IMPERIAL
Department of Electrical and Electronic Engineering

Optimal Control for Robust Dynamic Performance in Inverter-Dominated Power Systems: From Analytical to Data-Driven Solutions

Tomás Ochoa, Balarko Chaudhuri, and Mark O'Malley.

Problem Statement

Power systems are undergoing a fundamental dynamic transformation. As inverter-based resources (**IBRs**) displace conventional generation, their fast and nonlinear characteristics introduce dynamic behaviors that state-of-practice tools may fail to capture.

In this context, the selection of IBR control structures and the tuning of their parameters become critical levers for enhancing power system's security, resilience, and stability.

We formulate the Robust Optimal Control Problem (**ROCP**) **[1,2]** as:

$$(1) \quad \min_{\{u,K\}} \max_{\{z_\sqcap, r_\sqcap, x_{t_0}\}} \Psi = \int_{t_0}^{t_f} \psi$$

$$\text{s.t.} \quad \dot{x}_t = f(x_t; u, K, z_\sqcap, r_\sqcap),$$

$$u \in \mathcal{A}^u, K \in \mathcal{A}^K, z_\sqcap \in \mathcal{A}^z, \{r_\sqcap, x_{t_0}\} \in \mathcal{A}^r$$

where:

- **Control Design** $\{u, K\}$: is defined by the IBRs control structure configurations u and control parameters K.
- **Disturbance-dispatch** $\{z_\sqcap, r_\sqcap, x_{t_0}\}$: is defined by the stepwise large-signal disturbance $z_\sqcap$ (from pre- to post-disturbance at t_0), the stepwise reference signals $r_\sqcap$ (from Economic Dispatch to Automatic Generation Control re-dispatch at $t_i > t_0$), and the initial states x_{t_0}.
- The interplay between **Control Design** and **Disturbance-Dispatch** is governed by the system dynamics, $f(\cdot)$, and evaluated by the **dynamic error metric** Ψ.

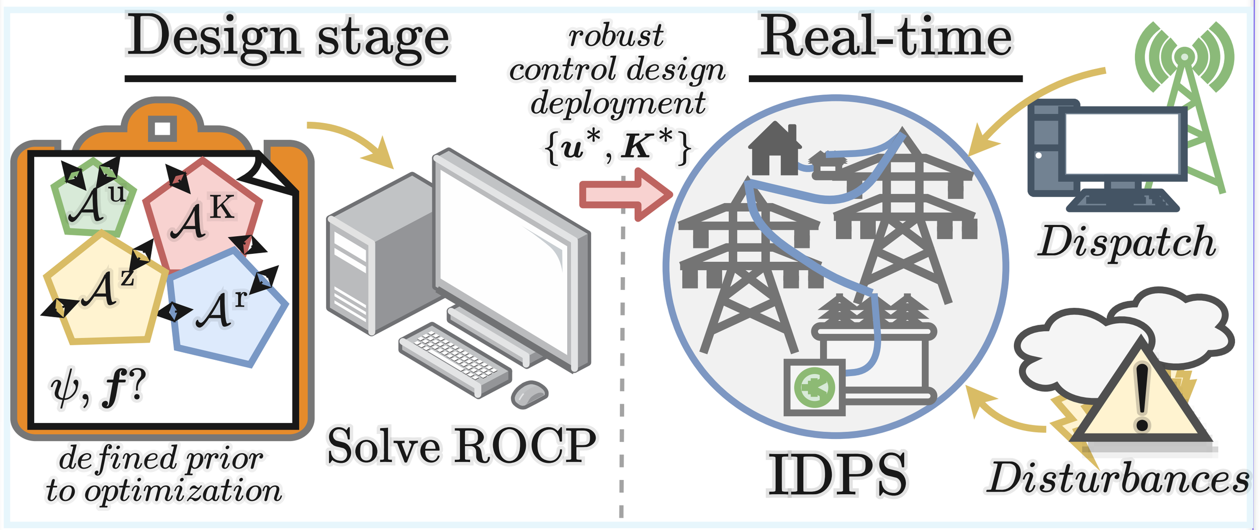

Fig. 1: The ROCP is solved at a dedicated design stage to determine a robust control design $\{u^*, K^*\}$, which is then deployed and held fixed during real-time operation.

The ROCP is formulated for be solved within a dedicated design stage, schematized in Fig 1.

