

Power-to-gas for the mobility sector

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Agenda

This research is part of the activities of SCCER CREST, which is financially supported by the Swiss Commission for Technology and Innovation (CTI).

- "Renewable Methane for Transportation and Mobility"
(joint SNF project in collaboration with HSR Rapperswil and other groups):
Study business cases, recommendations to policy makers
- Economic feasibility for mobility
- Investment analysis by real option approach
- Model components
- Optimization of P2G operations
- Preliminary results & discussion

Power-to-gas as energy storage

- Conversation of electricity to gas (hydrogen, methane)
- Synthetic methane can be stored in natural gas grid
- Links power and gas sector
- Long-term energy storage
(e.g., excess power from renewable generation in summer)
- Steps:
 - Electrolysis: $2\text{H}_2\text{O} (+ \text{electricity}) \rightarrow 2\text{H}_2 + \text{O}_2$
 - Methanation: $\text{CO}_2 + 4\text{H}_2 \rightarrow \text{CH}_4 + 2\text{H}_2\text{O}$ (exothermic)
- CO_2 sources: Biogas plants, waste incinerators, sewage plants, industry (e.g., cement mills), air, ...
- Overall efficiency $\approx 50\%$
- Economic feasibility?

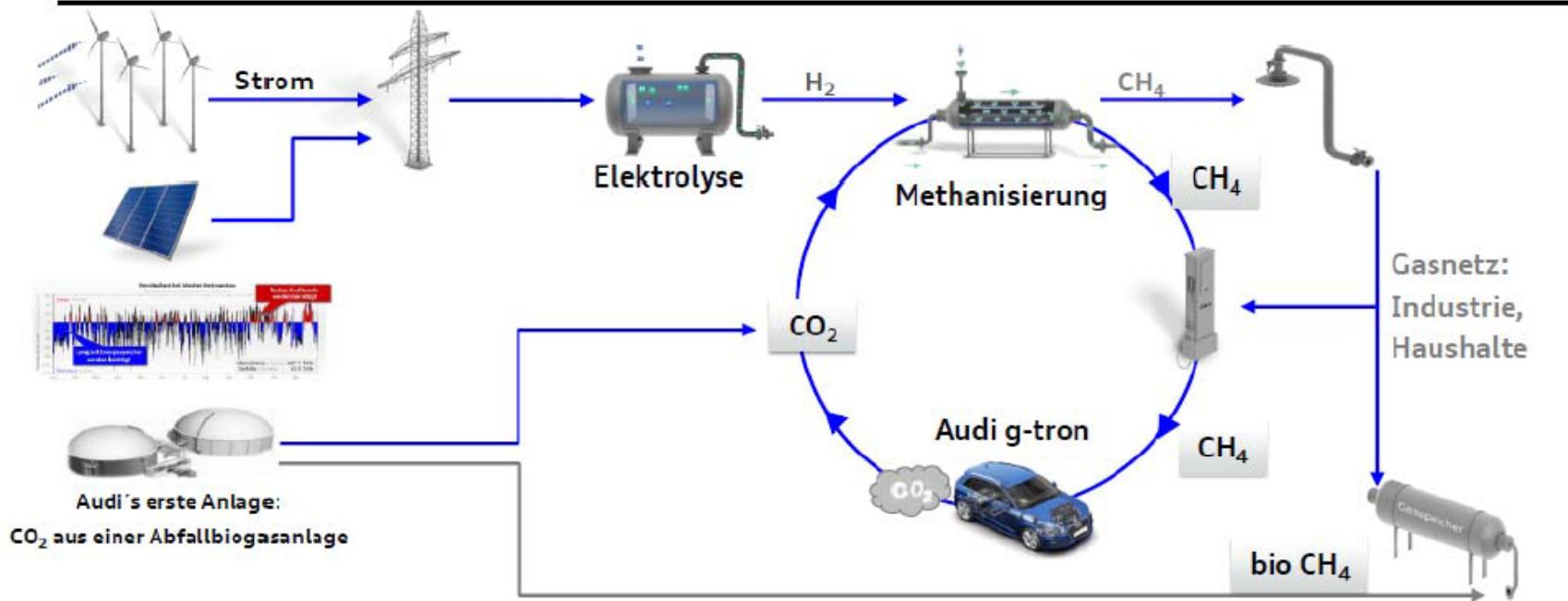
Economic feasibility of P2G

- The profitability of P2G suffers from large installation costs and low efficiency
- Capacity utilization should be high and electricity cheap (no grid fees etc.)
- Conversion of synthetic gas back to electricity reduces efficiency to $\approx 30\%$
- Substitution of fossil gas leads to CO₂ reduction (if SNG is "renewable")
- Use gas for applications in mobility and heat sector
- From 2020 on, the automobile industry faces severe penalties if a limit for the CO₂-emissions of newly sold cars is exceeded (95 EUR per unit)
- New law in Switzerland:
 - Car manufactures/importers may offset CO₂ emissions of their fleet if they provide synthetic fuels for cars sold by them during the assumed lifetime
 - Input factors electricity and CO₂ must be "green"
 - In particular, the production of synthetic fuels must not lead to an increase in demand for non-renewable electricity



Power-to-gas for mobility

Power-to-gas: Kopplung des Elektrizitäts- und Mobilitätssektors Das CO₂ kommt in Werlte aus einer Abfall-Biogasanlage



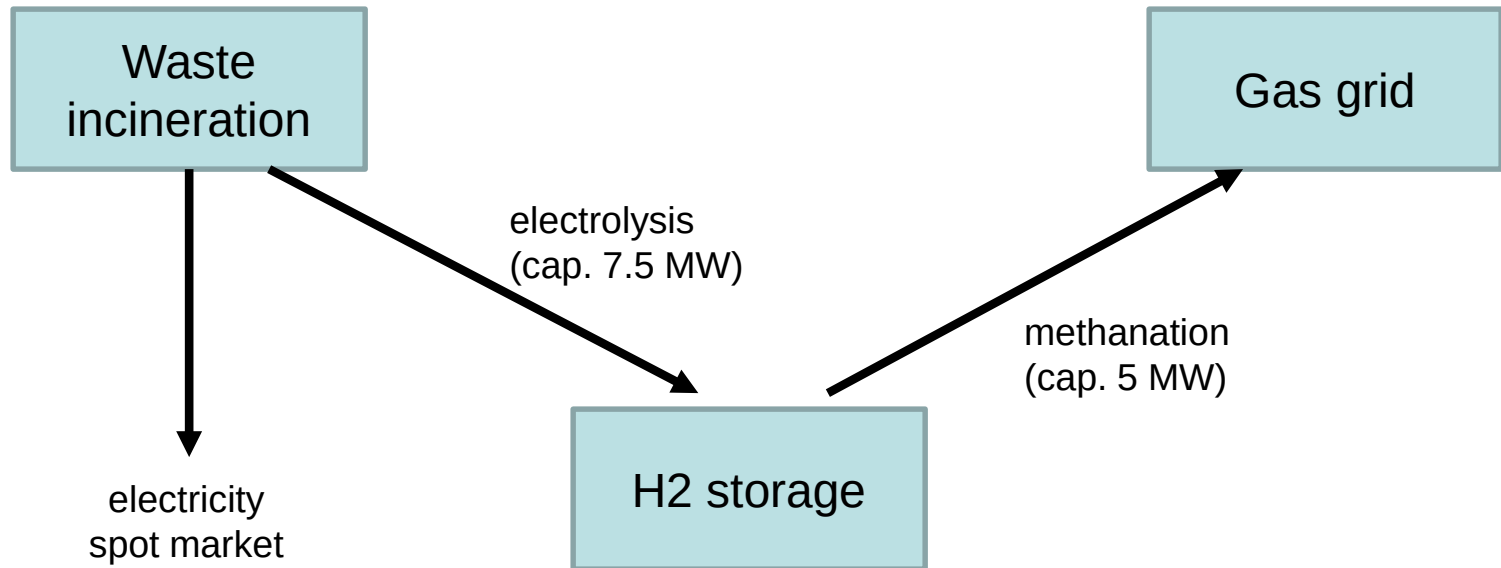
Business case: Renewable SNG for mobility

