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Unpacking Big Systems – Natural Language Processing meets Network Analysis A Study of Smart Grid Development in Denmark

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Unpacking Big Systems - Natural Language Processing meets Network Analysis

A Study of Smart Grid Development in Denmark [*]

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Abstract: Studies within the detection of technological trajectories and technology forecasting tend traditionally to rely on patent or bibliometric data. The main drawback of these invention-focused approaches is their inability to account for many mainly non-technical factors related to the social and institutional framing of technology. Value driven policies, technological and institutional path dependencies or user expectations and routines have major impact on the technological outcomes in a particular context. This paper suggests a new method for the mapping and analysis of large (technical) systems and contained technological trajectories on a national level using a combination of methods from statistical natural language processing, vector space modelling and network analysis. The proposed approach does not aim at replacing the researcher or expert but rather offers the possibility to algorithmically structure and to some extent quantify unstructured text data. The utilized filtered corpora consist of two types of Danish text-documents: 99 R&DD project descriptions and 574 (initially before filtering 813) non-academic/industrial journal publications dealing with the development of the smart energy grid in Denmark. Results show that in the explored case it is not mainly new technologies and applications that are driving change but innovative re-combinations of old and new technologies.

Keywords: Technological Systems, Smart Grid, Path Dependence, Natural Language Processing, Topic Modelling, Network Analysis

JEL classification: O33; C88; L94

1. Introduction

The past couple of years have seen the emergence and growth of industries related to the generation of renewable energy (e.g. IEA, 2011). In many cases these developments changed the paradigm in energy generation from energy-production to energy-harvesting thus imposing new challenges on the energy transmission and consumption

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side (Foxon et al., 2010). While in the "old" system production would be adjusted to typical consumption levels, now production levels are literally depending on the weather (Mattern et al., 2010). In addition electric mobility, solar cells on rooftops and other new applications on the consumer side are altering consumption patterns (Elzinga, 2011).

The upcoming technological paradigm - in a Dosian (1982) understanding - that is evolving as a *normal solution* to cope with the new dynamics of energy generation, can be found in the development of the *smart grid*.

Smartening the electricity grid means here the installation of a number of technologies along the generation-transition-distribution-consumption chain, that will enable the grid to control and balance itself automatically given the new patterns of energy generation and consumption (Farhangi, 2010).

Even though the *smart grid* is increasingly gaining momentum as *the coping technology*, it still leaves much free space for technological variety to emerge in the different contexts in which *smart grid* systems are evolving. This is in line with an understanding of the technological paradigm as a problem-targeting environment, which might contain a number of different technologies that potentially contribute to solving the defined problem. These technologies can be both, competing and compatible, and it is reasonable to assume that their composition will vary across different contexts given for instance the presence or absence of policies, targeting their development, or already because of existing technological path dependencies (David, 2007).

The analysis of this systemic development is important in order to understand the state of the overall sustainable transition, and it comes up with a number of challenges. The first and possibly most intriguing is the delineation of the *smart grid* with affiliated technologies and applications. Particularly, in the case of this infrastructure system, where regulations on national, regional or even local level have a strong influence on technological outcomes, the identification of technological trajectories within the borders of a particular country or region can provide valuable insights for understanding systemic change (Sawin, 2006).

This paper presents a new combined approach to assist scholars delineating complex systemic fields. It will be applied to map out *smart grid development* looking at both, the research- and the industrial landscape in Denmark, a country which pioneered in the large scale integration of wind-power (Garud and Karnøe, 2003) and as in 2011 was the country with the highest share of *smart grid* R&DD projects in Europe(Giordano et al., 2011). This share increased in the recent years (Copenhagen Cleantech Cluster, 2014).

Methodologically this research relies on the combination of methods from statistical natural language processing, vector space modelling and network analysis. The proposed methodology is not aiming replacing expert-insight, rather it should be seen as a tool that can help identifying patterns within complex set-ups, understanding the scale of components and to some extent their relations. The filtered data consists of two types of Danish text-documents: 99 R&DD project descriptions and 574 (initially 813) non-academic/industrial journal publications.

The paper is structured as follows. The following section provides a brief overview over the Smart Grid development in Denmark, some theoretical considerations related to the study of change in technical systems and a discusses various methodological approaches to exploring these. Then, section 3 presents the text data and the preparation process. Section 4 provides a detailed description of the proposed “method-pipeline”. Immediate (uninterpreted) results are presented in section 5. Section 6 and section 7 are short examples of how the results can be used to guide the preparation of cases. Finally, section 8 discusses the benefits and drawbacks of the proposed method, possible further developments. Besides, it summarizes the findings from the presented case.

2. Industrial Background, Theoretical and Methodological Considerations

2.1. Smart Grid technology in Denmark

The traditional architecture of the electricity grid assumes a unidirectional energy flow from centralized energy plants via the transmission and distribution grids to consumers, where energy production levels are constantly adjusted to match the over time fluctuating energy demand (Farhangi, 2010). Embracing the renewable energy paradigm, centralized energy production is gradually replaced by decentralized energy farming. The harmonization between production and consumption has thus to move from the traditional generation side into the transmission and consumption areas. ICT technologies will play a central role, supporting this process (Erlinghagen and Markard, 2012; Mattern et al., 2010).

In the Northeuropean set-up two - conceivably compatible - approaches to integrating intermittent renewable energy sources are currently discussed. Firstly, the construction of a European transmission *super grid*, to allow for instance energy exports from Denmark to Germany in wind-peak times (European Commission, 2010). Secondly, the development of a national *smart grid*, that is able to transmit energy and information in both ways, thus allowing for harmonization by the means of flexible consumption [1] This requires upgrading of the existing grid by adding a *layer of intelligence* - advanced measurement, communication and control technology - thus making the grid able to handle a higher share of decentralized renewable energy generation and the recently evolving consumption patterns (Elzinga, 2011). A potential socio-economic bonus of the technology: If flexible consumption can be activated by the introduction of smart functionality, costly investments in the reinforcement of the distribution system can be moved into the future or avoided (Forskningsnetværket,

[1] It is often argued that both approaches can easily be combined and develop alongside e.i. *super grid* on the transmission and *smart grid* on the distribution levels, yet Blarke and Jenkins (2013) argue that the technologies might be mutually exclusive, identifying both technological and socio-economic conflicts of interest between the systems. Even though that is an important discussion, the present article will not examine this possible technological incompatibility further.

Smart Grid, 2013).

When defining the technology areas that are supposed to become part of the *smart grid* the International Energy agency (Elzinga, 2011) and others refer to a framework by the National Institute of Standards and Technology (NIST, 2010), which identifies eight types of technology across six domains, spanning from generation to consumption. These are:

- Wide-area monitoring and control
- Information and communications technology integration
- Renewable and distributed generation integration
- Transmission enhancement applications
- Distribution grid management
- Advanced metering infrastructure (AMI)
- Electric vehicle (EV) charging infrastructure
- Customer-side systems (CS)

While these “new” technologies are without a doubt essential for the development of the *smart grid* infrastructure, it is not given that *smart grid* systems in different countries and regions will homogeneously include all of these technologies and exclude others.

Denmark is already today counting the largest amount of R&DD projects within the smart energy area in Europe (Giordano et al., 2011, 2013). The extremely high ambition of the national energy agreement, passed by the government in 2012 targets a wind-power share of 50 percent by 2020 and the more recently announced Smart Grid Strategy sees the country as a European laboratory for innovative energy solutions (KEMIN, 2013).

A recent report by the Copenhagen Cleantech Cluster (2014) suggests that in the Danish context it is more appropriate to talk about a “smart energy” system rather than a *smart grid* system. This argument has been made earlier by Lund et al. (e.g. 2012), who outline the importance of thinking about electricity grids as embedded into a wider energy system, including energy conversion and storage. Technologies related to the transformation of renewable energy to other forms of carriers then electricity should therefore play a major role in the *smart grid* architecture. Denmark has a historically high share of buildings connected to the district heating system (Lund et al., 2010) and has made significant experiences with heat pump technologies in the past. Thus, it seems natural that these "old" heating and energy conversion technologies will have some influence on the development of the *smart grid* in the Danish context, particularly in the areas of energy conversion and energy storage. An explorative analysis of the national *smart grid* should therefore go beyond the identification of "new" technologies, taking their presence as a kind of benchmark but also account for the upgrading and integration of "old" adjacent technologies that might acquire a new role in the evolving system. Rather then checking of technologies from a predefined list, it seems more appropriate search for involved technology components without preconceptions, and then try to position and describe them and their relations to the surrounding systems.

