Multi-Horizon Planning with Perfect Foresight

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Abstract

Sketch interface and math for PyPSA interface for multi-investment-period optimization with perfect foresight.

Keywords: renewable energy policy, storage, large-scale integration of renewable power generation

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1. Literature review

1.1. Model typology

Models optimize the net present value NPV of expenditures versus income in the energy system over several decades (e.g. 2020-2050), discounting cash flows a years after the present by the discount factor $(1 + r)^{-a}$ for interest rate r.

There are two ways of dealing with multi-horizon investment in the literature:

1. Using the full overnight cost in the year of investment

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2. Distributing annualised costs over the years in which the asset is active (lifetime years after build year)

Type 1 models include OSeMOSYS, DIMENSION, ESO, LUSYM, TIMES.

Type 2 models include SWITCH, Temoa, Balmorel and GENESYS2.

The problem with Type 1 is that the full cost of investments towards the end of the investment period (e.g. made in 2050) is paid while the full benefit (electricity generation after 2050) is not seen. OSeMOSYS gets around this by giving late investments a 'salvage value' for benefits after the investment period. DIMENSION gets around it by running simulations beyond the period of interest (e.g. up to 2070) but at lower intra-year resolution. ESO doesn't deal with this issue. It caused the GENESYS team problems I think before they switched to Type 2.

Type 2 models bypass this problem by always considering the annualized costs in each investment period.

Type 2 models also allow to use a different, even technology-specific WACC for the annualized costs than the global discount rate used for NPV. For example, in [1] a social discount rate of 2% was used for NPV, while a WACC of 7% was used for investments.

Both models can have issues if the end-of-life of an asset lands in the middle of an investment period (e.g. asset is dismantled in 2045 when we only have investment periods represented for 2030, 2040 and 2050).

Now for the mathematical formulaion.

Consider just power generation for simplicity. G_s [MW] represents the new generation capacity built for generator s with build year b_s at node n_s with lifetime L_s. If the asset is built in year b_s it is available from 1st Jan in year b_s up until 31st December in year $b_s + L_s - 1$.

The specific investment cost is k_s [$€MW^{-1}$]. The annualized investment cost is c_s [$€MW^{-1}a^{-1}$], which is related to k_s by:

$$k_s = \sum_{b=0}^{L_s-1} \frac{c_s}{(1+r)^b} \tag{1}$$

This is assuming that the investment cost is paid back by a loan for the full lifetime; Temoa has the option of loan lifetimes below the technology lifetime. 'Loan' could also be a mix of equity and debt.

The cost minimization objective for Type 1 then only has terms for generators built in year a:

$$\min_{\{G_s,\ldots\}} \sum_{a=0}^{A-1} \frac{1}{(1+r)^a} \left[\sum_{s|b_s=a} k_s G_s + \text{O\&M, fuel, etc.} \right] \tag{2}$$

The cost minimization objective for Type 2 is then:

$$\min_{\{G_s,\ldots\}} \sum_{a=0}^{A-1} \frac{1}{(1+r)^a} \left[\sum_{s|b_s \leq a < b_s+L_s} c_s G_s + \text{O\&M, fuel, etc.} \right] \tag{3}$$

They are only equivalent if $A \to \infty$. Check this by substituting (1) into (2) and replacing the summation of a with a new variable $c = a + b$. You get terms with a discount factor for $A \leq a < A + L_s$.

1.2. Discussion of other models in the literature

1.2.1. OSeMOSYS

Developed by KTH and others.

https://osemosys.readthedocs.io/en/latest/manual/Structure%20of%20OSeMOSYS.html#equations
https://osemosys.readthedocs.io/en/latest/manual/Structure%20of%20OSeMOSYS.html#salvage-value

Type 1. Uses salvage value in final investment period to avoid end-of-horizon effects.

1.2.2. Temoa

Developed by Joe DeCarolis et al.

https://temoacloud.com/temoaproject/Documentation.html#objective-function

Type 2, but has a sophisticated approach that takes account of different technology-specific discount rates for the loan (DR_t for technology t) different from global discount rate GDR used for NPV, loan lifetimes $LLN_{t,v}$ for vintage

(build year) v separate from lifetime $LP_{t,v}$. P_0 is beginning of the horizon and $LPA_{t,v}$ is the active lifetime before the end of the horizon.

So that long-lived technologies (nuclear, coal) are not disadvantaged by their investment costs being paid off by loans long before the full value over the lifetime is realised, the loan amortization is re-amortized with the GDR, spreading it over the full technological lifetime.

1.2.3. DIMENSION

Developed by EWI [2].

Type 1. Run model after period of interest (e.g. to 2070) to avoid end-of-horizon effects.

[2]: 'In addition, the model years 2060 and 2070 are included in order to account for long lifetimes of capital-intensive grid and generation capacities.'

1.2.4. ESO

Developed by Imperial College (Clara Heuberger et al) [3].

Type 1 but ignores end-of-horizon.