- Under the new regulation, the savings in penalties could be used to subsidize the production of green SNG with a premium of 90 EUR/MWh
- Research question: Assuming that a car importer is willing to pay this to the operator of a SNG facility, would it be profitable to invest in it?
- Business case: Power is produced by waste incineration plant:
 - 50% of the generation capacity count as renewable
 - Constant own generation, no grid fees, provides CO₂ for methanation
- Waste incineration plant has generation costs of 35 – 70 CHF/MWh, not competitive for sale on spot market, other must-run plants (e.g., run-of-river) have also costs around 30 CHF/MWh and higher
- Compare different configurations:
 - Sell electricity on market when prices are high instead of generating SNG
 - Take into account operational constraints (methanation should run continuously with > 10% of the capacity), add H₂ storage?



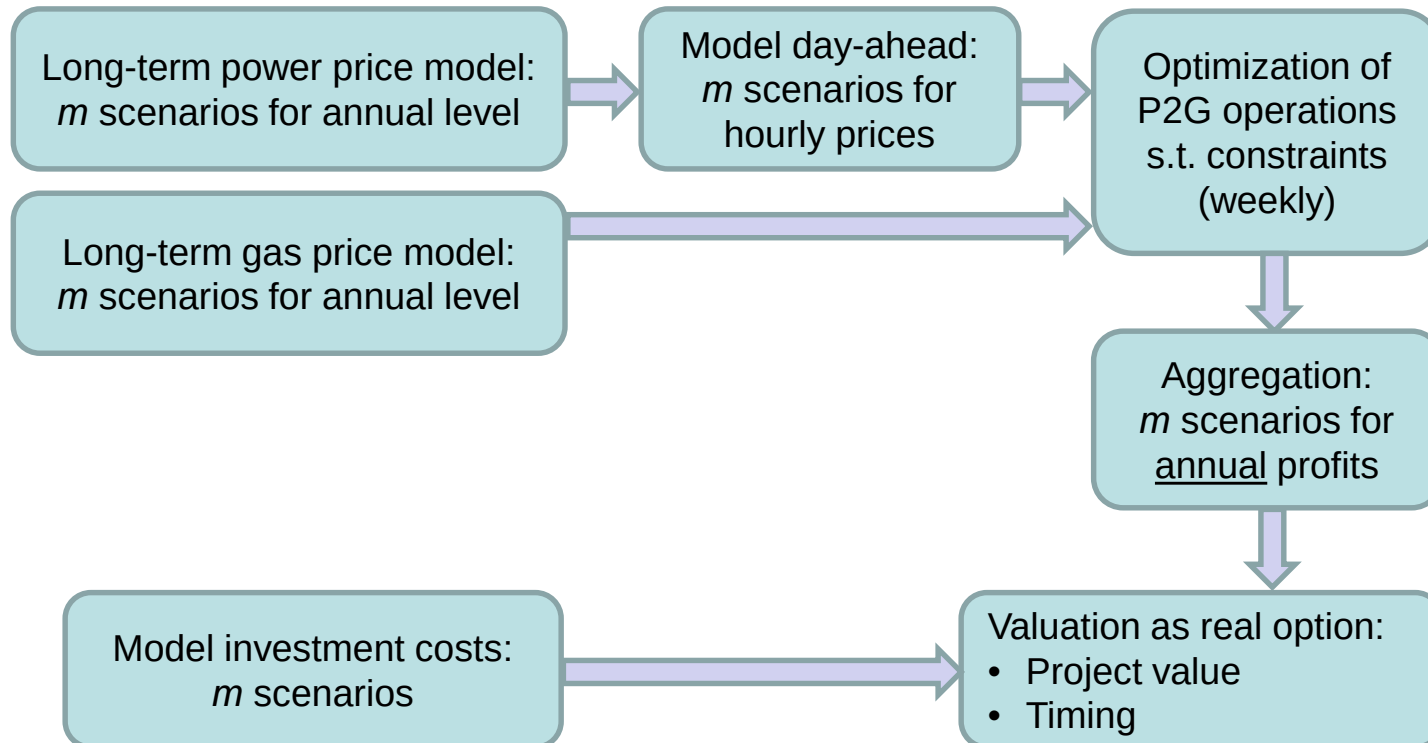
Configuration P2G plant (example)