2.2. Delineating the technology scope of an evolving technical system

The energy grid is a complex system with extremely interwoven technical, economic, institutional and administrative structures and therewith it is a great example for a large technical system as defined by Hughes (1987). The system includes physical artefacts such as hardware components for the transmission and distribution of electricity. In addition it contains organizations, such as manufacturing firms or utility companies. All these components interact with each other, following formal, normative and cognitive rules. Since energy grids are physically connected to energy producers on the one side and users on the other, the aforementioned components also interact with artefacts and agents external to the system. Work by sociologists of technology (e.g. Bijker, 1997) give highly important insights into agency and the social construction of the technology, doing so by increasing the scope and thereby the complexity. The same is true for much of the STS literature, which focuses on socio-technical transitions (e.g. Geels, 2002). While the theoretical frameworks proposed by this literature are relatively easy to grasp, multidimensionality, the high number of actors and feedback loops make them hard to operationalise.

This is also the case for innovation system approaches. An analysis based on the functionalistic Technological Innovation System (TIS) framework, which is often seen in energy industry studies, (Bergek et al., 2008; Hekkert et al., 2007) for instance builds on a clear *a pripri* identification of the technology in question. For the analysis of broader technological fields within the TIS framework Hekkert and Negro (2009) rely on interpretative assessment of TIS-related events, manually extracted from industrial publications.

An often taken approach, is focusing on technology niches. The STS-Transition Literature depicts niches as protected spaces on the micro level for the development of innovation within rigid socio-technical systems. This strategy allows for a close exploration of the development in a narrow technological area and its interaction with the meso and macro levels. Yet, this approach requires *a priori* identification and to some extent delineation of the relevant niches.

In the present case, deciding on a particular technology focus is challenging for at leas two reasons: The large number of interacting technologies and components on the one hand and the system history aspect on the other. The latter reason relates to path dependency and institutional factors in a national setting (Kaplan and Tripsas, 2008). History matters, and therefore a *smart grid* system in country **A** will not build on the same technologies and components as in country **B**. Consequently departing from a list of “novel” technologies such as the one on 5 can be misleading.

The approach suggested in this paper takes one step back and helps the researcher to detects relevant techno-thematic fields in a given context that belong to a higher-level system. It makes use of text data to algorithmically identify re-occurring themes in a text-document-corpus. Rather than identifying pre-defined patterns in an existing *system*, the intention is to detect patterns in unstructured data. The number of documents in particular clusters, the date of publication and other statistics can indicate the scope and scale of a technology component. Furthermore, the representation of the corpus as a network of documents allows to make educated guesses about the relations between single technologies, which can be studied, exploring the documents manually further in detail.

The analysis is similar to methods suggested within the stream of literature on technology- or patent mapping, which will be briefly presented in the next section. The tuning of the method towards the exploration of project descriptions and journalistic texts (rather then for instance patent abstracts) adds however social, political and organisational dimension to the otherwise purely technical analysis.

2.3. Methods for mapping of technological change

Patent analysis, particularly the exploration of citation networks has been widely used to understand technology change and support decisions in strategic technology management (Ernst, 1997, 2003). Such networks can capture cognitive proximity between inventors, inferred from joint awareness of literature that the inventors' patents have in common. The advantages and disadvantages of the usage of patent data is discussed in Griliches (1990). Based on the seminal work of Dosi (1982) on technological paradigms and trajectories and adapting a methodology suggested by Hummon and Dereian (1989), Verspagen (2007) modelled and analysed the "flow of knowledge" using a patent collection in the field of fuel cells. Patent citation networks were used to study knowledge diffusion (Ho et al., 2014) and small world phenomena (Guan and Shi, 2012). Erdi et al. (2013) construct dynamic patent citation networks to predict emerging technology clusters. Chen et al. (2012a,b) propose an alternative method, using bibliographic coupling and clustering of patents within sliding time-frames to detect technology trajectories applied to the very case of *smart grid.* The study compares the patents filed by US inventors to the rest of the world identifying technology areas, similar to those mentioned in Elzinga (2011).

In the last decade, various combinations of NLP and network analysis techniques have been increasingly used by a yet relatively small number of STI scholars. This research can majorly be associated with patent mapping or the detection of technology roadmaps.

Patent maps in their static-accumulative or dynamic versions are tools for the visualization of overall relationships among patents in a particular technology (Yoon et al., 2012). An established approach that incorporated NLP methods for the creation of such maps relies on pre-defined keywords and -phrases in a given patent set. More recent publications criticize the use of author pre-defined keywords as a machine readable representation of the patent and suggest to rather deploy NLP techniques to algorithmically extract phrases that are required for the calculation of similarity from patent text fragments. Subject-Action-Object (SAO) triples as basic extracted elements are currently seen in a growing number of studies (Choi et al., 2013, 2012, 2011; Park et al., 2011). The claim, supporting SAO, is that, being syntactically ordered structures, they include the key-concepts and technological objectives of the patent (Cascini et al., 2004). While these structures are qualitatively richer, they come at the price of sparsity. The whole process of identification of semantic similarity relies on repeated term-co-occurrence over several documents in a given corpus. The combination of terms into term-chains such as SAO structures, increase the number of unique terms in the corpus and thereby reduce the probability of encountering re-occurrence. This is however a speculation that is yet to be tested empirically.

The basic process – similar to what this paper is presenting – can be summarized in three steps: (a) Existing or extracted keywords from text data are standardized in their spelling across a corpus using statistical NLP methods such as stemming or lemmatization, (b) a (vector space) model for dimensionality reduction is used to generate a document dissimilarity matrix given keyword co-occurrence patterns, (c) the documents (patents) are clustered given the calculated similarity measures[2].

Results of such clustering exercises help to understand technology development but

[2] This basic structure is also applied in the present work. A detailed method description and introduction of the technical terminology is given in the following section.

can also be used to develop patent based company portfolios and technology roadmaps (Choi et al., 2013) or inventor profiles (Moehrle et al. 2005). They can indicate areas of competition trends, emerging, even disruptive trajectories (Kostoff et al., 2004) and death-ends. Given proper expert analysis, they can support strategic R&D and acquisition decisions (Choi et al., 2011; Park et al., 2013; Yoon and Kim, 2011). Yoon et al. (2012) suggested a method to dynamically map technological competition trends, identifying areas of "patent vacuum" and what they call "technological hot spots" with strong recent patenting activity. In fact, semantic patent analysis proved to outperform other more traditional types of novelty identification (Gerken and Moehrle, 2012). Semantic patent mapping has been used to detect and evaluate risk of potential infringement in the cases of DNA chips (Bergmann et al., 2008) and prostate cancer treatment technology (Park et al., 2011). Moehrle and Gerken (2012) applied patent text similarity techniques to monitor convergence between technology areas in relation to design decisions.

While patents are a well structured and reliable source of information about theoretically available technology and its development, they do not reflect the application of the technology in a systemic set-up. The main drawback of such invention-focused approaches is their inability to account for many mainly non-technical factors related to the social and institutional framing of technology. Value driven policies, technological and institutional path dependencies or user expectations and routines have major impact on the technological outcomes in a particular context. Thus, the conclusion made by for instance Chen et al. (2012b) that the observation of emerging US patents in a certain field can be interpreted as the presence of a particular technological trajectory in the US, would rely on strong assumptions about a straight relation between patents and technology outcomes.

This study is an attempt to use a similar NLP driven approach for the mapping of large systemic fields. Here the method is used for identifying present technological trajectories within the *smart grid* in Denmark, accounting for some of the cognitive and institutional factors, which shape the development of a technology in a national context (Kaplan and Tripsas, 2008).

3. Data overview & preparation

The analysis is based on two types of text-documents: Approximately 100 descriptions of smart grid R&DD projects and initially 813 non-academic journal articles in from Danish industrial publications. The former source is expected to represent the institutionally shaped technology development while the latter should provide rich information on the application, policy and business side.[3].

