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143 A conceptual framework for applying residential demand response strategies based on household characteristics: Results from a Swedish case study

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Abstract

Residential demand response (DR) has the potential to provide increased demand flexibility, realizing the benefits of smart grids for a more efficient and sustainable power supply system. The interest in DR strategies has increased over the last decade, along with the growing need to balance electricity supply and demand. DR helps account for variability of renewable energy production and new daily load profiles—with the incorporation of low carbon technologies such as electric vehicles—by dynamic pricing schemes.

The way in which people consume electricity (i.e. daily habits and routines) and the way that they respond to DR incentives (i.e. willingness to adjust their consumption patterns) greatly varies among demographics. Previous studies have found that the effectiveness of a residential DR program may be dependent on different socio-economic and dwelling characteristics. However, it is difficult for researchers and industry practitioners to identify where the challenges and opportunities of implementing specific DR strategies geographically lie, lacking the tools to quickly identify suitable areas to upscale successful DR programs.

This study presents a six-step conceptual framework that aims to address these challenges by proposing a systematic approach to visually identify the potential for applying DR strategies in different neighborhoods. The visualization tool will help implement more accurate DR strategies to curb electricity demand from appliances and devices, allowing for a more resilient smart grid. A case study in Stockholm was carried out to demonstrate the applicability and usefulness of the framework. The results analyzed and displayed neighborhoods that contained specific socio-economic compositions similar to the case study, enabling DR strategies to be upscaled.

This framework has the potential to support researchers, policy makers, and utilities and energy companies in finding suitable areas where DR programs can be customizable to residential needs and lifestyle patterns, thus saving significant time and resources.

Key words

Demand Response, Electricity Consumption, Data mapping, Grid Flexibility, Household

Introduction

New policy priorities and technological innovations have driven global, national, and local energy systems to change (UNIDO, 2018). From 2010 until 2017, there has been an average 8% increase per year in renewable energy capacity globally. In 2017, a new record was observed as renewable power generation accounted for almost a quarter of total global power generation in 2017 (IRENA, 2018). Nevertheless, the increase of variable renewable energy such as solar and wind power creates challenges for the current grid (IRENA, 2020). The increase in variable renewable energy is essential in achieving global climate goals, however as its supply is dependent on the uncontrollable resources such as solar and wind, it creates transmission congestion and introduces balancing challenges to the current grid (IPCC, 2007; IRENA, 2020). This has created a demand for flexible solutions where the consumption and production of electricity can be managed to the grid's requirements and energy balance. A key-solution to creating a more flexible and low-carbon grid is through demand response (IEA, 2017, 2018; IRENA, 2020).

Demand Response (DR) can be defined as the mechanism in which energy demand is temporarily changed in response to a price or another signal to provide a grid balancing service, while simultaneously creating the potential for consumers to save on electricity costs (Gellings, 2009; IEA, 2018; Palensky & Dietrich, 2011; Saini, 2007). It is estimated that in 2040, 20% of global electricity consumption will be available for DR (IEA, 2017). The realization of residential DR programs is affected by both the way in which people consume electricity (i.e. daily habits and routines) and the way they respond to DR incentives (i.e. willingness to adjust their consumption patterns) (IEA, 2018). A better understanding of these consumption patterns and interactions—visible in residents' daily load profiles, responses to residential DR programs, and use of appliances—will support advancements within DR strategies. This may lead to reductions in energy consumption and enable peak load shifting. In this paper, the term 'DR programs' will be used to describe specific hard- and software, as well as incentives that enable consumers to shift their load. 'DR strategies' will be defined as the umbrella-term that describes all potential approaches when managing DR. This study will focus on demand response within residential settings, therefore excluding any demand response in industrial settings.

The implementation of a DR program is non-trivial. Besides identifying new ways to save and manage energy consumption, knowing where to strategically deploy these programs geographically can be challenging as it is both time and resource consuming. Current studies focus on examining the impact of DR programs by studying household electricity usage and interaction with DR programs with respect to various characteristics such as age, income, and educational level (D'Oca et al., 2018). This provides insights on how, what, and when DR programs should be used to manage energy consumption. However, previous research has focused less on answering the question of *where* the challenges and opportunities of implementing specific DR strategies lie geographically.