power generation (capacity 10 MW
minus 2.5 MW own consumption)



Real options valuation

- Application of real option analysis (approach as in Bakke et al., CMS, 2016)
- Model components overview:



- Not shown: Stochastic exchange rate EUR/CHF

Model components

- Yearly power & gas price levels are modeled as geometric Brownian motions (estimated from synthetic 1Y future prices, correlation ≈ 0.6)
- Exchange rate follows also GBM
- Model for day-ahead market prices (similar to Paraschiv et al., 2015):
 - Markov regime switching model
 - Prices may jump to extremely high or low values for some hours and return then to their original level
 - Separation into deterministic and stochastic component with different intra-day seasonality and distribution parameters in summer vs. winter
- Deterministic component of electricity spot price model: Historic Swissix prices are explained by
 - Calendar information (season, weekday, holidays etc.)
 - Temperature data (Zurich)
 - Residual load Germany (impact of infeed from renewables on seasonality)

Model for investment costs

- Highly critical for resulting option values and timing decision (probability of investment)
- Wide range of assumptions in literature (over-optimistic?)
- Current prices: electrolysis ≈ 1.5 TEUR/kW_{el}, methanation ≈ 0.5 TEUR/kW_{el}, plus storage & auxiliary units
- Schoots et al. (2008): Investment costs for electrolyzers C_t at time t depend on installed capacity P_t :

