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The nationwide characterization and modeling of local energy systems: Quantifying the role of decentralized generation and energy resources in future communities

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1. Introduction

Urban communities currently account for over 70% of global en-ergy-related CO₂ emissions [\(Edenhofer et al., 2015](#page--1-0)). As such, municipal governments have an opportunity to contribute to energy demand and emissions reductions through local scale, long-term energy systems planning and policies ([Edenhofer et al., 2015](#page--1-0)). The introduction of transnational municipal networks (TMNs) has led to a rapid increase in the adoption of local energy strategies in recent decades ([Fünfgeld,](#page--1-1) [2015; Hakelberg, 2014\)](#page--1-1). TMNs are international partnerships which connect local governments in their efforts towards sustainable development and local climate governance. Notable transnational municipal networks include the International Council for Local Environmental Initiatives – Local Governments for Sustainability [\(ICLEI, 2017](#page--1-2)), C40 Cities Climate Leadership Group ([C40 Cities, 2017\)](#page--1-3), and Energy Cities ([Energy Cities, 2017\)](#page--1-4). Such TMNs have been credited for the recognition of urban communities as critical actors and stakeholders in the

global climate governance arena [\(Fünfgeld, 2015; Hakelberg, 2014\)](#page--1-1).

Alongside local governance, decentralized generation and storage technologies (DGSTs), and local energy resources play an integral role in the transition pathway towards local emissions reductions and improved energetic self-sufficiency. Significant emissions reductions through decentralized generation technologies (DGTs) have been demonstrated in [Akorede et al. \(2010\), Chiradeja and Ramakumar \(2004\),](#page--1-5) [Tsikalakis and Hatziargyriou \(2007\)](#page--1-5), and [Yazdanie et al. \(2016\),](#page--1-6) among others. Local sustainable energy resources can include solar, biomass, and small hydro, which can be harnessed by DGTs including photovoltaics, small combined heat and power (CHP) plants, and run-of-river technologies.

The shift towards increasingly decentralized technologies and governance introduces the need for methods to assess diverse local energy landscapes and the long-term role of DGSTs in them. This study presents one such approach for Switzerland. Clustering algorithms are applied to multidimensional, nationwide municipal datasets in order to

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Abbreviations: AP, Affinity propagation; BAU, Business-as-usual; CHP, Combined heat and power; DEC, Developed environment classification; DGST, Decentralized generation and storage technology; DGT, Decentralized generation technology; ERP, Energy resource potential; EUS, Energy usage share; NEP, New energy policy; POM, Policy measures; PV, Photovoltaic; RES, Reference energy system; TMN, Transnational municipal network

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identify characteristic urban, rural, and suburban municipal energy systems. These characteristic community energy systems are referred to as archetypes. Archetypes are characterized with respect to local energy resource potentials, energy infrastructure access, and existing energy usage shares for heat and electricity demand across residential, commercial, industrial, and agricultural sectors. A cost optimization modeling approach is then applied to key archetypes in order to provide insight into the community's cost optimal utilization of local resources and DGSTs until 2050 under different national energy policy scenarios. Overall, the application of clustering techniques provides a nationwide overview of local energy systems and enables cost optimization analyses to focus on a subset of characteristic municipalities which provide further insights.

Clustering algorithms seek to divide data sets into groups of similar objects based on specified criteria. Clustering has a wide array of applications, ranging from image processing to data mining, enabling the identification of patterns in large data sets. Clustering has been used in energy-related applications, including the classification of building energy performance ([Gao and Malkawi, 2014; Nikolaou et al., 2012;](#page--1-7) [Santamouris et al., 2007; Xiao et al., 2012](#page--1-7)) and inter-regional $CO₂$ emissions [\(Yu et al., 2012](#page--1-8)). Clustering on the residential heating technology mix of municipalities in a small Swiss canton was also conducted in [Trutnevyte et al. \(2012\)](#page--1-9).

