

1 Info on Simulation study

The following Simulations are generated with the class fro the mandetory as-
signment.In this simulationstudy we have changed the unit of measurement
to m^2 instead of Km^2 KWH instead of MWH.We devide the gridprice which
is said to have the unit \$/KWH by 10.

We conducted an evaluation of the provided microgrid system as part of
the mandatory assignment. Our approach involved employing deep rein-
forcement learning techniques within the Gym framework, utilizing a cus-
tom environment tailored to the Gym package. Prior to employing deep
reinforcement learning through Stable Baselines 3, we created a bespoke en-
vironment using Gym. In this segment of the study, we applied the PPO
(Proximal Policy Optimization) algorithm from Stable Baselines,with these
parameters,

PPO("MlpPolicy", env, verbose = 1, ent_coef = 0.01, learning_rate = 0.01).

The microgrid system features a key function named 'transition,' responsi-
ble for tracking the energy stored in the battery in kilowatt-hours (KWh).
Additionally, this function updates the '*working_space*' variable, a vector of
length 3. Each element of this vector can either be 1 or 0, signifying the status
of various energy sources. The first element indicates whether solar genera-
tion is active, the second for wind generation, and the last for the generator.
These values are updated through the '*action_adjust_workingstatus*' vari-
able, which shares the same length. For example, if '*action_adjust_workingstatus*'
is [1, 1, 0], it means the microgrid aims to generate energy using both wind
and solar sources.

Furthermore, each energy generation type corresponds to specific action vec-
tors. The energy generated can either support the load, store energy, or be
sold back to the grid. These actions are represented in the code as variables
named '*wind_action*,' '*solar_action*,' and '*generator_action*.' For instance,
if '*wind_action*' is [1, 1, 0], the microgrid utilizes generated wind energy to
support the load and charge the battery.

Another action determines whether to purchase energy from the grid. We
implemented this action deterministically, based on whether the microgrid
produces enough energy to meet the household load or not. Additionally,

there's an action to discharge the battery. Both of these actions are binary variables. While it was possible to include a binary variable within '*action_purchase*' to determine whether energy bought from the grid could be stored in the battery, we opted for a simpler approach.

The observation space of the microgrid environment encompasses windspeed, solar irradiance, total household load, the working status, and the State of Charge (SOC) of the battery.

Comparing our policy to random one for all simulations using 25,100 and 250 households, only using solar, we see an improvement in the reward. All plots of total accumulated reward show a more positive reward, which is denoted as the negative of the cost, for the learn RL policy. We see that random policy generates less solar for all simulations in addition to being less intelligent about its energy management when it comes to other energy source, how much to sell back and how much to buy from the grid. When we start using other energy sources as well, wind is more popular.

The new reward in question 4 is performs worse than the reward used in the first part of the assignment. The reward is defined only through the amount it buys from the grid. Since we defined our reward as the negative of the cost we want the reward to be large as possible. Since the new cost only is defined through using energy bought from the grid, it should have penalized buying from the grid, but the opposite is happening. Even for small purchases from the energy grid, the cost will increase nonlinearly. Since the microgrid cannot support the whole energy load it will have to buy from the grid, and even if it buys less it will still contribute the cost. One other reason might be that we haven't run the RL algorithm for long enough.