$$C_t = C_0 (P_t / P_0)^{-\alpha}$$

where α is the "learning index", which is related to the learning rate by

$$lr = 1 - 2^{-\alpha}$$

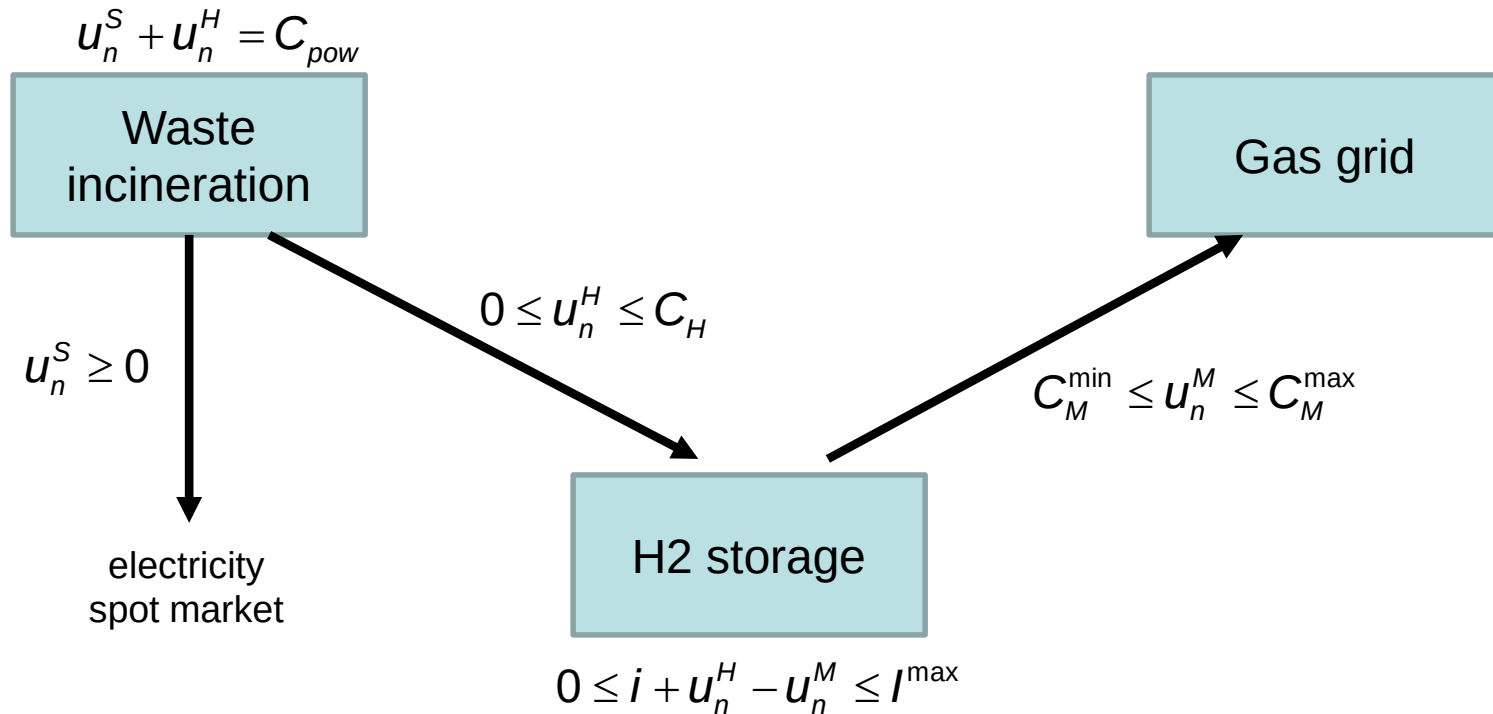
- The literature reports values $lr \approx 0.2$, which implies $\alpha \approx 0.32$
- Expert opinion: Number of P2G plants likely to triple within 10 years so that

$$C_t / C_0 \approx 3^{-0.32} = 0.7$$

- Assumption: Investment costs of other components stay constant



Optimization of P2G operations



$$f(n, z, i, u) = z_n^S \cdot u_n^S + \eta \cdot z_n^M \cdot u_n^M \quad (-C_{pow} \cdot c)$$

Optimization of P2G plant operations: RLMC

- Regress-later Monte Carlo, RLMC (cf. Balata/Palczewski 2017)
- Let (X_n, I_n) be the values of state variables (prices) and inventory (storage) at step n
- In *regress-now* MC methods, the conditional expectation of the value function at time $n + 1$ is approximated by regression w.r.t. (X_n, I_n)
- In *regress-later* MC, first a conditional expectation w.r.t. (X_{n+1}, I_{n+1}) is approximated by a linear combination of basis functions in a regression step (using randomly sampled training points)
- Then analytical formulas are applied to condition the linear combinations of functions of future values on current values (X_n, I_n)
- Backward iteration through generated scenarios
- After optimization of the current policy at step n , a forward iteration is performed to re-estimate the resulting profits in $n + 1, \dots, N$
- Effort is proportional to N^2



RLMC Algorithm (Balata/Palczewski 2017)

