Hierarchical intelligent real-time optimal control for LLRF using time series machine learning methods and transfer learning

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Nonlinear Model predictive control

System: LLRF nonlinear model

MPC’s optimization: Nonconvex optimization

MPC’s constraints: Constraints on RF amplifier, constraints on voltage and phase

MPC’s cost function: State-error and energy
Hierarchical intelligent learning algorithm

1) Do MPC offline and produce states and control input data

2) Obtain deep learning surrogate model (LSTM, RNN) from the data in step 1

3) Apply the surrogate model to the cavities and do the optimal control online

4) If the difference between the measurements and the predicted states is more than a threshold for each time step:
   - A) Apply transfer learning to fine-tune the surrogate model with the measurements of the cavities
   - B) Do MPC offline and produce states and control input data
   - C) Apply transfer learning to fine-tune the surrogate model with the data from step B

5) Go to step 3
Transfer learning

Training dataset \(\xrightarrow{\text{Training}}\) Surrogate model

Target dataset \(\xrightarrow{\text{Retraining}}\) Tuned surrogate model
Conclusion - Future Work

• 1) Online optimal control is going to be obtained with MPC and surrogate model

• 2) The Constraints are going to be satisfied for LLRF

• 3) Accurate system identification, optimal control, and reduction of computational cost are going to be obtained through surrogate model and transfer learning

• 4) In the future, this approach will be updated for Microphonics and each cryomodule

• 5) In the future, this approach will be updated into distributed intelligent hybrid control for all the components of particle accelerator.
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Selected references


