oemof developer meeting –
session on rolling horizon optimization

Implementation of a rolling horizon / myopic optimization approach in the ER fundamental power market model

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Motivation and background

Motivation

- General modelling approach: Using a **power market model** for
  - investment resp.
  - dispatch optimization

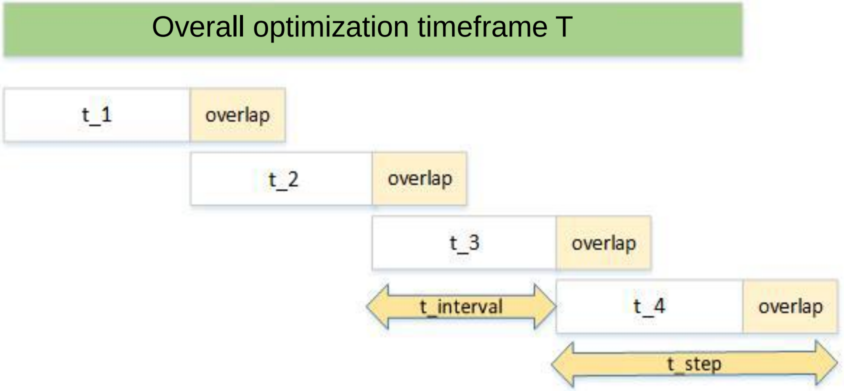
  for Germany implemented using oemof

- Need for measures for complexity reduction to fasten up solution times
  - dispatch model: Rolling horizon

  - investment model: Myopic optimization

  implemented as an option which can be chosen.

Basic concept



- Basic approach identical
  - dispatch model: shorter timeslices
    → a couple of days / weaks

  - investment model: longer timeslices
    → (multiple) entire years with limited foresight* and not necessarily an overlap

*drawback: no longer term prognosis on future earnings Integrated (yet) which would influence investment decisions

Implementation: dispatch example (1) – initialization

1. Initialize by setting / calculating necessary parameters

```
timeslice_length_wo_overlap_in_hours = 168
overlap_in_hours = 48

# starttime and endtime must be manually set here
timeseries_start = pd.Timestamp(starttime, freq)
timeseries_end = pd.Timestamp(endtime, freq)

# Calculate timeslice length as well as overlap length
timeslice_length_wo_overlap_in_timesteps = {'60min': 1, '15min': 4}[freq] * timeslice_length_wo_overlap_in_hours
overlap_in_timesteps = {'60min' : 1, '15min' : 4}[freq] * overlap_in_hours
timeslice_length_with_overlap = timeslice_length_wo_overlap_in_timesteps + overlap_in_timesteps

# Calculate amount of timeslices needed
overall_timesteps = timesteps_between_timestamps(timeseries_start, timeseries_end, freq)
amount_of_timeslices = math.ceil(overall_timesteps / timeslice_length_wo_overlap_in_timesteps)
```

*min uptime / min downtime constraints may be violated in our current implementation state when crossing timeslices.

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logging.info('Creating a LP optimization model for dipatch optimization \n'
             'using a ROLLING HORIZON approach for model solution.')

# Initialization of RH model run
counter = 0
storages_init_df = pd.DataFrame()
...
results = pd.DataFrame()
power_prices = pd.DataFrame()
```

Empty DataFrames used to store initial states:

- LP dispatch model: storage level only (1)
- MILP dispatch model: (1) + transformer states*
- LP invest model: (1) + all investment variables

*min uptime / min downtime constraints may be violated in our current implementation state when crossing timeslices.

Implementation: dispatch example (2) – model run; basically a for-loop

2. Iteratively build-up and solve model using a (simple) for-loop

```
# For loop controls rolling horizon model run
for counter in range(amount_of_timeslices):

    # (re)build optimization model in every iteration
    # Return the model, the energy system as well as the storage information
    om, es, timeseries_start, storage_labels, datetime_index \
        = build_RH_model(path_folder_input, filename_node_data, filename_cost_data,
                         AggregateInput, Europe,
                         fuel_cost_pathway, timeseries_start,
                         timeslice_length_wo_overlap_in_timesteps,
                         timeslice_length_with_overlap,
                         counter,
                         storages_init_df,
                         freq, year)
```

Build model using initial states

- Slice timeseries:
  - Use full length (incl. overlap) for reading in data
  - Set starting point of next iteration (excl. overlap)
- Set initial states:
  - Obtained from input sheets for first iteration
  - Stored in Dataframe elsewhise

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                         timeslice_length_with_overlap,
                         counter,
                         storages_init_df,
                         freq, year)

    # 14.05.2019, JK: Solve model and return results
    om, model_results, results, overall_objective, overall_solution_time, \
    power_prices = solve_RH_model(om, datetime_index, counter,
                                  timeslice_length_wo_overlap_in_timesteps,
                                  results,
                                  power_prices,
                                  overall_objective,
                                  overall_solution_time,
                                  solver = solver)
```

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Solve model

- optimize
- concat results (excl. overlap)

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                                  power_prices,
                                  overall_objective,
                                  overall_solution_time,
                                  solver = solver)

    # Set initial states for the next model run
    # initial status for the first iteration is obtained from input data
    storages_init_df = initial_states_RH(model_results, timeslice_length_wo_overlap_in_timesteps,
                                         storage_labels)
```

Build model using initial states

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Solve model

- optimize
- concat results (excl. overlap)

Obtain initial states

- get initial states (for next iteration)

Implementation: investment example – An overview on our myopic approach

- What differs compared to our dispatch implementation?
  - timeslices must be (multiple) entire years
  - a distinction between non leap years and leap years is included
    → leads to varying timeslice lengths
  - For this purpose, we introduced a timeslice_length_dict:

information stored for all iterations i

```
timeslice_length_dict = {i: (amount_of_years[i], timeslice_length_excl_overlap[i], timeslice_length_incl_overlap[i])}
```

  - …Most importantly: We call it myopic optimization, not rolling horizon optimization anymore. ;-)

Critical discussion and outlook

Critical discussion

- Drawbacks for our approach
  - General: We lose a global optimum
    → decide on the basis of the modeling task and the hardware available
  - High computational overhead:
    - necessary data is read in „in chunks“
    - energy system is build up in every iteration
  - Lacking elements
    - Dumps are not properly included (yet)
    - Interemporal linking constraints are missing
- Advantages for our approach
  - Functional structure enables reusability
  - Computational advantage for MILP

Outlook

- What we will (probably) do
  - Check whether we need this or whether other solutions can be found, like time series aggregation… or computing power
  - Reduce overhead
    - We prefer reading in the dataset upfront
    - Is there a workaround (planned) for not having to build the model everytime???
  - Close the gaps
    - We will add proper dumps and unfold these at the end
    - Introduction of linking constraints dependent on whether we will use MILP / need a rolling horizon approach at all…
  - Have a look on whether parts of the formulation can be generalized and made available in a small example

Literature

- Büllesbach, Fabian (2018): Simulation von Stromspeichertechnologien in regionaler und technischer Differenzierung. Freie wissenschaftliche Arbeit zur Erlangung des Grades eines Master of Science am Fachgebiet Energie- und Ressourcenmanagement der TU Berlin.
- Marquant, Julien F. ; Evins, Ralph and Carmeliet, Jan (2015): Reducing Computation Time with a Rolling Horizon Approach Applied to a MILP Formulation of Multiple Urban Energy Hub System. In: Procedia Computer Science 51 (2015),S. 2137–2146. – ISSN 18770509