Initially 102 project descriptions are obtained trough `www.energiforskning.dk`, the joint database of publicly (co-) funded energy research in Denmark. The database contains detailed information on nearly 2100 projects, classified into 7 broad technology areas. This classification is interesting as such, since it indirectly grounds on the (partly political) decision to fund a particular activity or not. Thus, it can be assumed that this *pre-classified* data implicitly carries information about the technology perception by the public sector. The descriptions are usually 500 words long and briefly outline the background and purpose of the project, technologies used and expected outcomes. Project start dates range from 1996 until 2013, however the distribution is highly skewed towards the latest 5 years (see Figure A.1). In some few cases result descriptions are included for terminated projects, providing additional or more specific information on the technological outcomes of the particular activity. Since this research is not interested in the evolution of particular projects, but rather aims at identifying general technology trends, where available, result descriptions are appended to the initial project descriptions. The projects span from basic research to deployment activities, which is explicitly indicated in meta-data available for each activity but also can be inferred from the finance mechanism applied. That opens up for the analysis of potential technology development cycles for particular technological

[3] The text-data used for this research was exclusively in Danish. Even though English descriptions are available for most of the projects, it is assumed that Danish descriptions are more accurate and rich. Text examples presented in this paper are translations by the author. Trajectory specific TFIDF-Keywords were however automatically translated relying on the Google Translate API.

trajectories. Yet, this question was not central for the presented study. Project duration, budget, number and type of participants were not analysed explicitly. However, since named entities in the texts were not systematically identified and excluded, actor name appearance did certainly have an influence on document similarity calculation (see 4.2). Finally selection filters were applied to exclude too short descriptions, that indicated that a proper description is yet to be posted. A language detection module sorted out description in other languages than Danish, leaving 99 documents for the analysis.

In order to map out the scope of *smart grid* applications in a national context, non-academic industrial publications have been explored. These were retrieved from the Danish national publications database *infomedia.* A search-string was systematically build up by exploring term frequencies, n-grams and collocations within the press releases by the Danish Smart Grid Alliance, which since it's initiation in April 2012 informs about the national *smart grid* industry[4]. An initial search returned 813 articles for the timespan 2004-2013[5].

The coverage of *smart grid* related themes remains marginal until 2009. The majority of articles before 2009 are published by the engineering journal *Ingenøren.* Only starting 2009, more practically oriented periodicals take up the topic, indicating the upcoming interest for the *smart grid* outside the engineering community. Overall, articles come from 61 different periodicals largely affiliated with engineering and construction themes (see Table A.4 for more details). However, 81 percent of the publications relate to 12 journals focusing on the national energy system, appliance installation, computer – and information science, the business part of the engineering and energy industry.

Just like for the descriptions, language detection was applied to exclude non-Danish articles. Also here, too short texts (shortest percentile) were sorted out. A quick search within the retrieved documents confirmed that industrial publications often report on

[4] `http://www.ienergi.dk/English.aspx`

[5] `(smartgrid OR (smart OR intelligent* OR klog*) DNEAR5 (grid OR energisystem* OR elnet*))`The english translation corresponds to: `(smartgrid OR (smart OR intelligent* OR clever*) DNEAR5 (grid OR energisystem* OR electricitygrid*))`, the `DNEAR5` command specifies that the distance between the array of adjective classifiers in the first parenthesis and the *grid*-synonyms in the second parenthesis is ≤ 5.

ongoing research projects or *smart grid* research in general. These reports are however not conducive for a detached exploration of technological trajectories in the domains of research and application. Documents that mentioned the term *project* or *research* in their titles or introductory abstracts were dropped. While most of the articles are clearly associated with national developments, it is possible that an article only covers to technology or market developments abroad. An additional filter selected out documents that wouldn't mention "Denmark" or "Danish"in any part of the document. As expected the number of in this last step excluded texts remained very low.

4. Methods

For both types of documents a three step analysis and in addition several visualization techniques were applied. A detailed overview over the "analysis pipeline" is presented in Figure 1 and Table A.1 contains explanations of language processing terminology used below. Project descriptions and the text-bodies of articles underwent (1) term extraction and filtering using basic Statistical NLP techniques. Arrays of nouns and nominal expressions were analysed for semantic similarity with the help of (2) vector space modelling. Thereby obtained document similarity estimates were used to construct a document network. (3) Network analysis algorithms were used to cluster the documents thematically. Finally NLP was used one more time to (4) retrieve representative keywords for particular clusters and *sub-clusters*[6].

The following describes the above lined up steps in detail:

4.1. NLP based term extraction

The goal of the term extraction is to reduce the text-documents into bag of words (BOW) representations - an array of terms of high information content. These are usually nouns and noun phrases. Firstly, important noun phrases are selected by

[6] NLP using the NLTK package (Bird et al., 2009), vector space modelling with the GENSIM package (Řehůřek and Sojka, 2011) within IPython, *community detection* and visualization within GEPHI

identifying high-document frequency (DF) bi-grams[7]. For project descriptions, which tend to use many standardized formulations, a domain specific stopword filter was trained and applied.

Part of speech (POS) tagging is performed using a Brill tagger, trained on the Danish Morphosyntactically Tagged PAROLE Corpus (Keson and Norling-Christensen, 1998) combined with two affix taggers. The POS identification accuracy ranges at 97 percent[8].

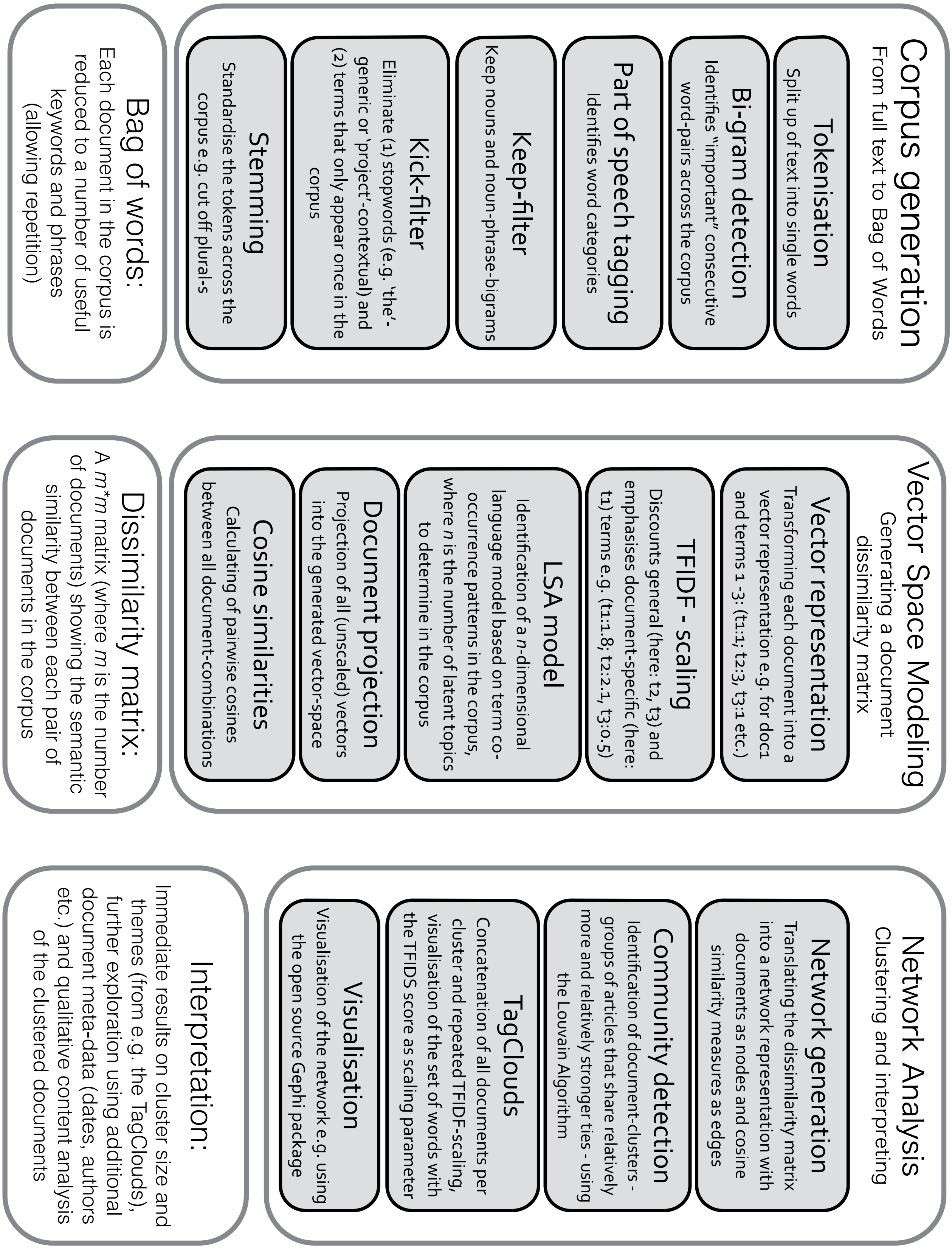
Not-nouns or noun expressions, domain specific- and general Danish stopwords, and low-DF words are dropped. For the presented analysis the low-DF threshold was set at 1, thus only excluding *singletons*- spelling-errors and very rare terms that would not contribute to the classification of documents. Finally, terms are reprocessed by stemming, which once again reduces the vocabulary by approximately 23 percent[9] .