[3]: "Towards 2050 the storage capacity stock reduces due to the end of lifetime of existing storage capacity to 2.9 GW in 2050. Additionally, as the end of the planning horizon is reached, no new capacity is build for years post-2050. So called "end-of-horizon-effects" can be circumvented by accounting for expected cost/revenues beyond the end of the planning horizon, however are outside the scope of this work."

1.2.5. SWITCH

Developed by Hawaii (Matthias Fripp et al).

Type 2.

https://ars.els-cdn.com/content/image/1-s2.0-S2352711018301547-mmc1.pdf (Section 4.3.5)

1.2.6. Balmorel

Developed by DTU (Hans Ravn et al).

Type 2.

http://balmorel.com/images/downloads/model/BMS303-20190311.pdf

Separates social discount rate ("society's perception of how future years' costs and benefits shall be evaluated today") from the rate for annualisation ("to represent the actors' (e.g., companies or TSOs) perception of financing costs, alternatives, expectations to profit, risks, etc").

1.2.7. GENESYS2

Developed by RWTH (Christian Bussar et al), not to be confused with GENESYS-MOD from DIW / TU Berlin. GENESYS2 is Type 2 I think. I think GENESYS1 was Type 1, but they changed it.

1.2.8. LUSYM

Leuven University SYstem Model (LUSYM) [4] considers both myopic and perfect foresight models.

The perfect foresight model is Type 1 with salvage value.

1.2.9. PRIMES

Type 2 with different social versus financial discount rates, according to Marta Victoria.

EU Reference Scenario 2016, in which discount rates are much better explained (section 2.6.1 and annexe 4.4).

"Assessing transition scenarios which have different distributions over time of investments and benefits requires in addition calculating present values, in which it is appropriate to use a social discount rate for discounting costs and benefits occurring in the future."

1.2.10. TODO: TIMES

[4] claims similar to LUSYM, i.e. Type 1 with salvage values.

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investment period a	represents	intra-year time periods T_a
2020	01.01.2020 - 31.12.2029	(summer,winter)
2030	01.01.2030 - 31.12.2049	(summer,winter)
2050	01.01.2050 - 31.12.2059	(spring,summer,autumn,winter)

Table 1: Investment periods in example.

index a	investment_weightings w_a	energy_weightings v_a
2020	$\sum_{a=0}^{9}(1+r)^{-a}$	10
2030	$\sum_{a=10}^{29}(1+r)^{-a}$	20
2050	$\sum_{a=30}^{39}(1+r)^{-a}$	10

Table 2: network.investment_period_weightings w_a for our example

1.2.11. TODO: PLEXOS

2. PyPSA suggested implementation and interface design

2.1. Overall

Use Type 2 since it takes better account of end-of-horizon effects and because it allows to use a separate discount rate for the NPV discounting to the annualization of capital costs.

Things to be careful for:

- constraints on total wind capacity at any time at a location

- CO_2 constraints on particular investment periods AND option to do budget over all investment periods

2.2. Code design principles

Should default to old single horizon behaviour.

It's OK if it only works with `pyomo=False` as long as there is a warning of missing functionality for `pyomo=True`.

2.3. Example use case for data design

Consider power generation at a single node with a single load and the options of wind and gas generation.

The investment periods a under consideration are: 2020, 2030, 2050, see Table 1. Each period can represent a different number of intervening years. For each investment period there are different intra-year time periods T_a to represent load and weather conditions $t \in T_a$. These can vary in number and e.g. weather conditions, since users may want a higher resolution in later years where there are more renewables and wind, and the weather may change due to climate change.

I suggest a new `pandas.DataFrame` called `network.investment_period_weightings` analogous to `network.snapshot_we` that encodes the investment weighting for the objective function w_a for investment period a as well as the energy weighting for CO_2 constraints etc v_a, see Table 2 for our case. This allows the user to customize the weighting. This would default to index= (now), weightings= (1, 1) with no multi-horizon optimization.

`network.snapshots` would now have a `pandas.MultiIndex`, see Table 3 for an example `network.snapshot_weightings` $w_{a,t}$, where t runs over the intra-year time periods T_a for each investment period a.

For a load `my_load`, `network.loads_t.p_set` $d_{a,t}$ would look like Table 4.

The generators would have a name s and have separate fields for the build year b_s, node n_s and lifetime L_s, see Table 5. Note that some generators have build years BEFORE the first investment period, so these existing generators take fixed capacity from `p_nom`. Note that lifetimes, capital costs, efficiencies, etc. can change depending on the build year. The `capital_cost` here is now the fixed annual costs, including annuity and FOM.

Note that not all technologies need to be represented with build years in each investment period. You may want to forbid new coal plants being built after 2020, or have new technologies like small modular nuclear reactors (SMR)

index (a,t)	snapshot_weightings $w_{a,t}$
(2020,summer)	4380
(2020,winter)	4380
(2030,summer)	4380
(2030,winter)	4380
(2050,spring)	2190
(2050,summer)	2190
(2050,autumn)	2190
(2050,winter)	2190

Table 3: network.snapshot_weightings $w_{a,t}$ for our example

index (a,t)	my_load
(2020,summer)	2
(2020,winter)	3
(2030,summer)	3
(2030,winter)	4
(2050,spring)	4
(2050,summer)	4
(2050,autumn)	5
(2050,winter)	5

Table 4: network.loads_t.p_set $d_{a,t}$ for our example

only available from 2040. Some technologies like PV and wind will improve capacity factors over time with e.g. better efficiencies and higher hub heights.

