Task 4.2

Title

Global observatory of electricity resources

Projects (presented on the following pages)

Modelling of dispatch of stored hydropower Martin Densing

Electricity Prices Under Energy Policy Scenarios and Profitability of Hydropower Martin Densing, Evangelos Panos

How will geothermal energy transform the environmental performance of Geneva's heating and cooling mix from a life-cycle perspective? Astu Sam Pratiwi, Evelina Trutnevyte

A stochastic method for spatial Multi-Criteria Decision Analysis: Application to Deep Geothermal Energy in Switzerland Matteo Spada, Marco Cinelli, Peter Burgherr

Energy system pathways with low environmental impacts and costs Laurent Vandepaer, Panos Evangelos, Christian Bauer, Ben Amor

Nonlinear Inverse Demand Curves in Electricity Market Modeling Yi Wan, Martin Densing

The potential & levelized cost of solar PV in Switzerland Xiaojin Zhang, Christian Bauer



[3] M. Densing. Explicit solutions of stochastic energy storage problems, 29th European Conference on Operational Research (EURO2018), Valencia, Spain, 8-11 July 2018.

today's generation capacity

seems to be properly sized.

13/1414/1515/10

Historical

2015/2016

Model



[3] Densing, M., Ramachandran, K., Panos, E., Kober, T. (2018): Final Report, VSE PSEL project, Aargau



[4] Bayer, P., Saner, D., Bolay, S., Rybach, L., & Blum, P. (2012). Greenhouse gas emission savings of ground source heat pump systems in Europe: A review. Ren Sustainable Energy Reviews, 16(2), 1256–1267. https://doi.org/10.1016/j.rver.2011.09.027

[7] Narula, K., Chambers, J., Streicher, K. N., & Patel, M. K. (2019). Strategies for decarbonising the Swiss heating system. Energy, 169, 1119–1131. https://doi.org/10.1016/j.energy.2018.12.082



The aim of this study is to develop a Multi-Criteria Decision Analysis (MCDA) Tool for Deep Geothermal Energy (DGE) systems in Switzerland. In particular, the tool aims to help decision makers to identify the most sustainable area for DGE plants using spatial MCDA, which combines Geographical Information Systems (GIS) capabilities with MCDA frameworks. The proposed approach uses a stochastic approach to combine spatial information from both explicit data (e.g., heat flow) and calculated ones (e.g., risk indicators, environmental impact indicators, etc.). For each indicator, marginal distributions for uncertain model inputs are generated based on specific *a priori* defined plant characteristics (e.g., capacities, number of drilled wells over lifetime). The marginal distributions are then used as input to the model to assess the sustainability of DGE in different areas of the Molasse basin, Rhine Graben, and Jura mountains regions.

Method

The spatial MCDA (sMCDA) framework consists of different steps. First, the characteristics of the technology to be used in the sustainability assessment have been selected. In this study, since no running DGE plants exist in Switzerland, a set of hypothetical power plants based on SCCER-SoE Phase 1 activities are considered (Table 1).

Table 1: Selected key physical parameters of DGE plant capacity cases considered in this study

Model Assumption	Unit	Doublet Plant			Triplet Plant		
		Poor	Base	Good	Poor	Base	Good
Net Plant Capacity	MWe	1.19	1.47	3.34	2.31	2.81	5.27
Life Time	years	20	20	20	20	20	20
Number of Wells	integer	2	2	2	3	3	3
Well Depth	km	5	5	5	5	5	5
Well Life Time	year	20	20	20	20	20	20

Next, criteria are established to cover all 3 pillars of sustainability (environment, economy and society). Furthermore, indicators are chosen for each criterion based on availability and potential spatial variability (Table 2).

Table 2: Selected criteria and indicators used in this study.

Criteria	Indicators	Unit	
	Climate Change	kg CO2 eq to air	
	Human Toxicity	kg 1,4-DCB eq to urban air	
Environment	Particulate Matter Formation	kg PM10 eq to air	
	Water Depletion	m3 (water)	
	Metal Depletion	kg Fe eq	
Economy	Average Generation Cost	Rp/kWhe	
	Non-seismic Accident Risk	Fatalities/kWh	
	Natural Seismic Risk	Ordinal Scale [1-3]	
Society	Induced Seismicity	Flow Rate [l/sec]	
	Proximity to Major Cities	Distance [km]	

Indicators are then quantified for the hypothetical plants in Table 1 and for a set of 32 potential areas defined using Heat Flux (HF) and Natural Seismic Risk maps (https://map.geo.admin.ch). Environmental and economic indicator values have been estimated based on the temperature gradient (ΔT) in the area of interest, since ΔT is the ratio between the HF and the thermal conductivity of rocks (on average 3 W/m*ºC in Switzerland [1]). On the other hand, the non-seismic accident risk indicator considers blow out risk and release of selected hazardous chemicals, which are related to the number of drilled wells [2]. The Natural Seismic Risk and the Proximity to Major Cities (> 100000 inhabitants) indicators are considered in this study as a proxy of social acceptance, meaning that high risk(scale 3)/short distance are associated with lower social acceptance of a DGE system. The Induced Seismicity Indicator is estimated based on the flow rate expected for the stimulation (i.e. higher the flow rate, the higher the risk of induced seismicity) for each of the plant capacities considered in this study.