The aim of this study is to provide increased understanding of the potential of demand response by developing a conceptual framework for identification, analysis, and visualization of household characteristics that affect the response to DR programs in specific geographical areas. The conceptual framework aims to support the development of residential DR strategies and help DR programs reach a greater potential by enabling more effective deployment. The conceptual framework can provide streamlined steps to strategically implement DR programs on a wider scale by matching different socio-economic households with recommended DR programs**.** Thus, the framework can assist researchers, policy-makers, and energy and utility companies to increase the effectiveness of flexible energy consumption and cost savings through DR programs, as well as provide insight into how future DR applications may vary and be optimized on a neighborhood scale.

This paper presents a conceptual framework for DR program designers (e.g. researchers, DSO's) and implementers (e.g. housing developers, governments) that shows where DR programs should be deployed to obtain the best results.

To demonstrate the framework's potential benefits, the six-step framework is applied to a case study in Stockholm, Sweden, which uses a DR program that includes home energy management systems (HEMS). The objective of the conceptual framework is to visualize the extent to which specific Stockholm neighborhoods show household characteristics that could be considered suitable for specific DR programs. The visualization can be represented in either *single* filter maps i.e. maps where one characteristic is visualized, or *multi* filter maps i.e. in which several characteristics are visualized. Moreover, applying multiple filters on maps, can help identify areas with a specific combination of household characteristics for upscaling and customizing future research.

This paper is divided into six main sections. The following section discusses related work and presents the most common and impactful household characteristics influencing energy consumption. Subsequently, Section 3 describes the proposed conceptual framework for demand response strategies in six steps. Section 4 applies this framework to a case study about Stockholm, with a special focus on the Stockholm Royal Seaport (SRS). Section 5 discusses the conceptual framework, its applications, limitations, and potential; moreover, it discusses the results of the Stockholm case study. Lastly, Section 6 provides conclusions to this paper.

Household characteristics influencing electricity consumption

A systematic literature review was conducted to understand and identify what household characteristics affect residential energy use and interactions with demand response programs. The keywords chosen for the literature review were “demand response”, “household” or” dwelling” or “residential” and “electricity” or “energy”, and “characteristic” or “behavior" or “factor” for example “household electricity behavior”.

The outcome of the literature review show that the majority of previous research mainly examined the household characteristics impact on electricity usage by considering appliance use and load profiles (Bedir & Kara, 2017; Hayn et al., 2014; Jones & Lomas, 2015; Kavousian et al., 2013; Matsumoto, 2016; Mcloughlin et al., 2012; Yohanis et al., 2008). Other studies focused more on how household characteristics impact the interaction of DR programs and the comparison of energy efficient appliances to DR strategies to reduce electricity use (Gram-hanssen, 2011; Podgornik et al., 2016; Vassileva et al., 2012a). However, the most influential factors vary in different studies. A review of a collective body of research was therefore conducted to identify the six most influential household characteristics related to behavior that could affect electricity use and energy feedback, as well as user interactions with DR programs.

Income

Income is one of the most studied household characteristics in regard to electricity use. Hayn et al. (2014), Matsumoto (2016) and Podgornik et al. (2016) all found that income was one of the most significant factors. Both Hayn et al. (2014) and Podgornik et al. (2016) found that increasing income leads to increasing electricity use. However, Hayn et al. (2014) explains that this could be because households with higher income tend to be of a bigger household and therefore use more electricity. Matsumoto (2016) on the other hand found that in fact not all cases show that high income households use more electricity as they tend to have newer and energy efficient appliances than low income households. High income households also spend more time outside of the house as they can afford to live more dynamic lifestyles leading to them using less electricity at home. Income also indicates the employment status of residents. Residents that work at an office will also lead to less time spent at home during the day (Matsumoto, 2016). This is also one of the reasons why high-income households have a different load profile from low-income households. Yohanis et al. (2008) found that residents in high-income households use 2.5 times more electricity during the evening and also consume significant electricity during the morning, whilst low-income households have a relatively constant consumption except for a peak around dinner time.

Age

Residents above the age of 60(±5) often use less electricity as they own fewer electricity-consuming gadgets like several TVs and PCs (Jones & Lomas, 2015) and are more resource-conscious (Kavousian et al., 2013). However, per capita, elderly people use most electricity (Matsumoto, 2016) as they often live in single households and spend more time at home (Hayn et al., 2014). In absolute numbers, middle-aged people, from 30+ to 60 (±5) years old, have the highest electricity consumption (Hayn et al., 2014; Matsumoto, 2016), primarily because middle-aged people often have children or teenagers living at home but less electricity per capita (Hayn et al., 2014). Concerning interactions with demand response programs, Vassileva et al. (2012a) found that 1) elderly people preferred to receive information via displays, 2) information via email was more suitable for middle-aged people working who already have to consult their email accounts, and 3) younger people preferred interaction through mobile applications with a more interactive and game-oriented approach.

