

EGU21-6563

<https://doi.org/10.5194/egusphere-egu21-6563>

EGU General Assembly 2021

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## Machine learning-based allocation of renewable power production

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The integration of renewable energy sources into the power grid is of the utmost importance for achieving the goal of zero carbon emission. Although there are feasibility studies showing that renewable energy might be able to cover 2050 global energy demand using less than 1 % of the world's land for footprint and spacing, see Jacobson and Delucchi (2011), nowadays renewable energy production is known to be highly intermittent due to substantial uncertainties in the weather conditions. One possibility to reduce such uncertainty (besides storage and employing hydrogen technologies) is spatiotemporally diversified allocation of renewable power capacities which (alongside with the transmission infrastructure) should guarantee that the power demand is met at any given time with a certain (high) probability. We treat the question of spatiotemporal diversification of renewable capacities as a Markowitz portfolio problem with the difference that instead of  $n = 1, \dots, N$  stocks we have geographical locations each with a certain expected level of renewable power production (instead of expected returns for stocks) and the corresponding variance. Another difference to a classical Markowitz portfolio problem is that we require additionally that at each given time point  $t = 1, \dots, T$ , we can reach a predetermined level of renewable power production with a certain probability, i. e. we solve so called chance-constrained problem. Finally, instead of solving one-step problem as it is the case with a Markowitz portfolio we reformulate our problem in the optimal control framework in continuous time and solve it with a reinforcement learning algorithm as suggested in Lillicrap et al. (2019). The advantage of this approach is that the optimal capacities (control) are updated continuously as a response to changing weather conditions (state). We exemplify our approach with the data from ERA5 data, see Hersbach et al. (2020), and suggest possible allocation of renewable energy sources across the European Union.