Marginal distributions for uncertain model in each area have been generated by fitting the indicator values estimated for each hypothetical plant. In general, uniform distributions fitted best each indicator in Table 2, except for the Proximity to Major Cities (lognormal distribution) and Natural Seismic Risk, where no variation among plants is considered, i.e. no marginal distribution has been further considered. The generated marginal distributions have been used as input for the Stochastic Multi-criteria Acceptability Analysis (SMAA-TRI) [3] applied to the spatial case. The SMAA-TRI algorithm is a classification method, which does not allow compensation between criteria and the weights are considered independent from the measurement scales. The SMAA-TRI assigns a class of sustainability (e.g., high, medium-high, medium, medium-low, low) to an area in probabilistic terms (Figure 1). It estimates the Class Acceptability Index (CAI), which measures the stability of the assignment to a class in terms of probability for membership in the class. The CAI is driven by the weights (if considered) of the indicators and according to the cutting level (λ), which gives a measure on how demanding the decision maker is (i.e., lower λ implies that a better class is easier to be reached). In this study, λ and the marginal distribution of each indicator are arbitrarily distributed parameters analyzed using 10000 Monte Carlo simulations.



Results

In this study, no stakeholder elicitation has been performed to assess weighting profiles, instead two approaches have been applied and compared:

- Missing information, where the indicator weights are sampled 10000 times using a Monte Carlo approach
- Four artificial preference profiles have been defined:
 - equal weights at all levels (both criteria and indicators in Table 2), which corresponds to the spirit of sustainability, where all pillars have the same weight.
 - three weighting profiles that strongly favor one of the sustainability pillars (weight 80%), whereas the two other are both weighted 10%, and all indicators are equally weighted.

As an example, the results based on sampling are presented in Figure 2. It clearly shows that DGE in Switzerland is considered from medium to highly sustainable, with the most sustainable areas being in North-East Switzerland.



Figure 2: Sustainability map for DGE in Switzerland

Conclusions

- The application of a spatial MCDA based on a stochastic method with GIS capabilities, demonstrates its suitability as decision-making tool for deep geothermal energy in Switzerland.
- Results from the missing information profile, and the profiles representing equal weighting and focusing on environment are quite similar. Generally, areas in NE Switzerland perform best.
- Results focusing on the economic dimension strongly differ, with the Western part of Switzerland achieving Low and Medium-Low sustainability.
- When focusing on social indicators, results for most areas fall into the Medium-High and High sustainability categories.

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Energy system pathways with low environmental impacts and costs

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Introduction

Energy systems cause substantial environmental impacts, spanning climate change, air pollution, resource depletion and ecosystem degradations.



Energy system models (ESM) that guide energy policies by generating future energy pathways, at the national and regional level, offer limited insights into such environmental issues.

Solution: environmental indicators based on the life cycle assessment (LCA) methodology are integrated into an (ESM).

Methods

Swiss TIMES energy model is used to represent the Swiss energy system: electricity, heat, and transport.

19 environmental categories are assessed: IPCC Global Warming Potential (GWP 100) and the ReCiPe method.



Fig. 1 integration LCA indicators into STEM and generating the energy scenarios, tools used per stage.

Energy pathways are generated for Switzerland up to the year 2050, resulting from the single- and multi-objective optimization of cost and environmental impacts.

Table 1 List of scenarios presented in the study, full name, primary objective, secondary objective(s), abbreviation, type and family

