SPATIALLY-EXPLICIT PROBABILISTIC PROJECTIONS OF GRANULAR ENERGY TECHNOLOGY DIFFUSION AT SUBNATIONAL LEVEL

Nik Zielonka, Renewable Energy Systems, Institute for Environmental Sciences, University of Geneva
Boulevard Carl-Vogt 66, CH-1211 Geneva 4, Switzerland
+41 22 379 08 26, Nik.Zielonka@unige.ch
Xin Wen, Renewable Energy Systems, Institute for Environmental Sciences, University of Geneva
Evelina Trutnevyte, Renewable Energy Systems, Institute for Environmental Sciences, University of Geneva

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Overview

Projections of granular energy technology diffusion can support decision-making on energy transition policies and infrastructure investments. However, such projections often do not account for uncertainties and have low spatial resolution (1–4). To project future installations of technologies, S-curve models are widely used but the results of the different models can vary significantly and are sensitive to the choice of model parameters (5–7).

Methods

We present a method to create spatially-explicit probabilistic projections of granular energy technology diffusion based on historical time series data and to evaluate which of the tested S-curve models perform best in terms of accuracy and uncertainty when compared to the real diffusion. As a case study, we investigate the growth of three granular technologies – solar PV, heat pumps, and battery electric vehicles (BEV) – at municipality level throughout Switzerland historically in 2000 – 2021 (evaluation) and until 2050 (projection).

For each of 2'148 Swiss municipalities, we create probabilistic projections by fitting twelve different S-curve models on the historical time series data of each technology's diffusion and then by combining the curves of historically similar municipalities to form probabilistic density intervals for each S-curve model. The chosen S-curves are logistic, Gompertz, Bass, Bertalanffy, a four-parameter and a five-parameter version of the generalized Richards model, and linear combinations of each model with itself, creating Bi-S-curves to model two growth phases, e.g., due to changes in policies. We evaluate each probabilistic projection using iterative hindcasting and performance metrics like mean absolute percentage errors (MAPE) and weighted interval scores (WIS) that approximate the continuous ranked probability score (8). We then convert the WIS scores of each probabilistic projection into weights that we use to combine the models to create a final probabilistic projection for each municipality. To create a national projection, we sum the quantiles of all Swiss municipalities.

Results

Consistently for all S-curve models and technologies, we find with hindcasting that the projected medians of the probabilistic projections have lower MAPE than the corresponding deterministic projections and thus probabilistic projections estimate the technology diffusion more accurately. While accuracy and probabilistic density intervals of the models vary across technologies, municipalities, and years, Bertalanffy and Richards models show on average lower MAPE and WIS and thus estimate the future diffusion with higher accuracy and precision than the ones of logistic, Gompertz, and Bass models. However, Bertalanffy and Richards and some Bi-S-curves highlight that projections of a model might be accurate while their probabilistic density intervals are either too narrow or too wide to be meaningful.

According to our forward-looking national probabilistic projections for Switzerland with training on historical data until 2021, the diffusion of solar PV, heat pumps and BEV is unlikely to reach the levels that most scenarios from literature estimate for a Swiss energy system with net-zero greenhouse gas emissions in 2050 (Figure 1a-c). The medians of the projections estimate for 2050 a solar PV capacity of 12.5 GW, 570'000 buildings with a heat pump and 1.4 million BEV. Looking across the Swiss municipalities, our spatially-explicit projections estimate for 2050 that higher capacities are generally concentrated most likely where population is higher, i.e., in the north-east of Switzerland and around larger cities (Figure 1d-f). Capacities are comparatively low in the south and in the north-west, which are both mountain regions of Alps and Jura. Regional differences are most extreme for BEV, where the number of BEV in the municipality with most BEV is 200 times higher than the median of all municipalities in 2050. For solar PV and heat pumps, the corresponding factors are 54 and 30, respectively.

Conclusions

With the examples of the three granular technologies of solar PV, heat pumps, and BEV, we show that our probabilistic projections provide both more accurate and robust results than the respective deterministic projections and at the same time provide a more complete picture on the uncertainty. At the same time, we find with our investigated models and evaluation criteria that combine different models into one weighted probabilistic projection reduce tradeoffs between advantages and disadvantages of single models. Based on such weighted probabilistic projections and training until 2021, we show that Switzerland has to increase efforts to reach its national energy transition targets with higher certainty by 2050.

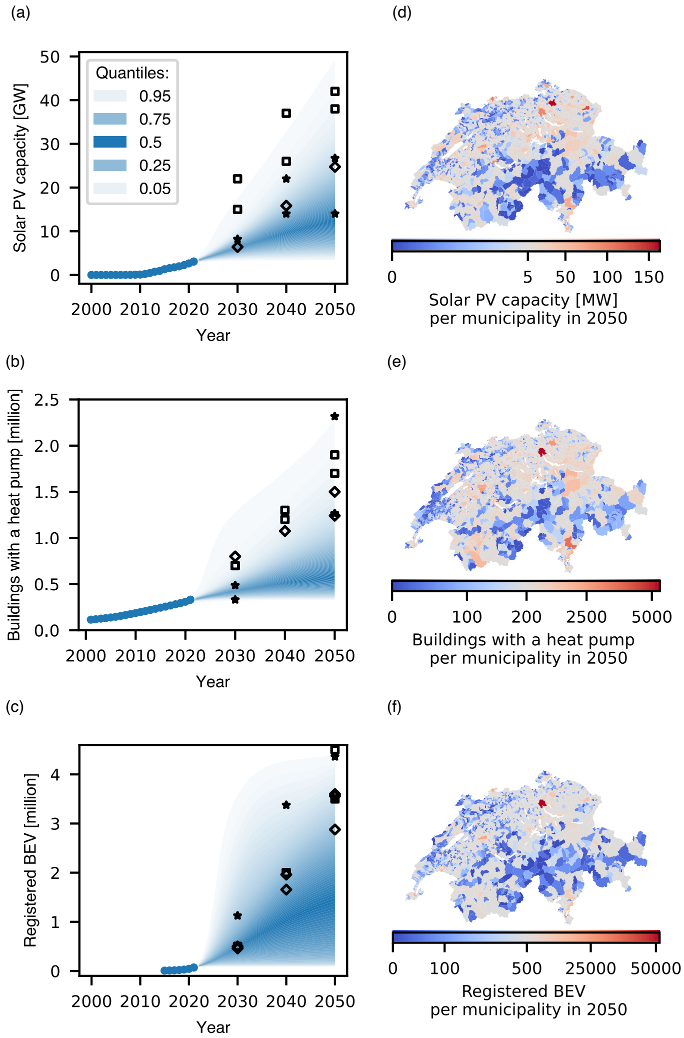

Figure 1. Probabilistic projections (a-c) of the diffusion of solar PV capacities, heat pumps, and BEV in Switzerland until 2050 and maps (d-f) with the projected median values of each municipality in 2050, both with a quantile coloring scheme. The quantiles of the national projections are the sum of the respective quantiles of all municipalities. The black marker set targets for reaching an energy system of net-zero greenhouse gas emissions by 2050, estimated in studies for the Swiss Federal Office of Energy (◊) (9), (□) (10), and for the association of Swiss electricity companies VSE (*) (11). If different scenarios exist, highest and lowest values are shown.

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