Household composition

Households with more than three residents often indicates a family that most likely consists of either children, teenagers, or both. Previous research shows that large households have a greater electricity use of residents however that per-capita, they have the lowest electricity use (Gram-hanssen, 2011; Hayn et al., 2014). Families with children—which sometimes entail adults working part-time—also spend more time at home (Bedir & Kara, 2017). Families with teenagers and children also use energy-intensive appliances such as dishwashers, washing machines, television, and computers more frequently (Jones & Lomas, 2015). Teenagers and children are less conscious of consuming energy and less concerned with financial implications (Jones & Lomas, 2015), however they tend to be more concerned about the environmental impacts that high energy-consuming lifestyles have with age, and they may become increasingly capable of lowering their energy use over time (Gifford & Nilsson, 2014).

Educational level

Another socio-economic factor studied is the level of education, and most studies have seen a significant correlation between a household's electricity consumption and the level of education (Gram-hanssen, 2011; Mcloughlin et al., 2012). Mcloughlin et al. (2012) found that education level was more related to social class and is perhaps more correlated to income, as previously mentioned (Hayn et al., 2014). Bedir & Kara (2017) showed that an observer group where the majority had a university education were more conscious about sustainable energy use and had more energy-saving lamps and solar panels. Another study by Bartiaux & Gram-Hanssen (2005) showed that their electricity consumption, in fact, did decrease with an increased level of education. Seemingly, as formal education increases, so does one's concern for the environment (Gifford & Nilsson, 2014).

Surface area

Several studies have shown that a household's surface area has a significant correlation with electricity consumption (Bedir & Kara, 2017; Hayn et al., 2014). As the surface area of a dwelling increases, so does the electricity consumption, because this often indicates more bedrooms (Hayn et al., 2014), thus more residents in the household.

Employment status

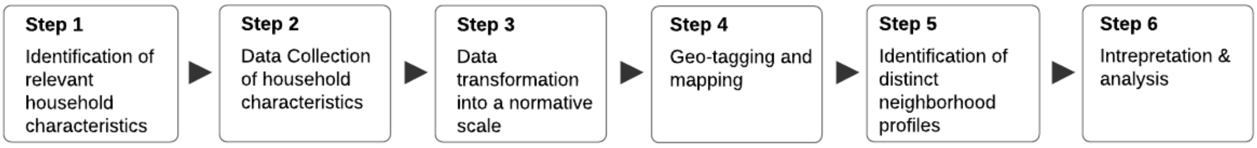
The employment status of residents can have a big influence on electricity use as it tends to impact time spent at home. Hayn et al. (2014) confirmed that unemployed residents had the highest electricity use, followed by self-employed residents as they tend to spend more time at home. Moreover, unemployed households were the largest share of single households making the electricity use per capita higher (Hayn et al., 2014). Self-employed also have more office equipment at home, which increases electricity use. Also, as mentioned previously in Section 2.1, households with all residents at work or school show clear peaks in the morning and evening, where high energy-consuming appliances like washing machines and dishwashers were used more frequently after work.

Based on the literature findings above, this study summarizes that it is difficult to predict user energy consumption patterns based on socio-economic and dwelling characteristics alone. It can be concluded that behavior is unique to each household and therefore different incentives and interactions are needed for an efficient use of DR programs. This paper allows these unique behavioral patterns to be visualized and mapped. By providing information on where specific household characteristics lie geographically, stakeholders can plan accordingly, resulting in more accurate DR program placement.

A conceptual framework for estimating the potential of DR

The six steps outlined in this section describe a structural method on how to create neighborhood profiles and analyze these with respect to any specific DR study or project. A flow chart summary of the steps is depicted in Figure 1.

Figure 1: The six-step conceptual framework to estimate the potential of DR in specific areas consisting of: 1) relevant household characteristic identification, 2) data collection, 3) data transformation, 4) geotagging and mapping, 5) distinct neighborhood profiles identification, and 6) interpretation and analysis.



Step 1: Identification of the relevant household characteristics

The initial step concerns the identification of the relevant household characteristics that influence consumption patterns and user interactions of DR programs. These vary greatly among different households as different households have different incentives to reduce electricity consumption. The literature review in Section 2 shows six paramount household characteristics that could affect electricity use and energy feedback. Note that these characteristics can differ slightly, depending on country, region, and neighborhood. Additionally, household characteristics can be weighed differently depending on the importance of specific characteristics.