Analytical Method

To solve the ROCP in (1), the analytical system dynamics are embedded via **direct collocation**, yielding a nonlinear program (NLP). Following a **local reduction strategy**, the resulting min-max structure is resolved by iteratively alternating between a max phase, which identifies the worst-case disturbance-dispatch scenario for a fixed control design, and a min phase, which optimizes the control design against the accumulated set of worst-case scenarios in $\mathcal{D}$, as shown in Fig. 2. To enhance reliability, candidate solutions at each phase are evaluated and selected based on high-fidelity EMT simulations.

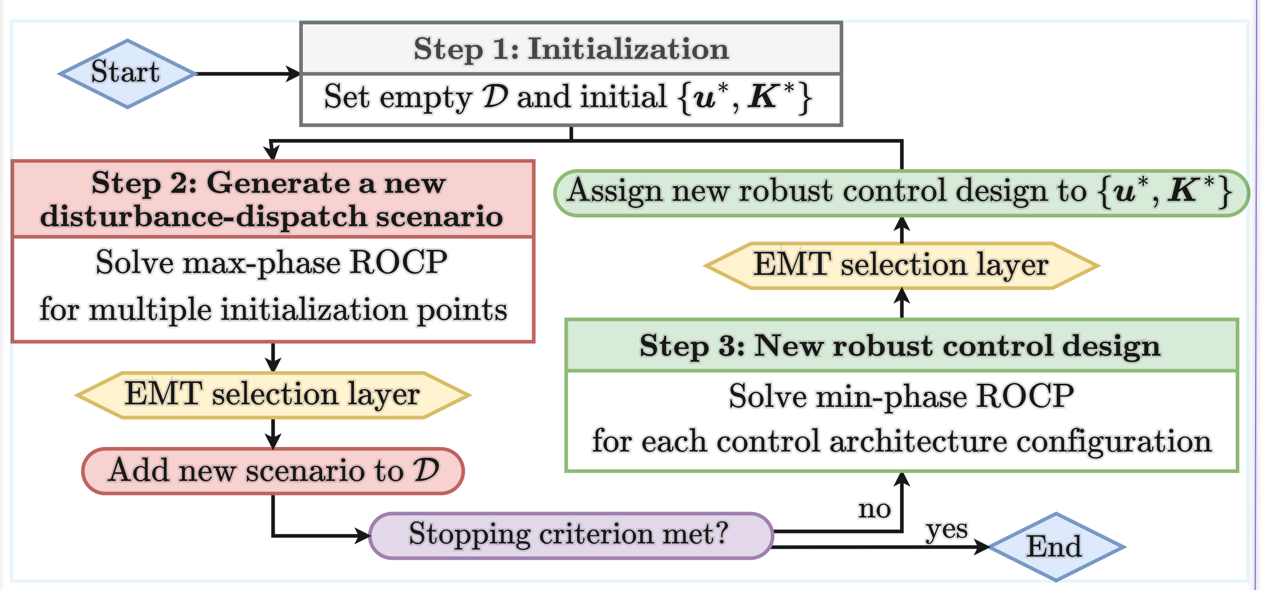

Fig. 2: Flowchart of the analytical solution method based on a local reduction strategy.

Application to the IEEE 9-bus system demonstrates that the method captures key large-signal effects with high fidelity, including nonlinear transients arising from current saturation, and yields improved robust dynamic performance relative to conventional control design practices. However, **two key challenges limit applicability** to real-world systems:

- **Scalability:** As the system grows in size and complexity, explicitly embedding $f(\cdot)$ within a model-based optimization framework becomes computationally impractical.
- **Confidentiality:** IBR models are often proprietary, meaning system operators may lack access to the analytical form of $f(\cdot)$.

To overcome these challenges, **we propose a data-driven approach** to solve the ROCP**.**

Data-Driven Method

Assuming the system dynamics $f(\cdot)$ and system performance Ψ can only be accessed through simulations, the Electro-Magnetic Transient (**EMT**) mapping: $f^{EMT}(u, K, z_\sqcap, r_\sqcap, x_{t_0}) \to \Psi^{EMT}$, is approximated using an Artificial Neural Network (**ANN**) able to capture the mapping from **control design** and **disturbance-dispatch** inputs to **system performance** .

Once trained, the differentiability of the ANN with respect to its inputs enables adversarial min-max optimization via **gradient-based search** over the **control design** and **disturbance-dispatch** agents, solving the ROCP without an analytical system model.