- 1: Generate training points $\{Z_n^m\}_{n=1, m=1}^{N, M}$ accordingly to the dynamics induced by X
- 2: Choose training points $\{Y_n^m\}_{n=1, m=1}^{N, M}$
- 3: Initialise the value function $V(N, Z_N^m, Y_N^m) = g(Z_N^m, Y_N^m), \quad \forall m$
- 4: **for** $n=N-1$ to 1 **do**
- 5: $\alpha_{n+1} = \operatorname{argmin}_{\alpha \in \mathbb{R}^K} \{ \sum_{m=1}^M [V(n+1, Z_{n+1}^m, Y_{n+1}^m) - \sum_{k=1}^K \alpha_k \phi_k(Z_{n+1}^m, Y_{n+1}^m)]^2 \}$
- 6: **if** value iteration **then**
- 7: For all m do

$$V(n, Z_n^m, Y_n^m) = \sup_{\substack{u \in [\underline{u}, \bar{u}], \\ \varphi(j, u, Y_j^m) \in [0, I_{\max}]}} \left\{ f(n, Z_n^m, Y_n^m, u) + \sum_{k=1}^K \alpha_{n+1}^k \hat{\phi}_k^n(Z_n^m, \varphi(n, u, Y_n^m)) \right\}$$

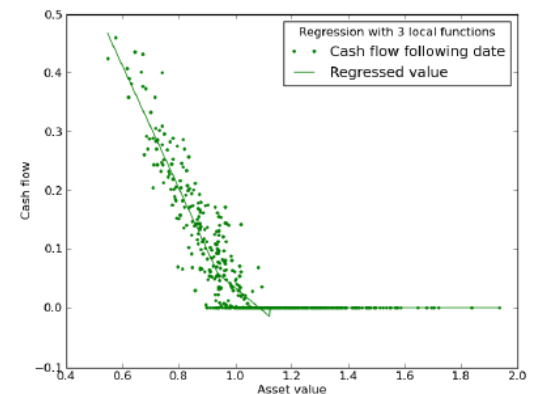
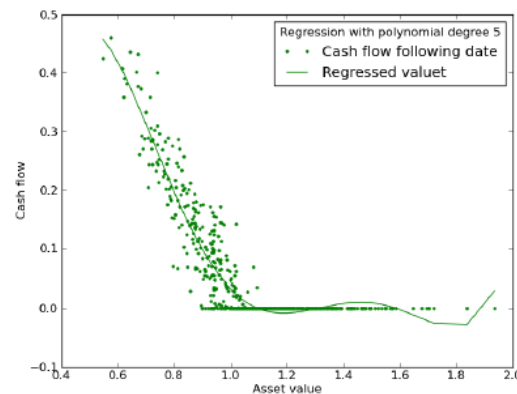
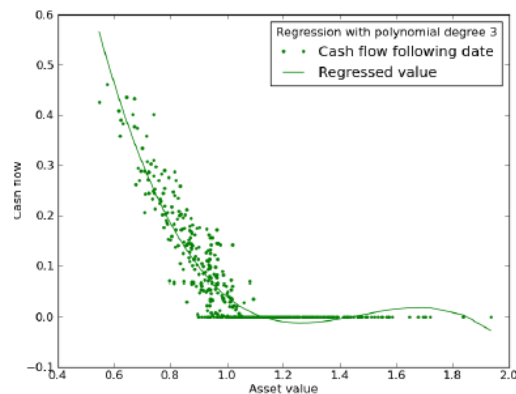
- 8: **if** performance iteration **then**
- 9: Define control mapping u_n^* by formula (22)
- 10: Apply **Algorithm 4**, or do the following:
- 11: Recalculate $\{Y_j^m\}_{j=n+1}^N$ for all m using control mappings $\{u_j^*\}_{j=n, \dots, N-1}$
- 12: $V(n, Z_n^m, Y_n^m) = \sum_{j=n}^{N-1} f(n, Z_j^m, Y_j^m, u_j^*(Z_j^m, Y_j^m)) + g(Z_N^m, Y_N^m) \quad \forall m$
- 13: **Evaluate the policy**

$$u_n^*(x, i) = \operatorname{argmax}_{\substack{u \in [\underline{u}, \bar{u}], \\ \varphi(n, u, i) \in [0, I_{\max}]}} \left\{ f(n, x, i, u) + \sum_{k=1}^K \alpha_k^{n+1} \hat{\phi}_k^n(x, \varphi(n, u, i)) \right\}. \quad (22)$$