[7] *n-grams* are consecutive term compounds of length *n*. Only compounds of nouns (e.g. "grid stabiliszation") and adjective noun phrases (e.g. "flexible consumption") were detected.

[8] The evaluation is performed by training the tagger on 90 percent (39190 sentences) of the PAROLE corpus and testing it on the remaining 10 percent (1022 sentences), which represent a previously unseen text (Bird et al., 2009).

[9] Stemming algorithms determine the root of any term and return it instead of the original term: *Innovation, innovative, innovations, innovating* → *innov.*

Figure 1: Detailed overview: Combination of utilized methods and techniques



Corpus generation

From full text to Bag of Words

Tokenisation

Split up of text into single words

Bi-gram detection

Identifies "important" consecutive word-pairs across the corpus

Part of speech tagging

Identifies word categories

Keep-filter

Keep nouns and noun-phrase-bigrams

Kick-filter

Eliminate (1) stopwords (e.g. 'the'-generic or 'project'-contextual) and (2) terms that only appear once in the corpus

Stemming

Standardise the tokens across the corpus e.g. cut off plural-s

Bag of words:

Each document in the corpus is reduced to a number of useful keywords and phrases (allowing repetition)

Vector Space Modeling

Generating a document dissimilarity matrix

Vector representation

Transforming each document into a vector representation e.g. for doc1 and terms 1-3: (t1:1; t2:3; t3:1 etc.)

TFIDF - scaling

Discounts general (here: t2, t3) and emphasises document-specific (here: t1) terms e.g. (t1:1.8; t2:2.1, t3:0.5)

LSA model

Identification of a *n*-dimensional language model based on term co-occurrence patterns in the corpus, where *n* is the number of latent topics to determine in the corpus

Document projection

Projection of all (unscaled) vectors into the generated vector-space

Cosine similarities

Calculating of pairwise cosines between all document-combinations

Dissimilarity matrix:

A *m***m* matrix (where *m* is the number of documents) showing the semantic similarity between each pair of documents in the corpus

Network Analysis

Clustering and interpreting

Network generation

Translating the dissimilarity matrix into a network representation with documents as nodes and cosine similarity measures as edges

Community detection

Identification of document-clusters - groups of articles that share relatively more and relatively stronger ties - using the Louvain Algorithm

TagClouds

Concatenation of all documents per cluster and repeated TFIDF-scaling, visualisation of the set of words with the TFIDS score as scaling parameter

Visualisation

Visualisation of the network e.g. using the open source Gephi package

Interpretation:

Immediate results on cluster size and themes (from e.g. the TagClouds), further exploration using additional document meta-data (dates, authors etc.) and qualitative content analysis of the clustered documents

4.2. Vector space modelling & Latent Semantic Analysis

The BOW extract of the documents is transformed into sparse vectors where each term is represented as (w, c_w^d) with w being the *word-ID* in the initially created dictionary and c_w^d the integer word count of w for the particular document. The resulting representation is then *tf-idf* (term frequency – inverse document frequency) weighted, in order to discount generic terms across documents and equivalently promote document-specific terms.

$$TFIDF[t_i^d] = TF[t_i^d] \cdot IDF[t_i] \tag{1}$$

Where TF is the term t_i frequency in a document d divided by the document length and IDF the logarithm of the number of all documents divided by the number of documents, containing the term.

The returned vectors in normalized unit length, of same dimensionality are then once again transformed into a vector space of lower dimensionality using the latent semantic indexing (LSI or LSA) algorithm (Deerwester et al., 1990; Dumais et al., 1988). See Figure 2 for a schematic representation of the process.

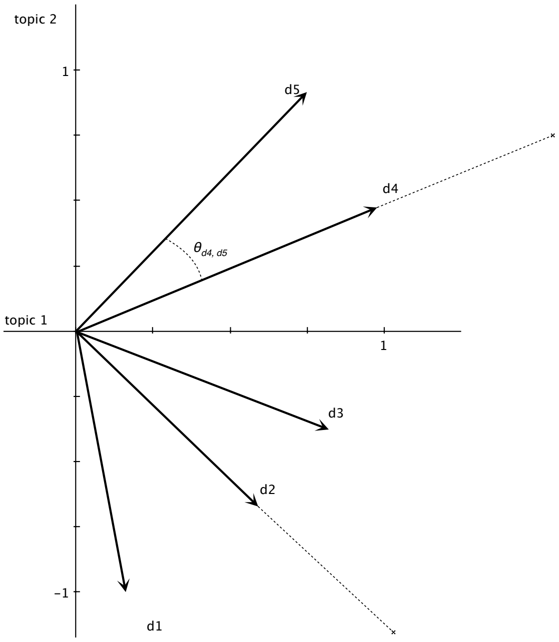


Figure 2: Schematic representation: Dimensionality reduction and similarity calculation within the LSA framework

Following Bradford (2008) a target dimensionality of 400 is chosen, where each dimension can be interpreted as a topic inferred from the whole input BOW corpus. Each document is now represented as a 400-dimensional vector.[10]

[10] This choice is always a trade-off between language particularity, fragmentation and computational cost. Bradford (2008) evaluated different dimensionality and corpus size combinations, concluding that for this type of topic modelling a diminsionality of 400 is a “safe” choice.

$$\text{similarity} = \cos(\theta) = \frac{A \cdot B}{\|A\|\|B\|} = \frac{\sum\limits_{i=1}^{n} A_i \times B_i}{\sqrt{\sum\limits_{i=1}^{n} (A_i)^2} \times \sqrt{\sum\limits_{i=1}^{n} (B_i)^2}} \tag{2}$$

Finally, cosines between the document vectors are calculated as a similarity measure.

4.3. Network analysis and community keyword extraction

The document similarity matrix is used as an input for a weighted undirected network where documents form nodes while edges are defined by the $\cos(\theta)$ values between the documents. The distribution of similarity values is highly skewed towards the lower bound. Therefore a cut-off is set at $\cos(\theta) \approx 0.1$.

For project descriptions a threshold value for edge creation is set at the 80 percentile that corresponds to a maximum cosine of 0.14, meaning that cosines below that value (80 lower percent) will not form edges. For industrial publication the percentile value was even higher (around 90 percentile). Modularity class calculation within *Gephi* is used to detect communities (Blondel et al., 2008). The basic intuition of the method is that ties within a community are more common than ties across communities. Yet, results suggest to re-run the algorithm on very large communities separately to split them up in *sub-communities*.

One observation is that industrial publications contain review-type documents that provide an overview on different technologies on the market and alike. These documents seem to be contra-productive for the clustering procedure, which implicitly assumes that each document is only associated with one particular technology or technology-area.

Therefore, for industrial publications nodes with very high degree are manually allocated in a class container [99] before modularity classification is performed.

Keywords describing the communities are extracted by calculating TF-IDF values for community-aggregated texts using the same kind of TF-IDF transformation as before on document-level. Scoring by TF-IDF values returns the most important keywords for a community (Salton and McGill, 1983). The TF-IDF weight can also be used for tag-cloud style visualization.