Step 2: Data collection

This step concerns the collection of data related to the identified household characteristics of the previous step. Data can either be collected from previous studies or be recollected from various data sources. Data sources may include governmental databases, corporate databases, or other agencies that hold relevant and trustworthy data. Moreover, data about the number of people in a neighborhood should always be collected as reference data. Lastly, the collected data should contain a set of geotags representing different blocks or neighborhoods in the area.

Step 3: Data transformation into a normative scale

This step concerns the transformation of the provided data to a normative format. A normative format enables characteristics to be easily visualized on different maps (Wilke, 2019). The format(s) in which the data is obtained can differ and may contain missing values; this is why the data needs to be transformed to a normative scale. A dataset containing the total number of households in the neighborhood should be used as a reference for the size of the neighborhood. If the number of elements of an individual household characteristic in each neighborhood is not equal to the reference size, the share of each element should be extrapolated to match the reference size. The extrapolated data for the household, residents, and education type characteristics is normalized per neighborhood. The integer value of these characteristics is divided by the reference size of the neighborhood, resulting in the share of people having a certain characteristic. This is called the Normative Unit, as depicted in Table 1. Table 1 provides an overview of the possible obtained data format and the required format for characteristic mapping. If data is already provided in a normative format, no transformations are needed.

Table 1: Overview of data formats required for household characteristic mapping.

	Type household	**Type neighborhood**	**Type normative (required)**	**Normative unit**
Average salary [SEK/year]	Decimal number	Decimal number	Decimal number	**[SEK/year]**
Households, residents, and education type	Boolean	Integer	Percentage	[%]

Average surface area [m²]	Decimal number	Decimal number	Decimal number	[m²]

Step 4: Geo-tagging and mapping

This step concerns geotagging the data in the format suitable for the mapping software (e.g, Tableau, GIS, Google Maps). Matching neighborhoods with corresponding zip-codes is a commonly used way of geotagging. However, if the neighborhoods and zip codes differ significantly, alternative tools can be used e.g. longitude and latitude coordinates. Subsequently, the geotagged dataset can directly visualize the presence of different characteristics in a specific area. Neighborhoods can then be filtered by their normative units using a filtering system. This step can be disregarded if the provided data set already contains adequate geographical information.

Step 5: Identification of distinct neighborhood profiles

This step describes the creation of neighborhood profiles by combining the transformed data depicted on the maps and the literature. In total two types of neighborhood profiles should be created. Firstly, the list of neighborhood profiles as developed in Steps 2-4. Secondly, a reference neighborhood profile. This profile should represent an ideal or preferred neighborhood for a desired DR program or research projects. This preferred neighborhood profile can be created by setting boundary conditions for each household characteristic. The conditions can be created based on the average household characteristics of previous studies or projects. For example, to research the effectiveness of a DR strategy for people with different levels of education, it would be preferable to have two fairly similar neighborhoods, except for the level of education.

Step 6: Interpretation and analysis

The last step concerns the interpretation of the maps, multi-filter mapping, and linking the results back to recommendations from Section 2. The realization of DR programs in specific neighborhoods can now be assessed for optimization. The individual maps of the aforementioned characteristics open up the opportunity for governments, utilities, corporations, and researchers to improve decision making when rolling out DR programs in particular neighborhoods. Multiple layers can filter specific requirements for a potential program and thereby reduce the time needed to find suitable neighborhoods. Moreover, the conditions of the reference neighborhood as described in Step 5 can be used as filters to find similar/preferable neighborhoods in the area, directly visible on a map.

The framework in practice: Stockholm case study

To demonstrate the applicability and potential benefits of the framework, a case study was conducted choosing Stockholm as the demonstration area. Stockholm was chosen for three main reasons. First, the energy system in Sweden is progressive in adopting a low-carbon economy and therefore likely to be an early adopter of a variety of DR programs (IEA, 2019). Second, the ambition of Stockholm to be fossil free by 2040 requires action in terms of energy saving in the built environment (City Executive Office Stockholm, 2016). This incentive creates demand for future DR. Third, Sweden, and Stockholm in particular, has available data about various household characteristics creating a suitable testbed for such research.