RLMC: Choice of basis functions

- A common approach for base functions are polynomials, but the optimal degree is often not obvious
- An increase may even lead to deterioration of results, see example for put:

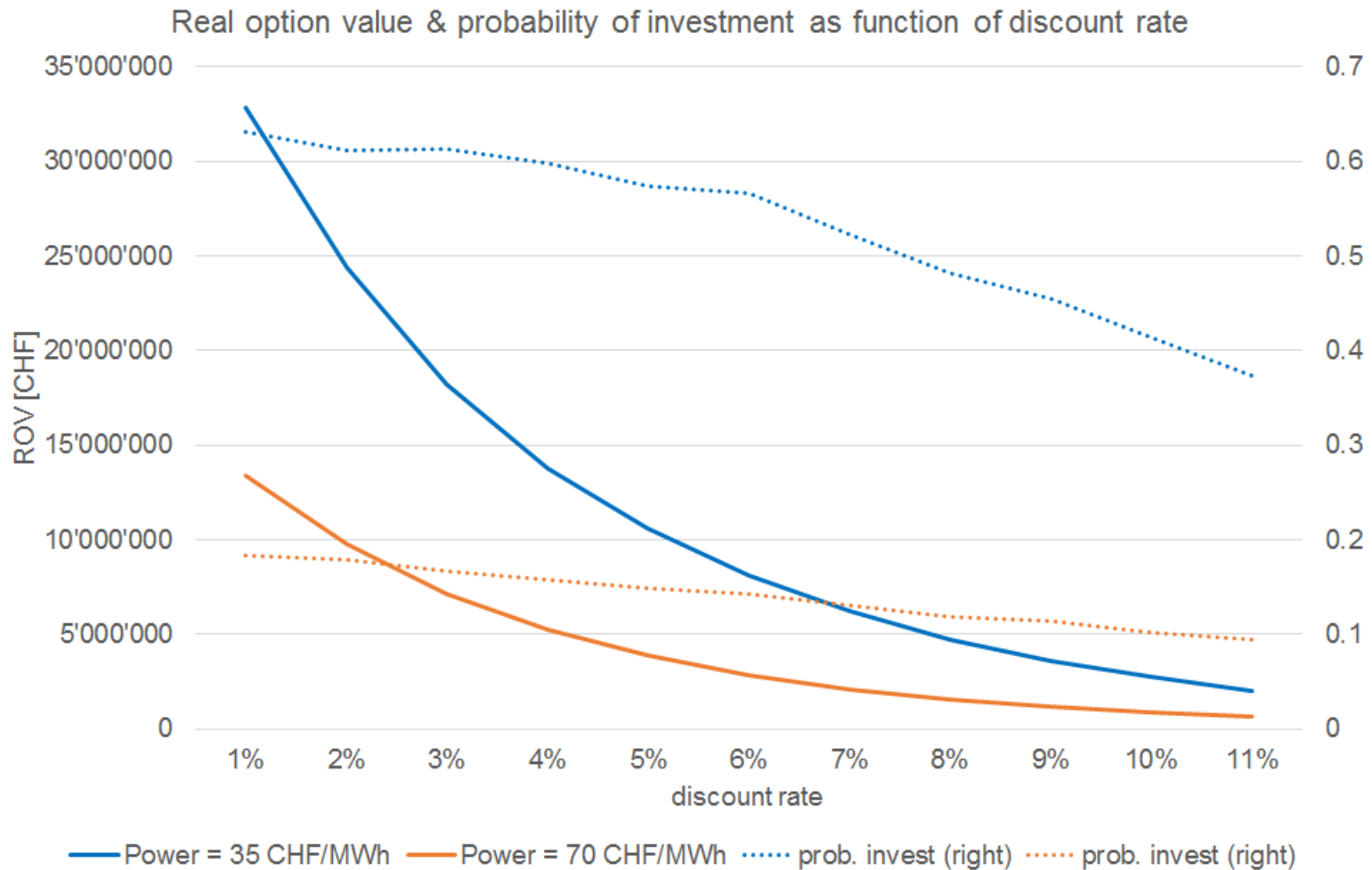


- Alternative (Bouchard/Warin 2012): Divide state space into hypercubes and choose affine functions within them, allows to capture complex shapes
- Here: Linear functions in spot price, gas price, inventory