5. Results

This section exhibits the results of the above described analysis. It starts with an overview over the main detected techno-thematic communities, looking at results from the research project analysis and the article database separately. A subset of interesting fields are thereafter discussed more in detail.

5.1. Main technological trajectories in energy research

The filtering procedure, described above, generates 99 project description extracts.[11] Applying LSA and the modularity classification algorithm[12], returns a modularity value of 0.338, suggesting that the clustering is not optimal and overlapping communities might exist. As clustering is based on the document similarity measure and single projects can bridge over or are explicitly designed to connect different technological domains, the existence of overlaps is actually not surprising. 12 communities are detected, with an average size of 8 nodes, the largest communities having 16 and the single smallest 1 node (see Table A.2 for more descriptives). Figure 3 shows the generated graph and indicates the thematic features of the communities in tag-cloud visualizations, where term size is determined by the respective TFIDF values.

Already the graph visualization indicates that the extent to which techno-thematic communities are clustered, varies across the the whole sample. Table A.2 in the Appendix provides a summary over the identified clusters and their features, Figure A.1 gives an overview over community sizes and start years for the constituent projects. Among the mostly identifiable technology centred communities we find projects related to the heat pump technology [4][13] and the large district heating cluster [11]. The later is however much less concentrated and seems to consist of two sub-communities, where one is more focused on the development of the technology itself and its systemic integration, while the other aims at connecting the technology to other technologies and applications. This community not only stands out in size but also is the oldest, meaning that its projects have the relatively earliest start-year on average.

Two further dense, yet rather application-focused clusters can be found in [8], which gathers projects that explore the flexibilisation of energy consumption and [5], which aggregates activities related to systemic integration. The extent, to which these thematic communities are diverse in their technology-composition will be discussed below. Smaller unambiguously identifiable technology-areas are electric vehicles [2] and [6], Decentralized communication technology and data security [0], and battery development [1]. An example for less identifiable communities can be found in [9]. Projects in this group are sparsely connected with each other. Also (significant) ties outside the cluster are few and weak.

5.2. Central technologies, themes and applications within the industrial discourse

The initial sample of 813 articles is stepwise reduced to a number of 574. Even though the filters applied might seem very conservative, the analysis shows that 32 articles remain in the sample that seem to be very research-project-related and have been automatically grouped into one class conditioned on the presence of "project-terminology". 5 documents with the highest degree-scores in the sample have been manually allocated to the class container [99] before clustering. The idea here was to

[11] An automatically translated BOW extract example `[u'concept', u'air air', u'heat pump', u'focus', u'climate', u'electricity consumption', u'demonstra', u'play solution', u'heat pump'...]`

[12] using a resolution of 0.6, considering edge weight and enabling randomization

[13] Modularity class number interpreted as community or cluster e.g. [4]

avoid "review" articles, that inherently relate to all possible energy technologies and applications. A detailed analysis of the texts showed, that indeed these 5 were very general in their contexts – providing an overview over the different *smart grid* technologies and applications that the future might bring. Apart from that, the modularity-class calculation with the same specifications as for the project descriptions, identifies 12 communities. A detailed overview over communities and their features can be found in table A2. As shown in Figure 4, the technological clusters (heat pumps [9], electric cars [8] and district heating [4]) that can be found in the project-analysis re-appear. They form very dense clusters, not only seen in the visualization but also in the TIFIDF-value distribution. These communities do however merely account for 22.5 percent of the sample. Another 18 percent are made up by the wind-power [10], energy optimization and installation (primarily by *Schneider Electric*) [0] and residential solar [2]. As in the project-analysis, consumption flexibilization [5] is very central. New are the areas energy business with a particular focus on export and collaboration with Asian countries [6], and the thematic policy-cluster [7]. Figure A2 summarizes the over-time development of the community sizes.

The remainder of the analysis will make further use of the thematic clustering to explore the overlapping technological area related to heat pumps more in detail. Furthermore, the business and export cluster, resulting from the publication analysis will be examined in order to evaluate the presented methods performance when applied in a less technical, and thus supposedly more abstract domain.

6. Trajectory Study: Heat Pumps

Heat pump units operate using electricity to drive compressors that concentrate and transport thermal energy. The thermal energy extracted from air or the ground can then be used for space and water heating, also the reverse process is possible to use the heat pump for cooling. In fact, using the technology for both heating and cooling simultaneously is most efficient, yet not a very common practice (Mathiesen et al., 2011a). Thermal energy can be stored for later use and pumps can also be combined with consumer side renewable energy generation units such as residential PV (Sanner et al., 2003). This options led to growing interest for this rather mature technology in the recent years, since it can potentially become an important component for efficiency increase and because of the storage option for the flexibilization of energy consumption. The latter is particularly important for the build up of a smart energy system that is able to integrate large amounts of fluctuating electricity generation, e.g. wind power (Lund et al., 2012; Mathiesen et al., 2011b).

While the first theoretical description of a heat pump as a devise for heating and cooling, by the French officer Nicolas Leonhard Sadi Carnot, dates way back to 1824, it was first in 1948 that the technology was applied in the Equitable Building, New York. Commercial heat pump unit distribution commenced in the 1950s but did not take up until the 1970s and the Oil Crisis, when rising energy costs made electric furnaces less competitive (Hepbasli and Kalinci, 2009). Other reasons for the heat pump "boom" were the growing heat and warm-water demand and the transition from single-room to central heating. However, this was only a boom in relative terms and the technology was merely making up an average 1 percent in the European residential market share with significant difference in individual countries (Laue, 2002). Environmental awareness and efficiency considerations can be count as reasons for the European renaissance of heat pumps in the mid 1990s. Today heat pumps are seen as one of the key technologies to decrease CO_2 and other greenhouse gas emissions.

Denmark adopted the heat pump technology right after the oil crisis in the 1970s. Many producers entered the market, offering products that ranged from high quality pumps, some of which are still in use today, to products of very poor quality that casted a bad light on the industry (Poulsen, 2007). Today, the Danish Energy Agency estimates a total of 100.000 small residential pumps and 5.000 large industrial scale units installed. Even though this total number of installations is relatively low, the Danish market is catching up with 20.000 small mostly air-air units and 5.000 geothermal pumps sold every year (Frost-Knudsen, 2013). A new general tax on all heating systems to be passed by January 2014 is expected to make efficient heat pumps even more attractive.

6.1. Heat Pump development within Danish research

The project analysis selected 12 activities into the "heat pump" class. The TFIDF-Keyword-Cloud does not really provide much information about the important themes that constitute the cluster. Given a larger number of projects, a further clustering and topic modelling could be applied to identify *sub-clusters*. In this case the direct "manual" analysis of the descriptions seems most appropriate. As shown in Figure A.2 the first project in the field was commenced in 2009. Until 2011 the number of newly started activities went up peaking at 4 new projects. A brief qualitative analysis of the descriptions reveals two broad fields of activities among the projects that focus on the usage of the heat-pump technology within the new *smart grid* paradigm.

On the one hand there is projects that explore options for the integration of large-scale heat pump and district heating systems, by connecting central heat and power plants (CHP) with large heat pumps, in some cases also solar systems. Such combined systems can become a more centralized way to allow for more intermittent wind power in the overall energy system, while combining the efficiency and storage options of heat pumps with the existing CHP infrastructure. On the other hand there is a significant number of projects that focus on residential small-scale applications. These activities aim at developing and testing standards for *smart grid* ready plug-and-play solutions, remote control of pumps, test protocols and other technology standards. While the units by themselves seem efficient and mature, knowledge about automatizes interaction with the grid has to be developed. Virtual power plant projects for small and large scale areas combine different ethnologies within a complex system with many components.

6.2. Heat Pump technology in national industrial publications

The distribution of industrial publications over time displays some similarities to the projects with overall 45 reports selected into the thematic heat-pump cluster. First reports that mention heat pumps in a *smart grid* context can be found in 2010.

Re-running of the clustering algorithm generates 4 *sub-clusters* that can guide the exploration. Two of those are obviously related to efficient residential housing and for the most part inform on different projects within new and old constructions. Much emphasized is the interaction between different domestic appliances, the heat pumps as heating devise of choice and the management by intelligent (partly remote) control systems.

