Decision-Focused Learning for Power Systems Optimization

Large-scale renewable energy portfolio optimization

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Context

Classical optimization tools were not designed to manage this level of uncertainty brought by renwables

A new operational challenge

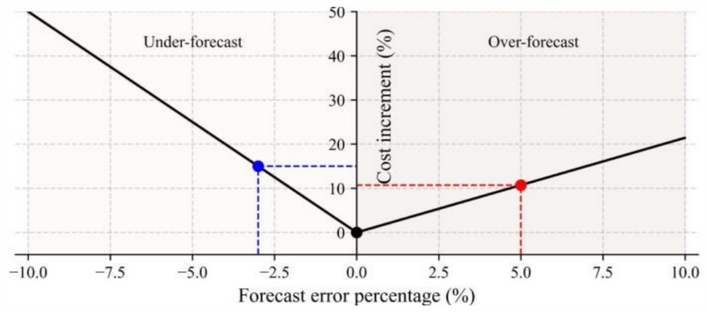
Improving decision-making under uncertainty

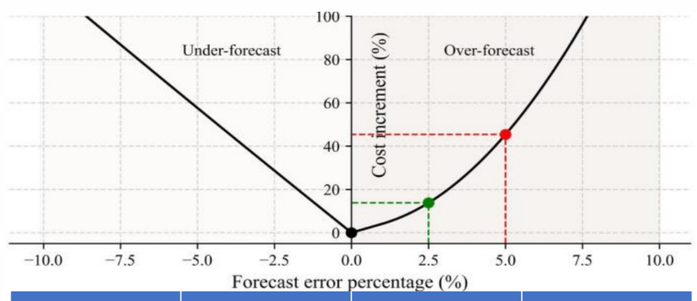
Better forecasts are required, but they should serve the decision, not be an end in itself

Aligning predictions with the decisions they drive

Decision-Focused Learning

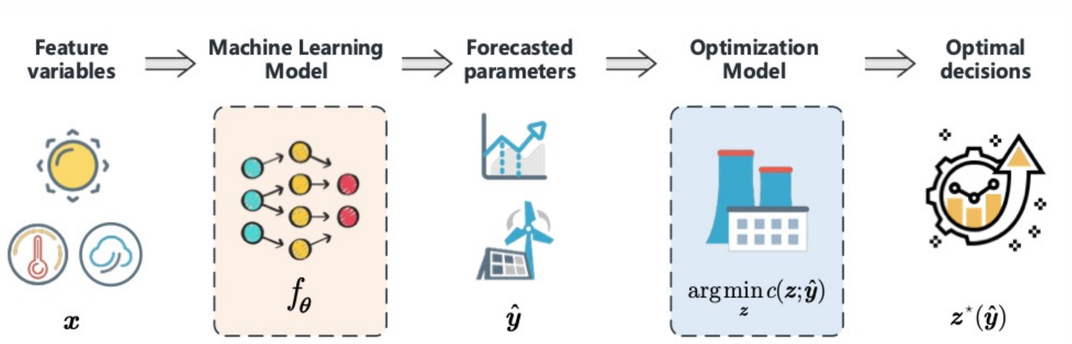
Better forecasts don't always yield to better optimization results



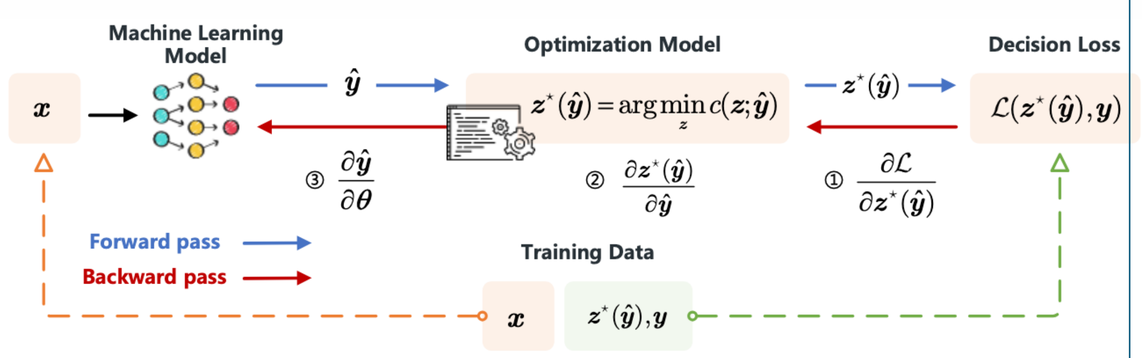


Label	True value (MW)	Forecasted value (MW)	Forecast error percentage (%)
	50	50	0
	50	52.5	5
	50	51.25	2.5
	50	48.5	-3

Predict then Optimize Framework vs Decision Focused Learning



Predict then Optimize



Decision-Focused Learning

State of the Art: Taxonomy of methods

Indirect approaches

Analytical Differentiation	Exact gradients computing by differentiating the optimality
Analytical Smoothing	Problem smoothing and relaxing to be able to perform analytical differentiation
Smoothing by random perturbations	Gradient approximation thanks to introduced random perturbations
Differentiation of surrogate methods	Task-loss or optimization problem surrogate introduced
Unrolling	Making explicit the steps of the iterative algorithm used to solve the optimization problem

Direct approaches

Feasible by design	Prescriptive trees
	But most approaches have issues to guarantee feasibility

To mitigate the feasibility problems

Post processing	Output is projected in the feasible region
Regurlarization	Constraints violations as a term in the training loss

TotalEnergies
FRANCE 2030 PROGRAMME DE RECHERCHE SYSTÈMES ÉNERGÉTIQUES & ÉNERGIES RENOUVELABLES
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Figures from « Decision-Oriented Learning for Future Power System Decision-Making under Uncertainty », Li et al