A research study was then chosen to demonstrate how the conceptual framework can support the continuation and expansion of research, as it geographically identifies where other potential research areas of interest lie. The study from Nilsson et al. (2018) at the Stockholm Royal Seaport (SRS) was examined in this research for three main reasons. First, this study was carried out in Stockholm, matching the region of our other dataset. Second, this study focuses on DR programs which are highly affected by household characteristics. This aligns with what Nilsson et al. (2018) found: "The fact that our study shows that households tend to act on HEMS highly individually emphasizes that household energy consumption not necessarily is driven by economically rational decisions but rather influenced by a wide range of behavioral factors." Third, this research also aims at increasing effectiveness and upscaling as described by Nilsson et al. (2018): “to provide a more comprehensive understanding of how HEMS are used and responded to among the average population requires studies of greater scale, including a larger sample of households of varying socio-economic characteristics.”

Stockholm case study: Data and methods

The first five steps of the conceptual framework were completed according to the process explained in Section 3 to comprehend the quantity and geography of household characteristics across Stockholm.

Step 1: Identification of the relevant household characteristics

The six characteristics identified for this case study are based on studies where both living conditions, weather, and climate are relatively similar to the Stockholm region as described in the literature review in Section 2. The six factors, as identified and elaborated upon in Section 2, are the following: Income, Household Composition, Education Level, Surface Area, Age, and Employment Status.

Step 2: Data collection

A dataset containing the relevant household characteristics was collected from a European engineering consultancy company active in the fields of construction, architecture, and environmental engineering located in Stockholm, Sweden. The dataset contained anonymized data of individual households of almost all neighborhoods in the Stockholm municipality. The characteristics discussed in Section 2 were presented in the dataset for each neighborhood.

Socio-economic and dwelling characteristics

- Number of residents
- Number of people in the age group 0-20, 20-64, 65+
- Average salary per person
- Amount of households with composition: single without children, single with children, couples without children, couples with children, household with children, household without children
- Amount of people who achieved a maximum educational level of elementary school, high school, and post-high school
- Amount of buildings from before 1930, 1931-1940, 1941-1950, 1951-1960, 1961-1970, 1971-1980, 1981-1990, 1991-2000, 2001-2010, and 2011-Present

Moreover, the collected data from the Nilsson et al. (2018) study was requested to create a profile for this specific neighborhood. The socio-economic and dwelling characteristics as described above were taken from this dataset.

Step 3: Data transformation into a normative scale

First, neighborhoods with missing data were removed from the datasheet. Missing fields accounted for less than 1% of the total dataset. Afterwards, all data was cross-checked for correctness, taking into account common demographic data. Secondly, all values were transformed from absolute values to relative values as described in Table

1. All absolute occurrences were divided by the size of the neighborhood. If the total sum did not add up to 100% due to missing data, the ratios were extrapolated to enable comparisons. Thirdly, the division of household type was changed from the original format to a more generally used format (single, couple, family), i.e. columns of 'single with children,' 'household with children,' and 'couples with children' were merged and labeled as *family*, the categories 'household without children' and 'couples without children' were merged and labeled as *couples*, and the category 'single without children' was relabeled as *single*. Data from the Nilsson et al. 2018 study was similarly transformed and normalized to the same format as de

Step 4: Geotagging and mapping

All zip codes covering the neighborhoods were identified and tagged to the name of neighborhoods using open source zip code data. The newly composed dataset was used as input for a visualization software. The geotag enabled the visualization software to map, using different colors, the intensity of different characteristics for specific neighborhoods.

Step 5: Identification of distinct neighborhood profiles

A list of neighborhoods profiles with their respective characteristics were composed from the main dataset, and the dataset from Nilsson et al. 2018.

To identify relevant neighborhoods the filters as depicted in Table 3 are applied. These filters were determined based upon the Parameter-Sweep method in which the upper and lower bound filter variables were swept across a range of values between 5 to 95%, and -5 to -95%, in intervals of five, respectively. Identification of neighborhoods satisfying the socio-economic characteristics was the main indicator of success of filter selections. The highest accuracy was obtained at a lower bound of -10% and an upper bound to +10%, equal to a total margin of 20%. Adjustments were made as the SRS has some outspoken socio-economic characteristics because of its small sample size compared to the neighborhoods in Stockholm.

The households in the SRS research were primarily highly educated, with 97% of the residents having a post-secondary education. This would be the highest percentage in the complete Stockholm dataset. Therefore, the Parameter-Sweep method was applied again, resulting in a 20% extra margin on the lower bound. Moreover, the reformatting of household types (couples, singles, and families) arguably decreases the reliability of this characteristic. Therefore, an extra 5% was accounted for to address possible errors.

Table 3: Overview of upper and lower bounds for the nine household characteristics in the Stockholm Royal Seaport case study, based on the Parameter-Sweep method.

