Accelerate Energy Decarbonisation by Efficient Forward and Inverse Energy System Design using Machine Learning

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1 Background

Existing energy systems were designed for a grid based on conventional generation and transmission technologies which are dominated by large, centralised fossil fuel power plants. The rapid development in recent years of low-carbon resources, including intermittent renewable resources (wind and solar), energy storage, and distribute energy systems have created a new set of challenges for power system and local energy system design.

2 PhD project: forward and inverse energy system design using machine learning

In current energy system planning phase, system designers generally use physical models of energy systems to find an optimal solution through a traditional forward design process (as illustrated in Figure 1).This PhD project seeks to enhance the productivity in the execution of the planning phase of the technology development process by **developing two-way tools that improve energy system design using machine learning for accelerating energy decarbonisation**: 1) accelerated forward design (as illustrated in Figure 1) by automating the optimisation of the system configuration and by lowering the cost of running the physical model based evaluation process; 2) accelerated inverse design (as illustrated in Figure 1) to reduce design time and iteration by leveraging the universality of deep neural networks (DNN) to develop explicit function representations for designs as functions of their performance targets/objectives.

Accelerated Forward Design: the project seeks to enhance the capability of designers to solve the optimisation problem, frequently Mixed Integer Non-Linear Problems (MINLP), in forward design of energy systems. This overarching optimal design capability may be further sub-divided into two supporting capabilities: 1) intelligent automated system design for an improved initial system configuration for forward system design that improves the convergence; and 2)low cost automated system model evaluation that minimises the computational time.

Accelerated Inverse Design: iterative design procedures using optimisation algorithms is often time-consuming and expensive due to the multiple iterative costly objective function evaluations. Machine learning (i.e. DNNs) offers the potential to be universal function approximators, which could provide explicit function representations for finding (near) optimal design parameters as functions of their techno-economic objectives.

3 MSc project: PV-storage system optimal design

The MSc project focuses on a specific design problem of photovoltaics (PV) plus storage for meeting varable electrical demands. In 2018, cumulative PV installed capacity is 512 GWp, contributing to more

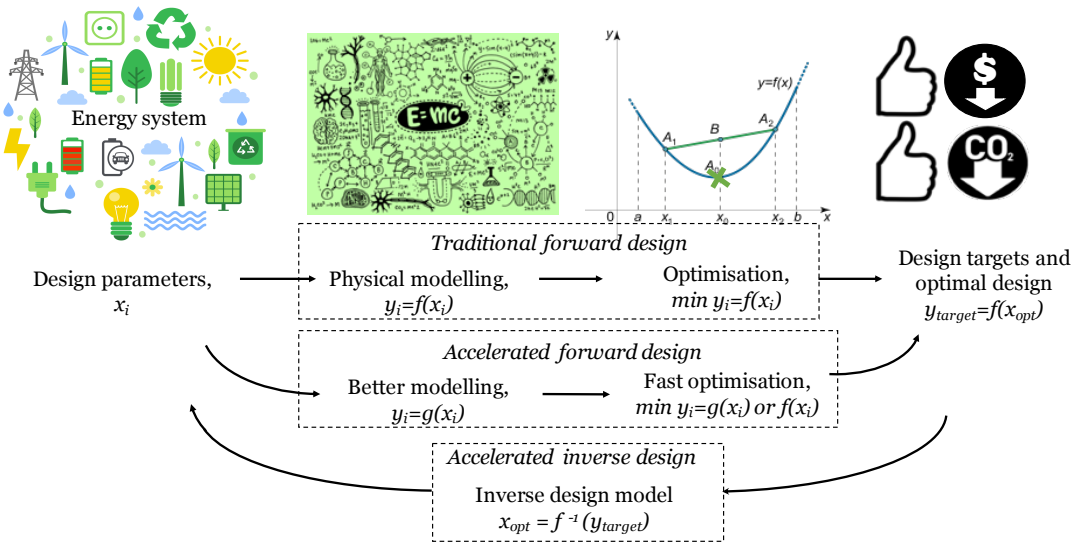

Figure 1: Illustrated traditional forward design, accelerated forward design, and accelerated inverse design processes.

than 8% annual electricity consumption in the world. To further accelerate the use of solar energy worldwide, cost reduction of solar plus storage is important.

Research content of the MSc project: in PV-storage system forward design, reinforcement learning (RL) is used to enhance the efficiency of the MINLP optimisation process by providing "more intelligent" system design updates using a well-trained RL policy. In the PV-storage system inverse design, with the optimal design results from the forward design process, a DNN-based inverse design approach is used to develop an explicit functional representation for the unknown system size design parameters (power/energy capacity of each component) given the desired performance (e.g. cost and reliability) and electrical demands need to meet.