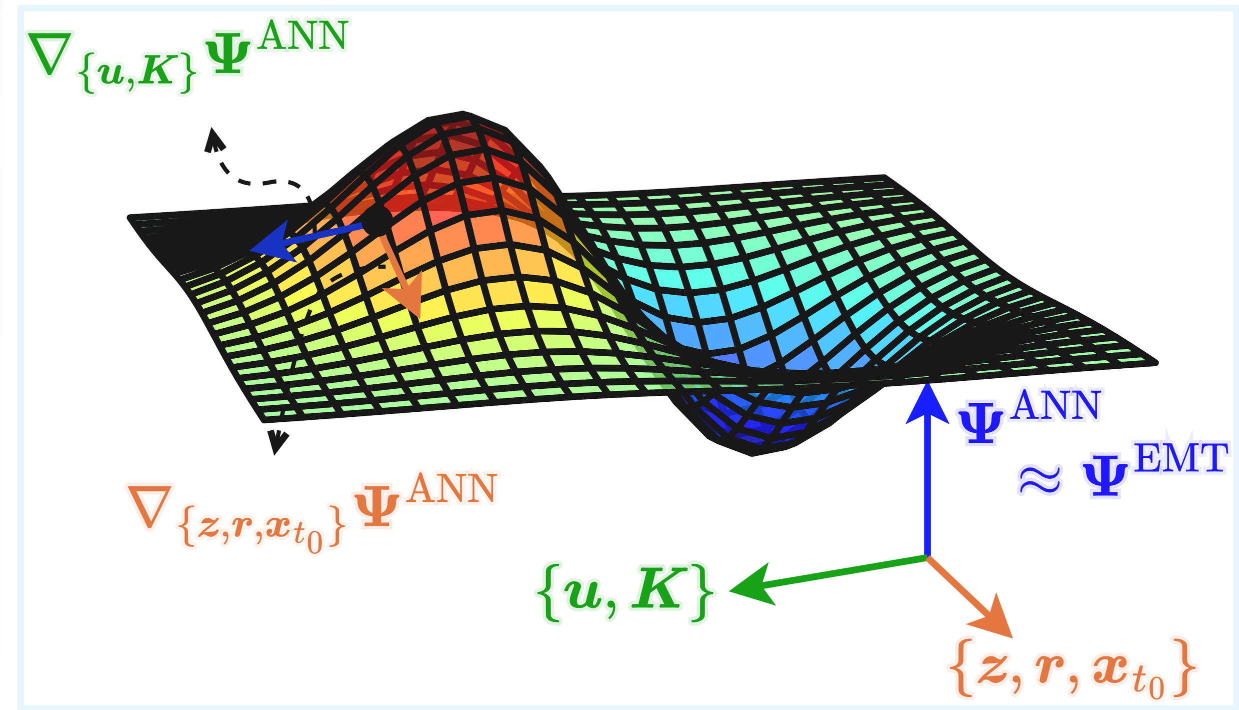

Fig.3: Illustration of gradient-search over ANN approximation of EMT mapping.

Within the **gradient-based** search, **disturbance-dispatch** agents aim to maximize the ANN-approximated dynamic error, $\Psi^{ANN} \approx \Psi^{EMT}$, while a **control design** agent aims to minimize the worst-case dynamic error. The overall method can be enhanced by:

- Using genetic algorithms to train ANNs,
- Using multiple agents per gradient search,
- Validating ANN accuracy against EMT,
- Re-training ANN as new data is gathered.

This **data-driven loop** seeks to find the optimal **control design** (among $\mathcal{A}^u$ and $\mathcal{A}^K$) that remains **robust** across a wide range of **large-signal events** ($\mathcal{A}^z$) and **operating conditions** ($\mathcal{A}^r$), without requiring access to proprietary IBR model details. ***Implementation of this method is currently in progress.***

References

[1] T. Ochoa, B. Chaudhuri, M. O'Malley. Optimal Control for Robust Dynamic Performance in Inverter-Dominated Power Systems. Part I: Modeling and Problem Formulation. TechRxiv. August 07, 2025.

[2] T. Ochoa, B. Chaudhuri, M. O'Malley. Optimal Control for Robust Dynamic Performance in Inverter-Dominated Power Systems. Part II: Optimization and Results. TechRxiv. August 07, 2025.

UKRI Engineering and Physical Sciences Research Council
LEVERHULME TRUST