	Lower bound	**Upper bound**
Average salary	-10%	+10%
Percentage couples	-15%	+15%
Percentage singles	-15%	+15%
Percentage families	-15%	+15%
Percentage children	-10%	+10%
Percentage working age	-10%	+10%
Percentage Elderly	-10%	+10%
Percentage post-secondary education	-30%	+10%
Average surface area	-10%	+10%

Stockholm case study: results and discussion

Step 6: Interpretation and analysis

A variety of maps visualize the different household characteristics in Stockholm. These maps provide direct insights to where and to which extent specific household characteristics are present in neighborhoods. Figures 2, 3 and 4 demonstrate single filter maps based on income, household composition, and age. Figure 5 presents a multi-filter map that displays neighborhoods conforming to the multiple characteristics examined in the Nilsson et al. (2018) study.

Single-filter maps

Figure 2 shows the areas with the highest household income in the Stockholm region. Referring to the findings of the literature review in Section 2 (Hayn et al., 2014; Matsumoto, 2016; Podgornik et al., 2016), a possible explanation could be that households in this area own a lot of electrical appliances as well as more smart appliances than the average income household. Households that own more smart appliances might be more interested in implementing DR programs since their smart appliances could potentially be connected to the system. High-income residents will also be more likely to be able to afford solar panels or electric vehicles, where a DR program can become essential for the residents. From the results in Section 4.2, it was also discovered that high-income people have a different lifestyle behavior than low-income. High-income households live more dynamic lives and can afford to travel or eat out more frequently (Matsumoto, 2016). Therefore, a DR program could be beneficial for high-income residents especially when it is well connected with all household appliances and remotely accessible for its occupants.

Figure 2: The average salary in SEK is depicted from low (dark orange) to high (dark blue).

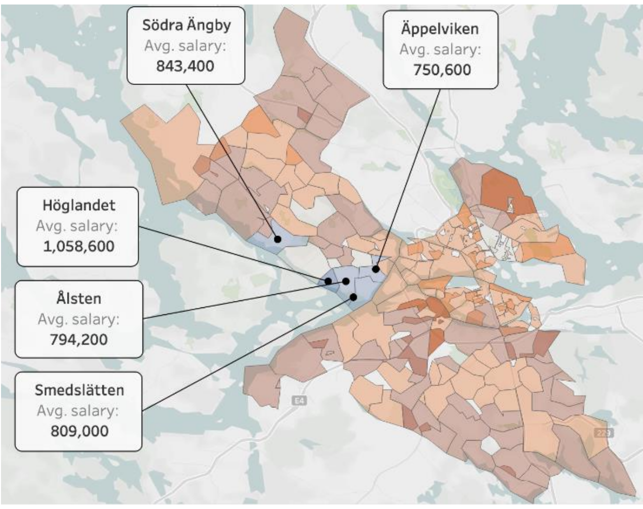


Figure 3 shows the top five areas with the highest concentration of families. The literature review indicates that households with families consume most electricity, primarily due to the fact that they tend to own and use more energy consuming electrical appliances such as washing machines and dishwashers. Teenagers and children also spend more time watching television and on computers (Jones & Lomas, 2015). Studies also show that families spend more time at home leading to an increased use of household electricity (Bedir & Kara, 2017). Regarding efficient use of energy, families tend to be less efficient than other household compositions, which could be because children are less conscious of consuming energy and less concerned over financial implications (Jones & Lomas, 2015). A DR program with only environmental and financial incentives might not therefore be optimal for a family. A strategy would be to implement some sort of gamification to increase child engagement. Nevertheless, as mentioned previously in Section 2, as age increases, children tend to use resources more sustainably (Gifford & Nilsson, 2014). Another strategy could therefore be to have a DR program that can adapt to different ranges of age.

Figure 3: The percentage of Family households is depicted from small (dark red) to large (dark green).