One of the *sub-clusters* takes a more industrial installation-perspective on the technology. An article (nr. 314) for instance outlines the market potential and job creation opportunities once more heat pumps will be installed. It estimates up to 1 million new units until 2020. Other central topics of the *sub-cluster* are remote control standardization and the energy renovation of old buildings.

The largest *sub-cluster* is more (heat pump) technology focused. It outlines more generally the opportunities that the available technologies offer for the development of the energy grid, particularly concentrating on the energy storage options that are expected to facilitate the integration of more wind power and other fluctuating renewable energy sources. Another technological focus is the already in the research-analysis shown combination of heat pumps with solar. Furthermore it groups market analysis and policy reports covering the area.

Overall the brief analysis shows that there is a significant overlap between applications, developed in research projects and the expectations towards the technology that is expressed in industrial publications. The deployment of heat pumps as a grid stabilization technology seems clearly to be one of the dominant technological trajectories within the Danish *smart grid* development.

Figure 3: Overview: Research project graph and cluster level TFIDF-Keywords

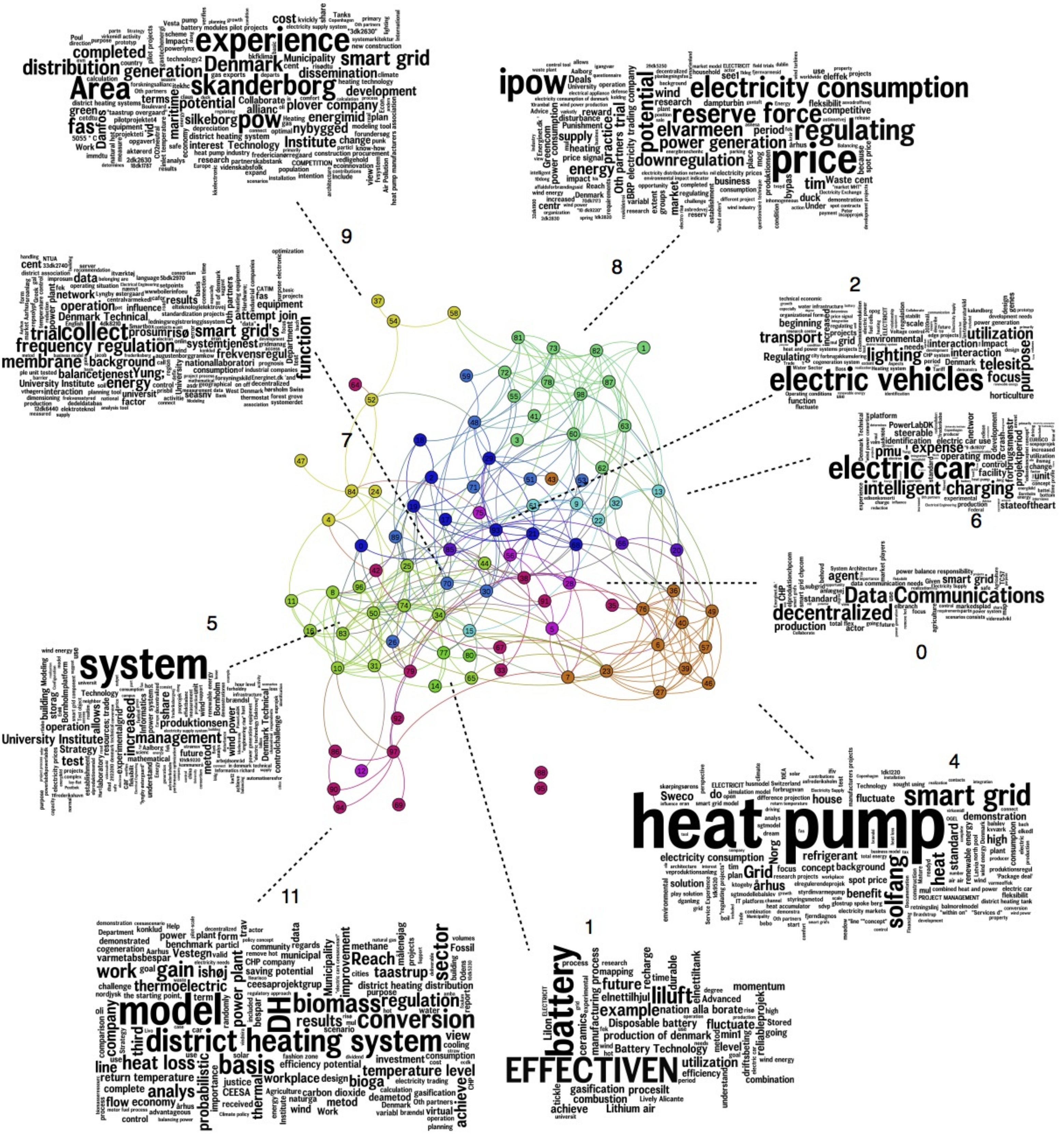
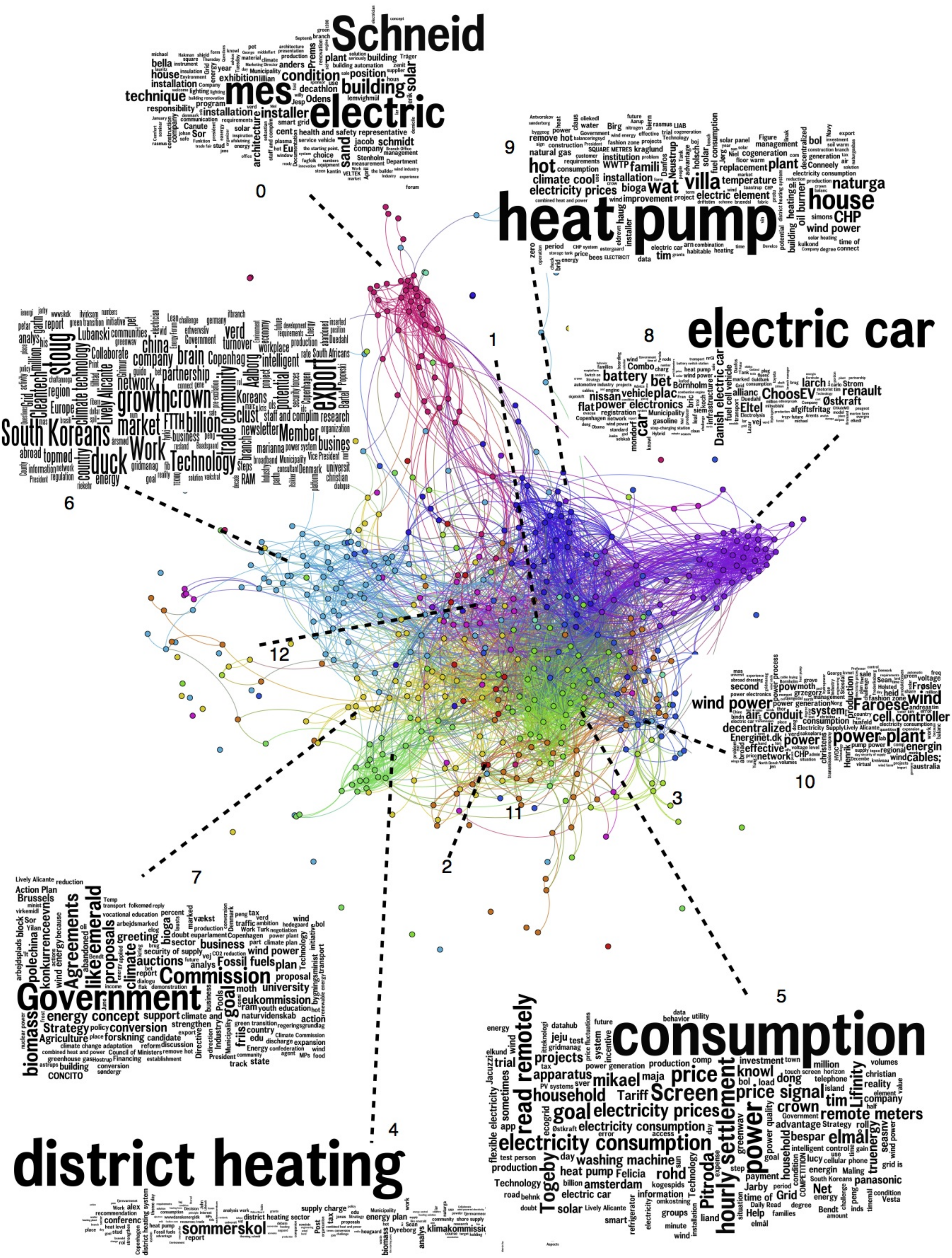


Figure 4: Overview: Industrial publications graph and TFIDF-Keywords



7. Thematic Field Study: Smart Energy Technology Business and Export

Gathering almost 20 percent of the publications, the Technology Export and Business cluster – as it can be called given the TFIDF-Keywords - is the largest thematic community. It has obviously no technological focus but some of the specific targeted markets can already be identified in the extracted keywords. The clustering algorithm is used once again to generate 6 *sub-clusters*. 5 of which make up at least 97 percent of the initial group. One of the *sub-clusters* takes up 40 percent, the other 4 around 14 percent each.