Note that the `build_year` and `lifetime` attributes are only used to determined whether the generator is active in a particular investment period a. They are NOT used to annualize the costs to get the `capital_cost` - this is done by the user. I can imagine situations (like transmission lines) where we set `capital_cost` based on 40 years, but set `lifetime` to 100 years since we don't know exactly when each line was built, but want it there in all investment periods.

Note that the `p_nom_max` for each generator is now the installable limit for this build year.

We will need separate constraints for the total capacity $\bar{G}_{r,n,a}$ of each technology r (e.g. wind, solar) existing at each node n in each year a that sums up the active assets for the total installable potentials for each technology at each node. This can change with a if e.g. more or less land becomes available due to changes in agriculture / city development.

The availability factors $\bar{g}_{s,a,t}$ for generator s in investment period a at time t are given by `network.generators_t.p_max_pu` like in Table 6. Availabilities for years where the generator is inactive are ignored and can be set to zero.

Results from optimization the generator optimal capacities `network.generators.p_nom_opt` for the active investment periods as well as the `network.generators.p` indexed and columned like `network.generators_t.p_max_pu` in Table 6.

For Links, Lines, Stores, StorageUnits, Transformers, etc, just follow the scheme for Generators.

2.4. Optimisation problem in math

We have objection function of Type 2

$$\min_{\{G_s,g_{s,a,t}\}} \sum_{a \in A} w_a \left[\sum_{s|b_s \leq a < b_s + L_s} \left(c_s G_s + \sum_{t \in T_a} w_{a,t} o_{s,a,t} g_{s,a,t} \right) \right] \tag{4}$$

Where now $g_{s,a,t}$ labels the generation of generator s in investment period a and time t.

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index s	build_year b_s	lifetime L_s	capital_cost c_s
gas-10	2010	30	50
gas-20	2020	30	50
gas-30	2030	30	40
gas-50	2050	30	40
wind-15	2015	25	130
wind-20	2020	25	120
wind-30	2030	30	110
wind-50	2050	30	100

Table 5: network.generators for our example

index (a, t)	wind-15	wind-20	wind-30	...
(2020,summer)	0.3	0.32	0	
(2020,winter)	0.5	0.52	0	
(2030,summer)	0.3	0.32	0.35	
(2030,winter)	0.5	0.52	0.55	
(2050,spring)	0	0	0.4	
(2050,summer)	0	0	0.5	
(2050,autumn)	0	0	0.5	
(2050,winter)	0	0	0.6	

Table 6: network.generators_t.p_max_pu for our example

We have constraints for the energy balance (would in reality be for each node with transmission lines, etc.):

$$\sum_{s|b_s \leq a < b_s + L_s} g_{s,a,t} = d_{a,t} \qquad \leftrightarrow \qquad \lambda_{a,t} \qquad \forall a, t \in T_a \tag{5}$$

Then for generator constraints:

$$0 \leq g_{s,a,t} \leq \bar{g}_{s,a,t} G_s \qquad \forall s, a \in [b_s, b_s + 1, \ldots b_s + L_s - 1], t \in T_a \tag{6}$$

CO_2 can be defined in `network.global_constraints` either for a particular year a:

$$\sum_{s|b_s \leq a < b_s + L_s} \sum_{t \in T_a} \frac{e_s}{\eta_s} w_{a,t} g_{s,a,t} \leq CAP_a \qquad \leftrightarrow \qquad \lambda_a \qquad \forall a \tag{7}$$

or as a budget for all investment periods (note that now we're using the energy weighting v_a):

$$\sum_a v_a \sum_{s|b_s \leq a < b_s + L_s} \sum_{t \in T_a} \frac{e_s}{\eta_s} w_{a,t} g_{s,a,t} \leq CAP \qquad \leftrightarrow \qquad \lambda \tag{8}$$

For the total installable potential $\bar{G}_{r,n,a}$ for each technology r and each node n due to land restrictions, etc., we will need something like:

$$\sum_{s|b_s \leq a < b_s + L_s \& r_s = r \& n_s = n} G_s \leq \bar{G}_{r,n,a} \qquad \forall r, n, a \tag{9}$$

For this we will need to tell PyPSA that e.g. wind-15, wind-20, wind-30, wind-50 are technology r (could be just `carrier`?) and then what the $\bar{G}_{r,n,a}$ are (new type of global constraint?).

For endogenous learning, we will need to sum up all the capacity ever built from wind, solar PV, electrolysers etc.

Lisa Zeyen had investment budgets per investment period in her MA thesis, which reflected limits to the amount of financing that can be raised in each year.

Lisa also had costs for dismantling plants early, but we agreed to leave this feature for now. It gets complicated to track O&M costs etc.

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