Example calculation

- Option lifetime: 10 years
- Lifetime of plant: 30 years
- Assumed premium on gas price: 90 EUR/MWh
- Initial price levels:
 - Electricity: 37.15 EUR/MWh
 - Gas: 18 EUR/MWh
 - Exchange rate EUR/CHF: 1.17
- Costs of own production: 35 CHF/MWh vs. 70 CHF/MWh
- Investment volume today: 15 Mio. EUR
 - 11.25 Mio. EUR are costs for electrolyzer, decrease over time

Investment values & probabilities



Discussion

- Further steps:
 - Assess impact of basis functions/partitions
 - Market price is not known at time of decision making
 - Alternative power generation sources (wind, ...)
 - Inclusion of ancillary services (capacity prices of secondary reserve power can be explained by storage levels and Swissix prices)
 - Concept may also be applied to other
 - energy storages (pumped-storage hydropower, batteries) and
 - markets
- possibly with reduced modelling uncertainties

Appendix: Spot price model

- Regime switching model with base, lower & upper spike regime:

$$X_t = \begin{cases} \ell_t^L - \xi_t^-, & \text{if system in lower spike regime} \\ s_t + r_t, & \text{if system in base regime} \\ \ell_t^U + \xi_t^+, & \text{if system in upper spike regime} \end{cases}$$

- Variables at time t :

X_t spot price (day-ahead market)

r_t stochastic component

s_t deterministic component (seasonality)

ξ_t^- spike downwards

ξ_t^+ spike upwards

ℓ_t^L lower regime limit

ℓ_t^U upper regime limit



Spot price model: Stochastic component

- The stochastic component follows an Ornstein-Uhlenbeck process (OU) around zero:

$$dr_t = -\kappa_\alpha r_t dt + \sigma_\alpha dZ_t$$

- Parameters κ_α , σ_α may be time-dependent, $\alpha := \alpha(t)$ maps time t to an index (e.g., to distinguish different dynamics in summer/winter)
- The deviations from the regime limits in the spike regime follows Weibull distributions:

$$\xi_t^- \sim \text{Wei}(\lambda_\beta^-, k_\beta^-), \quad \xi_t^+ \sim \text{Wei}(\lambda_\beta^+, k_\beta^+)$$

- Again parameters may be time-dependent (different characteristics in summer and winter; working days, weekends or holidays)
- $\beta := \beta(t)$ assigns to time t a certain parameter set



Regime limits and transition matrix

- Definition of regime limits relative to deterministic component:

$$\ell_t^L := s_t - a_\gamma^L, \quad \ell_t^U := s_t + a_\gamma^U$$

- Again the parameters $a_\gamma^L > 0$, $a_\gamma^U > 0$ may be time dependent to take into account differences between seasons, where $\gamma := \gamma(t)$ maps to time t a parameter index
- Probabilities for transitions between regimes (or remaining in the current regime) are described by the – possibly time dependent – matrix Π_δ :

$$\Pi_\delta = \begin{pmatrix} 1 - \pi_\delta^{LB} & \pi_\delta^{LB} & 0 \\ \pi_\delta^{BL} & 1 - \pi_\delta^{BL} - \pi_\delta^{BU} & \pi_\delta^{BU} \\ 0 & \pi_\delta^{UB} & 1 - \pi_\delta^{UB} \end{pmatrix}$$

where $\delta := \delta(t)$ assigns to time t an index

- We distinguish in general two seasons (summer/winter), distribution characteristics are significantly different