The first rather loose *sub-cluster* does not refer much to business or trade but to job creation in the Danish installation and to some extent IT-industry. Opportunities arise, according to the grouped articles, from the connection of new hardware to the grid and the development of communication solutions.

The other nearby 16 percent *sub-cluster* is more dense and to a higher extent focused on the installation industry. Many of the publications present studies and estimations about the market opportunities related to the grid development and more broader the energy system transformation. In the desired case, the industry is expected to earn 5 billion DKK (approx. 900 million USD) yearly up to 2020. Other market estimations also mention the most central national technology competences within the *smart grid* area: Grid-automation, smart-home appliances and measurement technology have the potential to generate 2.500 jobs in Denmark and further 2.000 in the EU.

One smaller 12 percent *sub-cluster* summarizes more generally articles about required investments and changes in order to develop the *smart grid* in Denmark. While the the creation of IT and hardware solutions is important, coordination is emphasized to be key in this technological system. One important step was the initiation of the Intelligent Energy alliance in 2012 that brings together around 130 players with interest in *smart grid*. A central publication outlines the importance of incentive creation for the utility companies that are the central actors in the current grid infrastructure.

The last small *sub-cluster* focuses on growth. It brings together further market development studies, reports on policies and initiatives that (could) perpetuate growth from the energy system transformation, where *smart grid* development is always central.

The large *sub-cluster* is primarily looking on the energy technology market and export development. *Smart grid* technologies are expected to repeat the success of wind power and district heating technologies that still drive Danish energy technology export. Outside the EU, the US, with the in late 2012 announced *smart grid* strategy, represent an important market. Much more pronounced is however the Asian marketplace and here particularly Korea as both market and strategic partner in the development of technology. The Asian country embraced the green paradigm rather late but is moving fast and expects *smart grid* investments of 7.2 billion through 2030. The Global Green Growth Forum, initiated in 2011 between Denmark, South Korea and Mexico provides another platform to facilitate interaction and trade. In 2012 also Qatar, Kenya and China joined the organization. Collaboration between different actors, especially the utility companies is outlined as a key condition for success on the international markets.

8. Discussion

The depicted brief analysis demonstrates how the presented method can be used to map technology development and help structuring and describing the socio-economic environment, consisting of applications, expectations, markets, policies and organizations. A detailed exploration or the elaboration of a case study or narrative was not intended. Research project descriptions in summarized form as obtained through `energiforskning.dk` seem to be a concise and in the same time sufficiently rich and reliable source of data to map the various technology focus-points in the national research landscape. The brief summaries usually name the involved technologies, applications and the technical context in which these are embedded. Yet, they vary in length and detail. The extracted industry publications contribute with many diverse and interesting insights into the variety of applications and environmental factors. They open up for the understanding of the cognitive level, or as proposed by Kaplan and Tripsas (2008) the collective technology framing. This seems to be useful for exploratory and descriptive studies of a complex systemic field. The applied topic modelling and clustering generates a structure and indicates the most pronounced aspect of the environment. However, in comparison with the project-analysis the trade-off between rich and structured data becomes obvious. While project summaries follow a implicit structure as for instance research paper abstracts would do, industrial publications are inherently "messy". Smaller issues as for instance repeated reporting about one single event or policy, can be avoided by limiting the analysis to only one journal, perhaps even only on one particular format within the journal. In the presented case the Danish Energy Periodical (Nyhedsbladed Dansk Energi), which was the source of 44 percent of all articles could have been chosen (see Table A.4). Even though the applied filtering of extracted text-files can be called rather conservative and the clustering did for the most generate coherent thematic communities, the multidimensionality of the technology and particularly of its surrounding environment complicates the interpretation of the grouped publications. Often it is unclear whether a cluster can be interpreted as a dimension such as policy or market, or rather represents a technical component such as the heat pump as part of the technology-dimension.

While not yet implemented here, automatized entity recognition could make the mapping more powerful. The exclusion of actor-names from the topic modelling would decrease the impact of actual actor interaction on the thematic structuring, while actor-context linking could indicate the activity of actors in particular technological or thematic fields. This in turn could enrich the analysis of "real" networks, e.g. research collaboration networks by generating actor-covariates. Another way to optimize the method could be through implementation of automatized hierarchy/taxonomy building as suggested by Henschel et al. (2011) .

Turning to the *smart grid* case, the exploration shows that *smart grid* technology is more than merely a combination of artefacts and services that are often mentioned under the collective notion of the *layer of intelligence*. These new ICT-heavy technologies are essential for precise controlling of the “new grid”. Yet, in the Danish context, mature consumption side technologies such as heat pumps and district heating systems will become evenly important since flexible energy consumption and storage is necessary in order to integrate the growing amount of sustainable energy generation. *Smart energy* technologies are expected to contribute to economic growth and spur energy technology export. In the international context, a particularly interesting country - also for future comparative research - is South Korea. The Asian country does not only move quickly in the development of smart grid technology - yet obviously creating different technological paradigms - but also seems to have a great interest in collaborating with Denmark.

A. Figures and Tables

Figure A.1: Projects modularity classes over time (smallest excluded)

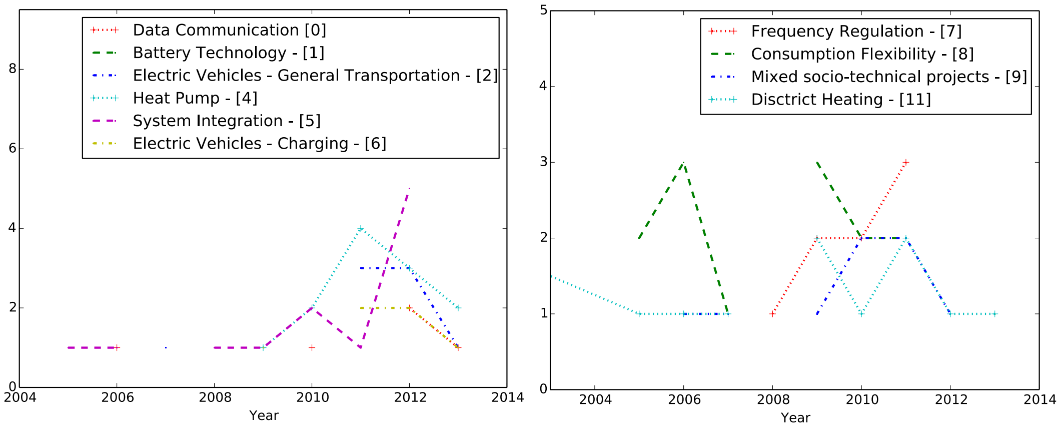
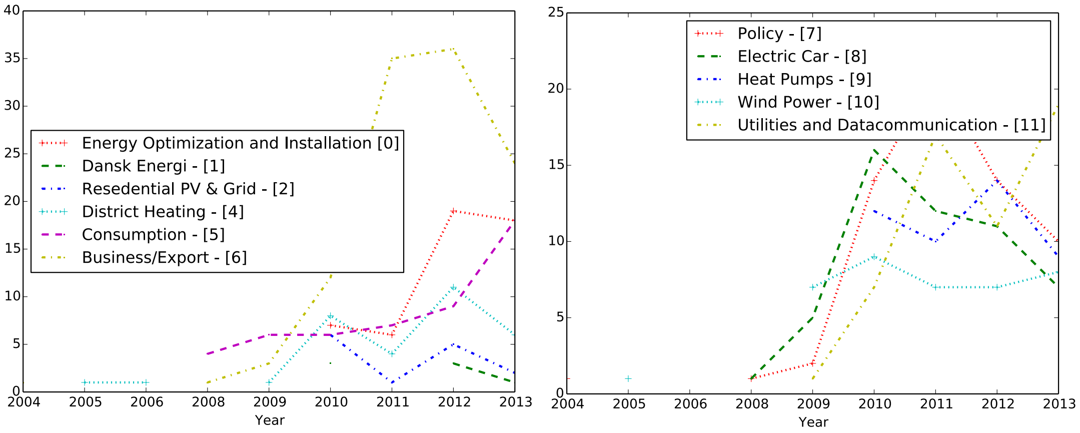


Figure A.2: Publications modularity classes over time (smallest excluded)



Notes: Year indications are taken from project start years and article publication years respectively.

