfies the constraints and minimises the cost function. For linear systems, the optimization is convex and has one local optimum. In nonlinear systems, the optimization is non-convex and the optimization has to find the global optimum. MPC provides us with an optimal control with the cost of great amount of computation due to the non-convex optimization with constraints. With the recent advances in computation resources, including high performance computing (HPC), MPC can be done offline and implemented online with a time series ML-based surrogate model. Linear and nonlinear MPC controls have been widely used in spacecraft [4, 13] and particle accelerators [9]. RNN and LSTM deep learning can learn the time series data from MPC [4, 14].

Simulations of particle accelerators are essential for designing and analysing the optimal particle accelerator configurations, including the LLRF. High fidelity simulations may be computationally expensive, spanning over a few hours; and obtaining beam time for experiments is limited [10]. Surrogate model can learn the simulation data set, and fine-tune the surrogate model with TL [15]. Transfer learning in ML is transferring knowledge from one domain to another related domain. In deep learning neural networks (DL), first DL is trained on one data set, and next, the trained DL is retrained on the target data set.

LOW LEVEL RF MODEL

A nonlinear model of an SRF cavity and the LLRF feedback loop was developed by the LNBL LLRF team. For each cavity with multiple electromagnetic modes, each mode is given by a resonant circuit model, see Fig. 1.

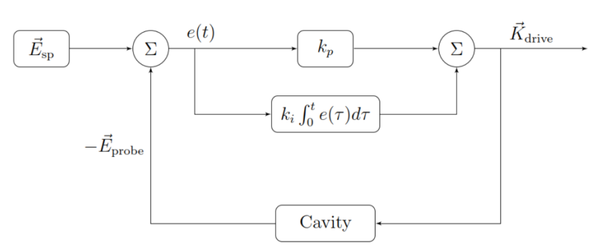

Figure 1: Circuit model of a resonant mode in a cavity [16].

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The electrodynamics equations of the system are given in [16]. The states of LLRF $\boldsymbol{x}$ are voltage and phase with control input signal $\boldsymbol{u}$. The state-space equation is defined as $\dot{\boldsymbol{x}} = f(\boldsymbol{x}(t), \boldsymbol{u}(t))$. State measurements are represented as $\tilde{\boldsymbol{x}}$, and state estimations are represented as $\hat{\boldsymbol{x}}$.

MODEL PREDICTIVE CONTROL

MPC minimizes the cost function C for a finite-time horizon, while only applying the current u_t. In the next time slot, the optimization happens from the next time slot for the next finite-time horizon while only applying u_{t+1}. This optimization is iterated during the simulation. As a result, there is a sequence of inputs, denoted as $\boldsymbol{U}_{t+k}$, and states, denoted as $\boldsymbol{X}_{t+k}$. The cost function for the optimization is

$$C = E + we. \tag{1}$$

Where w weights e over E, e is the state-error in the finite-time horizon, and E is the energy spent by the RF amplifier in the finite-time horizon. The optimization condition is formulated as

$$\min_{\boldsymbol{U}_{t+k}} C(\boldsymbol{U}_{t+k}), \tag{2}$$

$$s.t : \dot{\boldsymbol{x}} = f(\boldsymbol{x}(t), \boldsymbol{u}(t)).$$

The nonlinear MPC solves the minimization problem (2) with nonconvex optimization algorithms with the given constraints.

SURROGATE MODEL

Nonlinear auto-regressive exogenous model (NARX) is used to model LLRF as the following

$$\hat{\boldsymbol{x}}_t = G(\boldsymbol{x_t}, \boldsymbol{x_{t-1}}, ..., \boldsymbol{u_t}, \boldsymbol{u_{t-1}}, ...) + \epsilon_t. \tag{3}$$

The function G is the surrogate model defined by LSTM and RNN. ϵ_t is the error of the estimation characterised by mean squared error (MSE). The surrogate model is updated by Algorithm 1.

Algorithm 1: Hierarchical Intelligent Learning

1) Do MPC offline and produce data for $\boldsymbol{X}$ and $\boldsymbol{U}$;
2) Obtain G from the data in step 1;
3) Apply G to the LLRF and do the optimal control online;
4) If $|\tilde{\boldsymbol{x}}(t) - \hat{\boldsymbol{x}}(t)| > \delta$
   A) Use TL to fine-tune G with $\tilde{\boldsymbol{x}}(t)$;
   B) Do MPC offline and produce data for $\boldsymbol{X}$ and $\boldsymbol{U}$;
   C) Apply transfer learning to fine-tune G with the data from step B;
   End;
5) Return to step 3.

TRANSFER LEARNING

The first TL is to run MPC simulation for the LLRF model in order to produce data. RNN and LSTM are trained on these data and we refer to this network as the initial surrogate model. With sufficient data and a ML surrogate model architecture, the initial surrogate model should predict the states $\hat{\boldsymbol{x}}(t)$ with minimal error, i.e. $|\tilde{\boldsymbol{x}}(t) - \hat{\boldsymbol{x}}(t)|$ stays close to zero. However, this condition does not always holds true, and TL uses $\tilde{\boldsymbol{x}}(t)$ to fix the bias of surrogate model and fine-tune it. Figure 2 shows the transfer of surrogate model from one domain of data set to another domain of the data set. In TL, after training the initial surrogate model, the weights and biases in the majority of the layers of the deep learning are kept fixed except in the very last layers. The weights and biases in the last layers are retrained with the target data set.

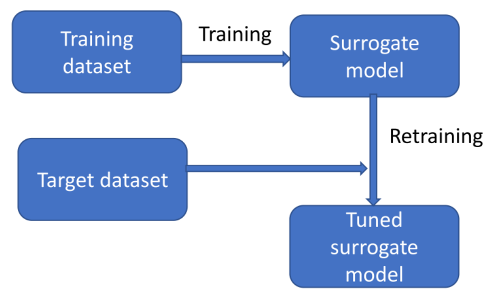

Figure 2: TL.

SUMMARY AND FUTURE WORK

With ML and TL, online MPC can be used to apply constraints and cost functions to LLRF to increase its performance. HPC is used to produce data, do MPC offline, and train the surrogate model. Online measurements from LLRF and data from MPC fine-tune the surrogate model with TL. The surrogate model does the optimal control on LLRF online. Different nonconvex optimization, objective functions, and constrains will be examined for MPC to obtain the best configurations of MPC for LLRF.

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