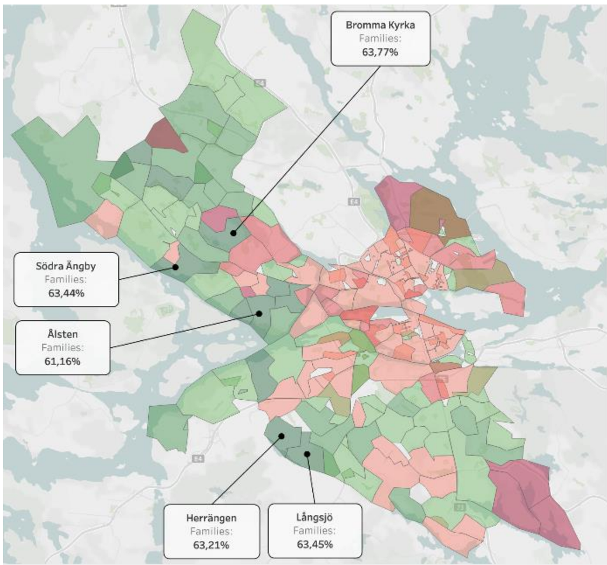
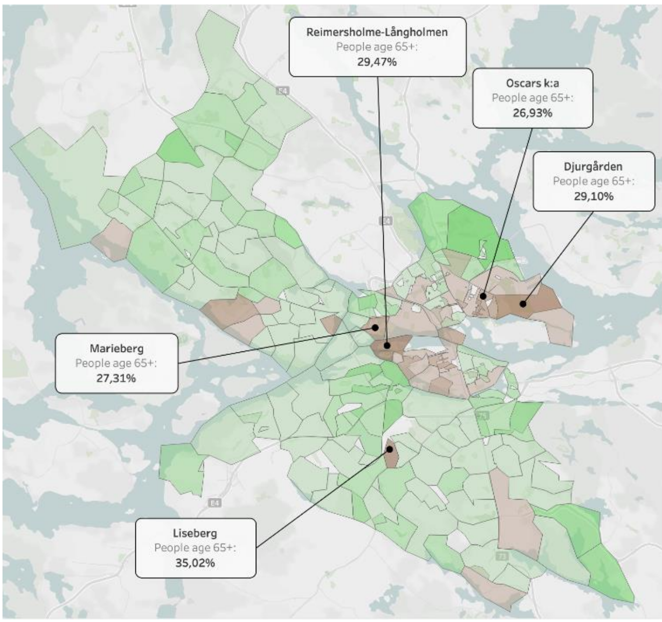


Figure 4 shows the areas where most elderly people live. Elderly residents are those households that consume most electricity per capita, as they tend to live in single households, spend more time at home (Hayn et al., 2014; Matsumoto, 2016), and have less energy-efficient appliances (Jones & Lomas, 2015). A strategy before installing DR programs in elderly households would be to implement some more efficient, smart appliances connected to the DR program, initiating a more efficient DR program. Elderly people enjoyed receiving energy feedback on displays more because it was easier to use (Vassileva et al., 2012b). A strategy would be for DR programs to adapt an interface that is more compatible for the elderly.

Figure 4: The percentage of people above 65 is depicted from small (dark blue) to large (dark green).



Multi-filter maps

The upper and lower bounds in Step 5 are now applied to filter neighborhoods for each household characteristic dataset. The resulting dataset will only contain the `filtered` neighborhoods, which are visualized on a map. All six characteristics were applied in figure 5, i.e. household income, composition, education, surface area, age, and employment status. Nilsson et al. (2018) desires to upscale in a neighborhood similar to the SRS as described in Step 5. The boundary conditions, as depicted in Table 3 filter out all neighborhoods except for Mariehäll, Stadshagen, and Hjorthagen-Värtahamnen. Figure 5 shows these five neighborhoods. It is expected that deployment of a DR program in these neighborhoods would result in similar outcomes, challenges and opportunities as the Stockholm Royal Seaport, based on their household characteristics.

Figure 5: Neighborhoods that display most similar household income, composition, education, surface area, age, and employment status to the

Stockholm Royal Seaport after layering all maps created with their respective boundary conditions.

By changing the boundary conditions in Table 3 according to the preference of the

stakeholder, different neighborhoods can be identified as the most suitable places for future projects. In the case of the Stockholm Royal Seaport, future research in different neighborhoods with similar characteristics yet with a significantly lower level of education, could be targeted. Västra Matteus, with more than 50% of its population not having any post-secondary education, could be a potential neighborhood to do such research in. Similarly, Kälvesta is a neighborhood relatively similar to the SRS yet the percentage of family households is much larger. Therefore, a study focussing on the differences in DR programs in family households could be suitable in Kälvesta. The analysis showed that layering multiple household characteristics on a map filtered by the boundary conditions for specific neighborhoods using DR programs can be beneficial for finding areas for future research and upscaling.

Discussion

This study contributes to previous research as it proposes a conceptual framework which can be used to efficiently identify *where* future DR programs and projects could be suitable. The conceptual framework assists researchers, policymakers, housing developers, and energy companies in future works.