Energy scenario name	Primary objective	Secondary objective(s)	Abbreviation	Туре	Pamily + (Background LCI databases)
Cost-optimized climate scenario	Cost		Clim, cost opt.	Single-objective optimization	Least-cost scenarios (BAU)
Cost-optimized Business as usual scenario	Cost		BAU, cost opt.	Single-objective optimization	Least-cost scenarios (BAU)
Least climate change scenario	Climate change		CC opt.	Single-objective optimization	Least-LCIA scores scenarios (BAU)
Least metal depletion scenario	Metal depletion		MDP opt.	Single-objective optimization	Least-LCIA scores scenarios (BAU)
Least human toxicity scenario	Human toxicity	-	HT opt.	Single-objective optimization	Least-LCIA scores scenarios (BAU)
Least climate change scenario, with o % cost increase	Climate change	Cost (relax. fac.: o= 5%, 30 %	CC opt., + o % least cost	Multi-objective optimization	Least-LCIA scores scenarios with constraints based
from optimal value Least metal depletion scenario, with o % cost increase	Metal depletion	and 50%) Cost (relax. fac.: σ = 5%, 15%	MDP opt., + o % least cost	Multi-objective optimization	on the single-objective optimal value (BAU) Least-LCIA scores scenarios with constraints based
from optimal value		and 30 %)			on the single-objective optimal value (BAU)
Least human toxicity scenario, with o % cost increase	Human toxicity	Cost (relax. fac.: σ = 5% and	HT opt., + σ % least cost	Multi-objective optimization	Least-LCIA scores scenarios with constraints based
from optimal value		30 %)			on the single-objective optimal value (BAU)
Least climate change scenario, with o % cost increase	Climate change	Cost (relax. fac.: $\sigma = 5\%$ and	CC opt., + σ % least cost & + μ	Multi-objective optimization	Least-LCIA scores scenarios with constraints based
and µ % increase of metal depletion level from optimal		30 %), Metal depletion (relax.	% least MDP		on the single-objective optimal value (BAU)
values Cost-optimized climate scenario, without additional	Cost	fac.: µ = 5% and 30%)	Clim, cost opt., no battery	Single-objective optimization	Scenarios evaluating the influence of external drivers
investments on energy storage Least climate change scenario, without DAC and CCS	Climate change		CC opt., no DAC & CCS	Single-objective optimization	(BAU) Scenarios evaluating the influence of external drivers
technologies Cost-optimized climate scenario, with climate background LCI database	Cost		Clim, cost opt., Cli.DB	Single-objective optimization	(BAU) Scenarios evaluating the influence of external drivers (Climate)
Least climate change scenario, with climate background	Climate change		CC opt., Cli.DB	Single-objective optimization	Scenarios evaluating the influence of external drivers
LCI database					(Climate)
Cost-optimized climate scenario, with climate background	Cost	Climate change (relax. fac.: µ	Clim, cost opt., Cli.DB and least	Multi-objective optimization	Scenarios evaluating the influence of external drivers
LCI database and least climate change value		- 0%)	CC value		(Climate)

Results

It is possible to generate energy pathways with low life cycle greenhouse gas (GHG) emissions with moderate increase in the costs (e.g. CC opt, +5% least cost).



Fig. 2 Cumulative cost (x-axis) against cumulative LCIA scores in terms of climate change (y-axis), metal depletion (size of the bubbles), and human toxicity (color scale) for the different scenarios between the years

2010 and 2050. The cost shown as relative to the cost-optimized climate scenario ('Clim, cost opt,', red circle). The metal depletion shown as relative to the optimal value from least metal depletion scenario ('MDP opt').

Minimization of the life cycle impacts on climate change generates:

- (i) Trade-offs, increasing the impacts of metal depletion (i.e. large bubble) and human toxicity (i.e. color scale toward yellow) caused by the upstream extraction and manufacturing stages.
- (ii) Substantial environmental co-benefits with regards to air pollution, ozone depletion, acidification, and land transformation (not in Fig.2).

Ambitious reduction targets of direct GHG emissions of 95% for the year 2050 might still result in substantial climate change impacts if emissions embodied in the infrastructure and upstream supply chain are not mitigated jointly (see red circle in Fig.2 cost-optimized climate scenario, and Fig.3.a)



Fig. 3 Life cycle climate change impacts of the (a) <u>cost-optimized climate scenario</u> from 2010 to 2050, total, distribution per sector and comparison with the total impact of the cost-optimized business as usual scenario; (b) least climate change scenario from 2010 to 2050, total, distribution per sector and comparison with the total impact of the cost-optimized climate scenario.

Contributions

Multi-objective optimization allows to create pathways with minimized impacts at moderate cost.

The integration of the environmental impact minimization as an objective gives access to additional part of the solution space.

The environmental indicators consider the future evolution of the environmental performance of energy processes represented in the ESM, through prospective LCA including foreground and background LCI changes

This work is replicable to perform similar integration of LCA indicators either into other ESM or Integrated Assessment Models.

owledgements: The authors needwed financial contribution from Wallow-Becuelles International (WBI) through the WBI-Wold Excellence Scholarship, and from he Natural Sciences and Engineering Research Council of Canada through the Discovery Grants Program. This work was partially funded by the Commission for Technology and atorin in Subtratend of UT) within the Swiss Competence Center for Enging Research United Sciences and Engineering Research United Sciences and Engineering Research United Sciences and Engineering Research United Sciences and Responses and

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Nonlinear Inverse Dem	and Curves in Electricity Yi Wan, Martin Densing Laboratory for Energy Systems Analysis, Pau	Innovation Age Market Modeling
Motivations (MA Procession Contractions)	Results (cont.)	
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EMP are combined.	Fitting nonlinear Conjectural Variation:	
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mechanism is implemented as well.	80	
 EMP is a generalization framework that can derive conditions automatically and allows multiple formations 	optimality	
reformulation, including MCP.		
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ay hours:	Panos, E., Densing, M. "The prices is view of the implementation	future developments of the electricity
	current trends prevail, or a re	eversal is ahead?." Energy Economics
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	Wan, Y., "Non-linear demand Youngdae K Ferris M "So	t curves", Msc Thesis, ETH Zurich, 20 Iving equilibrium problems using
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	Panos, E., Densing, M., Sch	medders, K. "Oligopolistic capacity
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- Figure 1: System investment costs of various system sizes in Switzerland, 2018; from top left to bottom right: size up to 100 kW_{p} , 30 kW_{p} , 10 kW_{p} and 6 kW_{p} .
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