Table A.1: Overview table: Natural language processing terminology used in the article

Term	**Abbreviation**	**Definition**
Bag of words	BOW	Unsorted collection of not unique words that are meant to represent a document, usually nouns and noun phrases
Noun phrases		Expressions consisting of a noun and one or more other non-nouns that carry a specific meaning in this particular combination and sequence
(Bi-) n-grams		Combinations of n words following each other in a document
stopwords		Common generic terms in a any language that as such are not carrying contextual information, for instance prepositions and pronouns
Part of speech tagging	POS	Algorithmic identification and annotation of word types in a text
Brill tagger		Inductive and resource efficient algorithm to perform POS based on identified rules about any language learned from a training-corpus
PAROLE Corpus		Large collection of manually annotated text in Danish, which can be used to “train” a tagger
Document frequency	high/low-DF	Words that appear disproportionately often or seldom (1 time – singletons) in a text collection. While the former are often stopwords, latter cannot be used to induce similarity between several documents, as they only appear once
Stemming		Algorithmic process for reducing inflected (or sometimes derived) words to their word stem in order to increase identical terms across documents in a text collection
term frequency–inverse document frequency	TF-IDF	Numerical statistic that is intended to reflect how important a word is to a document in a collection. The tf-idf value increases proportionally to the number of times a word appears in the document, but is offset by the frequency of the word in the corpus, which helps to adjust for the fact that some words appear more frequently in general. (adapted from Wikipedia)
Latent Semantic Analysis	LSA (or LSI)	A technique in NLP, in particular in vectorial semantics, of analyzing relationships between a set of documents and the terms they contain by producing a set of concepts (topics) related to the documents and terms. LSA assumes that words that are close in meaning will occur in similar pieces of text and allows to calculate semantic similarity values between documents in a collection. (adapted from Wikipedia)
Target dimensionality		LSA uses singular value decomposition to reduce the number of unique terms in the collection to a pre-defined number of topics, which are in the same time the dimensions in the vector space model.
Document similarity matrix		Square matrix of all documents in a collection obtained by multiplying the rectangular matrix between by LSA identified topics its transponse.

Table A.2: Descriptive statistics, Project description clustering

MC	Technology/Topic	Start Year	AVD	Size	Rel. Size
0	Data Communication	2010.6	1.96	5	5.10
1	Battery Technology	2008.3	1.38	3	3.06
2	Electric Vehicles – General Transportation	2009.9	2.26	9	9.18
3	Water/Mambrane Energy storage	2012.0	0.00	1	1.02
4	Heat Pumps	2011.3	2.95	12	12.24
5	System Integration	2008.8	2.98	13	13.27
6	Electric Vehicles – Charging	2011.3	2.04	6	6.12
7	Frequency Regulation	2008.9	1.91	9	9.18
8	Consumption Flexibility	2008.4	2.48	14	14.29
9	Mixed socio-technical projects	2009.5	1.21	8	8.16
10	Consumption & Frequency control	2008.3	1.89	3	3.06
11	District Heating	2005.4	1.28	16	16.33

Notes: Modulatiry Class (MC), Technology/Topic interpretation from TFIDF-Keywords, average project start year for each modularity class, average (edge)weighted degree (AVD), Relativa Size in percent.

Table A.3: Descriptive statistics, Industrial Publications clustering

MC	Technology/Topic	Publication Year	AVD	Size	Rel. Size
0	Energy optimization and installation	2012.0	15.64	50	8.71
1	Dansk Energi (company)	2011.3	32.26	7	1.22
2	Residential PV & Grid	2011.2	23.60	14	2.44
3	Dong Energy (company)	2011.4	15.08	18	3.14
4	District Heating	2011.1	18.75	32	5.57
5	Consumption	2011.3	32.71	50	8.71
6	Technology Export & Business	2011.5	15.44	112	19.51
7	Policy	2011.1	21.60	63	10.98
8	Electric vehicles	2010.9	27.59	52	9.06
9	Heat Pumps	2011.4	27.90	45	7.84
10	Wind	2010.8	23.66	39	6.79
11	Utilities and Data-communication	2011.7	20.81	55	9.58
12	R&DD Projects	2011.2	21.92	32	5.57
99	Excluded-Too high Degree	2012.0	78.88	5	0.87

Notes: Modulatiry Class (MC), Technology/Topic interpretation from TFIDF-Keywords, average publication year for each modularity class, average (edge)weighted degree (AVD), Relativa Size in percent.

Table A.4: Overview: Sources industrial publications

Source/MC	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**99**	**Total**	**%**
Alt om Data				1		1	2					1			5	0.9
Bedre Hjem		2				1				1				2	6	1.0
Bo Bedre										2					2	0.3
BygTek										2					2	0.3
Byggeri	1														1	0.2
Byggeteknik					1	1		2							4	0.7
CSR	2	1					2		1						6	1.0
Computerworld				3		1	10	1	2	1	1	1			20	3.5
DI Business				1		1	8	3	1			1	6		21	3.7
DI Indsigt							1								1	0.2
DSbladet					1								1		2	0.3
Dagens Medicin						1									1	0.2
Dansk VVS	2		2				1	1		2	1				9	1.6
EksportFokus							3						1		4	0.7
El og Energi								1	1						2	0.3
Electra	3		1			4	2	4	1	1	3	1	2		22	3.8
Elektrikeren	2		1			1	4		1	1	1	1			12	2.1
Elektronik & Data													1		1	0.2
Energiwatch							1					1			2	0.3
Erhvervsbladet							1								1	0.2
Erhvervsmagasinet Installatør	2														2	0.3
Fjernvarmen					15					6		2			23	4.0
Fritidsmarkedet						2				1					3	0.5
Hvidvare-Nyt	1					1		1						1	4	0.7
Ingeniøren	1	1	4		5	12	4	7	3	8	9	5	1		60	10.5
Installatør Horisont	8	1				1	3	1		3		1	1		19	3.3
Jern Og Maskinindustrien	6				1		5	1					1		14	2.4
Jern og Maskinindustrien	2								2	1	1				6	1.0
Karrierevejviser											1		1		2	0.3
Kommunen							1						1		2	0.3
LandbrugsAvisen								1							1	0.2
Magasinet Finans												1			1	0.2
Magasinet Statsindkøb	1							2							3	0.5
Magisterbladet							1	1							2	0.3
Mandag Morgen				1			2	3			1	1	1		9	1.6
Mandag Morgen Navigation						1									1	0.2
Mandag Morgen News							3								3	0.5
Maskinmesteren		2			2		3		1		1	1	1		11	1.9
Mester & Svend										1					1	0.2
Mester Tidende	3						1		1						5	0.9
Motor-Magasinet									3						3	0.5
Natur & Miljø									2						2	0.3
Nyhedsbladet Dansk Energi	13		6	7	7	19	51	34	33	13	20	36	13	1	253	44.1
Optimering														1	1	0.2
Pack Markedet	1														1	0.2
Proces-Teknik				2											2	0.3
Prosabladet							1								1	0.2
Samdata										1					1	0.2
Teknovation				2											2	0.3
Telekommunikation				1			2								3	0.5
Tænk						3									3	0.5
byggeplads.dk	2											1			3	0.5
danskVAND										1			1		2	0.3
Økonomisk Ugebrev CFO												1			1	0.2
Totals															**574**	**100**

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