First, researchers can find (new) areas to upscale and study DR programs, as it is a simple and replicable method. Different visualization tools can be used for this framework, since it is not limited to a specific software. This study focuses on electricity consumption and efficient use of DR programs; nevertheless, this framework can be used for any studies that examine the relation of household characteristics and the use of different resources, e.g. water consumption or waste management in different locations.

Second, policy makers on all national, regional, and local levels have goals to reduce their energy consumption or emissions. However, not all policy makers have the same level of expertise on what projects to develop, and *where*. This conceptual framework can help identify neighborhoods with a specific potential for DR related programs in a variety of neighborhoods. Especially in areas with building development projects, it can provide insights in what approaches are useful to enable an energy efficient built environment. The framework provides guidance in decision making processes when planning future energy reduction and DR strategies. Policy makers can in this way address lower income areas in an optimal way, depending on the other characteristics.

Third, energy and utility companies need to market products more effectively and appropriately. Industries commonly use customer segmentation to divide customers into various groups depending on characteristics. Currently, several utility and energy companies are starting to sell and implement different DR programs in order to control and save energy for customers (ABB 2020; E.ON 2020; Siemens 2020; Vattenfall 2020). However, as this study confirms, different consumers have different patterns that affect the use of DR programs. The conceptual framework presented in this study can therefore assist energy and utility companies in targeting potential customers. Similarly, energy utilities can combine these maps with transmission lines and identify and target neighborhoods optimally with specific DR strategies to decongest and reduce potential investments in the grid.

In this study, several considerations should be made. It should be noted that this study was conducted prior to the COVID-19 pandemic; data collection can vary depending on lifestyle changes due to the pandemic and where the study is conducted. Some corporations and organizations have different policies which can cause hindrances to accessing data, which can lead to incomplete results. Additionally, the framework does not identify the absolute optimal places for the implementation of DR programs; it will only provide stakeholders with insights that could potentially help them determine the optimal location for implementing and upscaling DR programs. Finally, the household characteristics that are used in the study are generalized at a neighborhood scale. Although this study acknowledges the differences within neighborhoods (each individual household is different than the neighborhood), these are not considered for simplicity reasons. Moreover, the study acknowledges that the household characteristics used in the analysis are not exhaustive, and therefore could be expanded upon.

Future work regarding this framework should be in applying this framework on more cases to validate several assumptions. In particular, validating the effects of characteristics in different settings, and the extent to which a household characteristic has an impact on effectiveness of a DR program. Moreover, the extent to which the characteristics are interrelated is often unknown. While many studies point out the correlation between different characteristics, it is hardly discussed whether a specific combination of household characteristics requires a different DR strategy than the individual strategies for each individual characteristic combined. However, combining household characteristics in so-called lifestyle profiles is not something new, and already used in, for example, the (Ons Water, 2020) from the Dutch government. Here, they successfully developed different water saving campaigns for different groups of people based on demographic characteristics (Ons Water, 2020). A similar approach can be taken as a next step in this framework. Lastly, it would be valuable to look at different sizes of neighborhoods or blocks. Neighborhoods represent the average of the sum of different blocks and streets in the area, creating a less representative area to assess and address. The optimal balance between a large enough size to roll out a DR program and the homogeneity of an area could be explored in the future.

Conclusions

The six step process presented in Section 3 first analyzes and identifies the household characteristics which impact electricity use and behavior that affects the use of demand response, which in this study is demonstrated in Section 2. Through geographic and numeric data collection of the identified household characteristics, the data is then visualized in single- and multi-filter maps which geographically pinpoints the location of various household characteristics either solely or combined. If DR program designers (e.g. researchers, DSO's) and implementers (e.g. housing developers, governments) need to deploy a specific DR strategy, they can use the single- or multi-filter maps to identify where this research can further be assigned. As demonstrated in Section 4, the framework can also be applied to previous research and assist it in further upscaling research that previously was limited to a smaller scale. This was demonstrated by applying the framework in Stockholm and to the research study Nilsson et al. (2018). If research and deployment of DR strategies can be expanded and used more efficiently, the DR can become a more efficient flexibility solution.

The framework has limitations in taking into account the complex interrelation between different household characteristics. Future work should validate the presented insights and could further explore the interrelatedness of the characteristics to provide more resilient and holistic recommendations for DR strategies. Moreover, this framework could be applied for the studies that examine other relations of household characteristics with the use of different resources, e.g. water or waste management in different locations.

Potential outcomes of the proposed framework increase the effectiveness of DR programs, user interaction, and could help households become more conscious about their energy consumption. Ultimately, this study contributes to creating a more flexible and low-carbon smart grid by leveraging demand response.

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