The nationwide characterization of local energy systems using clustering techniques, combined with cost optimal characteristic community modeling is a new approach to evaluating the role of decentralized generation in future local energy systems. This comprehensive approach to local energy systems analysis is the main contribution of this work. The approach enables, first, the identification and definition of key, characteristic local energy systems (archetypes) and, second, the quantification of the cost optimal, long-term deployment of DGSTs and local energy resources in them. This information can be utilized by policymakers on different levels. It allows policymakers to identify which types of communities are the most suitable for DGST deployment within a larger scope. This information can, in turn, aid decision-makers to strategically allocate limited resources towards target communities (for example, through demonstration projects), and also to identify the sets of communities which would be expected to exhibit similar behaviors. Case-specific studies can then be performed on targeted communities to formulate individual municipal policy recommendations. Local policymakers can also identify which local energy resources, technologies, efficiency measures, and policy measures should be considered as part of case studies using this approach.

The Swiss case is of interest as a decision was recently made to pursue a climate-stringent energy policy focused on renewable energy, DGSTs, and efficiency measures (Swiss Federal Offi[ce of Energy, 2017](#page--1-10)). Swiss municipalities also have significant legislative power, making Switzerland an interesting testbed for the implementation of DGSTs and local energy strategies. The results of this study may be used to inform policy and project developments in these contexts. However, the proposed general approach can be applied to any region and scale where appropriate data sets are available.

2. Methodology

The approach consists of three main steps which are further detailed in subsections.

- 1) Archetype definition: clustering algorithms are applied to multidimensional municipal-level data sets in order to define archetypes
- 2) Archetype selection: archetypes representing the largest shares of national energy demand are selected for further analysis
- 3) Archetype modeling: each selected archetype is modeled using a flexible cost optimization community model which is developed using the TIMES framework

Fig. 1. Municipal developed environment classification [\(Swiss Federal O](#page--1-11)ffice of [Statistics, 2016a\)](#page--1-11).

2.1. Municipal energy system clustering

2.1.1. Municipal characteristics

Switzerland consists of approximately 2300 municipalities. Each municipality is defined by three characteristics in this study: the developed environment, local energy resource potentials, and energy usage shares across sectors. Each characteristic and the multidimensional data inputs used for clustering are described below.

Developed environment classification (DEC) (1-dimensional). Each municipality is defined as urban, rural or suburban based on data available from the Swiss Federal Offi[ce of Statistics \(2016a\)](#page--1-11). Developed environment classifications are defined based on statistical data, including morphological and functional features. Criteria include spatial densities of inhabitants, employees, commuters, and building function (e.g., residential, commercial, services, etc.), amongst others (Swiss Federal Offi[ce of Statistics, 2014\)](#page--1-12).

The municipalities included in each developed environment class are illustrated geographically in [Fig. 1](#page-1-0).

Local energy resource potential (ERP) (5-dimensional). Five local resource potentials are considered for each municipality: rooftop solar photovoltaic (PV), waste biomass, manure, wood, and small hydro. Resource potentials refer to total available technical potentials and have been approximated on a municipal level based on available data sets. Raw data is given on a municipal level for all local energy resources except for wood, which is given by forest district. A graphical summary of regional potentials is presented in [Fig. 2.](#page--1-13)

Annual rooftop PV potentials ([Fig. 2](#page--1-13)(a)) have been estimated in [Assouline et al. \(2016\)](#page--1-14) and provide an indication of average rooftop solar irradiance. These estimates are based on existing rooftops, but are assumed as maximum potentials over the modeling time frame due to a lack of available long-term data. Ground and building façade PV potentials are not considered due to a lack of municipal data.

Municipal waste and manure potentials ([Fig. 2](#page--1-13)(b) and (c)) have been approximated based on GIS data from within a Swiss Competence Center for Energy Research (SCCER) project (Buff[at, 2016; Vögelin](#page--1-15) [et al., 2016](#page--1-15)). Data has been calibrated with national potential estimates in [Panos and Ramachandran \(2016\).](#page--1-16) Waste includes sewage sludge, food industry waste, paper, cardboard, and other biowaste.

Municipal small hydro potential shares are estimated according to GIS data from [Hertach \(2012\),](#page--1-17) and are calibrated with national small hydro potential estimates by Swiss Federal Offi[ce of Energy \(2013\)](#page--1-18) ([Fig. 2\(](#page--1-13)d)).

Annual wood production potentials ([Fig. 2](#page--1-13)(e)) are illustrated by forest district based on [National Forest Inventory \(2016\)](#page--1-19). Municipal potentials are approximated by distributing the forest district potential Download English Version:

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