2 The Role of Behavior in a Renewable Based Energy System

In a broad sense, the role of behavior for any energy system, not just renewable energy systems, is that some behaviors require power to be performed or have as consequence that power is consumed. For example, using an electrical hairdryer will not work without power supply and pressing the on button on the washing machine results in power consumption by that appliance. Those types of behavior are often referred to as energy behaviors because such a behavior is associated with power consumption and a certain amount of energy consumption. Denoting this type of behavior (using an appliance which results in electrical load) by the term *energy using behavior* instead of *energy behavior* can be clarifying, as there are also broader conceptualizations for energy behaviors. For example, Lopes et al. (2012) describe energy behaviors as "those leading to end-use energy consumption. Thus, when referring to energy behaviors there are always two implicit dimensions: the behavior in itself and the associated energy consumption, in which the second is a consequence from the first and quantifies it. Therefore, the energy consumption may be generated by the use of technologies, the purchase or the adoption of new technologies, or the users aspirations or various interrelationships between these." (Lopes et al., 2012, p. 4096). Thus, in addition to energy using behaviors, Lopes et al. (2012) also identify behaviors such as buying, purchasing, adopting, aspiring or wanting technologies as part of what is referred to as energy behaviors in energy research literature. Within this broader conceptualization a distinction is often made between energy efficiency behaviors and energy conservation (sometimes also curtailment or savings) behaviors. Despite the distinction, the categories overlap in the way they are employed (Lopes et al., 2012; Stern & Gardner, 1981b, 1981a), which makes them less useful if left unspecified. Energy efficiency mostly refers to adopting and investing in technologies that have better energy efficiency (Lopes et al., 2012). With

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acknowledging the use of the term efficiency from Stern and Gardner (1981a) as referring to "changes that can achieve savings of energy without any loss of the services the energy provides." (p. 427), energy efficiency behaviors denote those that lead to a reduction in energy consumption without changing energy using behaviors, while energy conservation behaviors are those that lead to an overall reduction in energy consumption by changing any aspect of an energy using behavior (e.g., overall frequency of behavior, overall duration of behavior or setting of an appliance).

With the goal of increasing the amount of energy supplied from renewable energy sources, questions regarding the role of behavior in the residential sector in offering flexibility within a renewable energy system are becoming an important research focus in energy behavior research (e.g., Klaassen, Kobus, Frunt, & Slootweg, 2016; Schuitema et al., 2017). The questions mainly target two aspects, the role of behavior in the demand for energy and in the supply of energy by offering power from energy generating and / or storing units in a household (Schuitema et al., 2017). Even though in principle when it comes to realizing a sustainable energy system, measures toward energy demand conservation, furthering energy efficiency and offering supply flexibility on the household level are important perspectives, the focus here is on the demand side of what will be conceptualized as energy using flexibility.

2.1 Energy Behaviors in an Interdisciplinary Research Field

Part of describing the role of behavior in an energy system means also to acknowledge that it is one aspect of many that are analyzed in this interdisciplinary field of energy studies, when determining energy and power consumption. Often perspectives from social sciences which focus on explaining human behavior have been described as neglected in comparison to technical and economic perspectives in energy research (Sovacool, 2014). Sovacool (2014) corroborates this statement by a review of disciplines, methods, concepts and topics published in three major energy journals from 1999 to 2013. It is beyond the author to give a systematic review of the reviews and meta-analyses that have described energy research and models of energy use from an interdisciplinary, integrative and / or disciplinary perspective. Instead, a selective overview is given, tipping towards aspects discussed in psychological models of energy behavior as an example of pro-environmental behavior.

Concerning the prediction of energy demand, one strand focuses on modelling energy behavior based on different characteristics coming from social and environmental psychological theories and their combinations with socio-demographic characteristics. Building factors, attitudinal and other socio-demographic variables like for example income, norms and self-reported behavior variables are combined to predict energy demand (Abrahamse & Steg, 2009, 2011; Huebner, Hamilton, Chalabi, Shipworth, & Oreszczyn, 2015). In this vein, also integrative pro-environmental behavior models have been proposed to explain energy behaviors based for example on personal characteristics (e.g., attitudes, past experience, habits, current practice) and situational variables (e.g., technical skills, social norms, expectations and know-how) (Wilson & Dowlatabadi, 2007).

Reviewing different theoretical models on energy consumption and conservation behavior, Frederiks et al. (2015) take an integrative approach as well, sorting the influencing factors of household energy using behavior into two broad categories: individual and situational predictors. Focusing their review on individual predictors, they find that socio-demographic and psychological variables are associated with household energy consumption and conservation, "but that these associations are not always substantial, straightforward or consistent, making it difficult […] to draw definite conclusions across studies" (Frederiks et al., 2015, p. 597). Socio-demographic factors like household-income, dwelling type and size, home ownership, family size and composition are suggested to be strongly associated with household energy using behavior, even though the exact pattern of relationship is not always clear. In case of psychological characteristics, a robust association is assumed for normative social influence. However, there are also intervention studies which employed normative variables to influence energy conserving behavior and did not find it to predict energy using behaviors in a relevant way (e.g., Abrahamse & Steg, 2009, 2011). Concerning other psychological characteristics like values, beliefs, knowledge and awareness, attitudes, goals and motives, Frederiks et al. (2015) identify as one key problem the discrepancy between those variables and actual behavior. This is a problem in social and environmental psychology models of energy behavior which reoccurs in discussions of other reviews and is mostly referred to as attitude-behavior gap or intention-behavior gap. For example, Poortinga, Steg and Vlek (2004) report attitudinal variables consisting of seven value dimensions (e.g., self-enhancement, environmental quality), general environmental concern and concern about global warming and socio-demographic variables (age, income, level of education, household size) to explain 15% variance in home energy use. Exclusion of the socio-demographic variables decreased the explained variance to 2%.

They conclude that "a purely attitudinal motivational model to explain environmental behaviour may be too limited." (Poortinga et al., 2004, p. 89) and that "future research [...] should also focus on the role of contextual factors that may influence abilities and opportunities." (Poortinga et al., 2004, p. 90).

Combining prominent theoretical models in the field of environmental psychology, Klöckner (2013) and van den Broek, Walker and Klöckner (2019) developed and evaluated a comprehensive action determination model (CADM). It incorporates the theory of planned behavior (*TPB*; Ajzen, 1991)[1], the norm-activation-theory (*NAT*; Schwartz & Howard, 1981), the value-belief-norm-theory (*VBN*; Stern, 2000a), ipsative theory (Tanner, 1999) and habit conceptualized as automatic behavioral response to contextual cues facilitating goal attainment (Verplanken & Aarts, 1999). Tested by a meta-analytical structural equation model, it explained 36% of different pro-environmental behaviors, among them home energy use (Klöckner, 2013). In a recent study focusing only on energy saving behavior of 247 mostly young people and students, applying structural equation modelling to online questionnaire data results in 61% explained variance in energy saving behavior using habitual processes, intentions and situational influences (perceived behavioral control and objective control) as specified in CADM as predictors (van den Broek et al., 2019). The authors attribute this large difference in explained variance to "the strong habitual nature of energy behaviour" (van den Broek et al., 2019, p. 816) which was the focus of this study in comparison to the meta-analysis approach in 2013 which included also other pro-environmental behaviors such as waste behavior, car purchase, water use, food related behavior, green tourism, switching electricity providers, environmental activism and investment in wood pellet stoves (Klöckner, 2013). Additionally, it is worth noting that the model specifications in terms of integrated variables and relationships differ between 2013 and 2019[2]. Normative and intentional variables were of little predictive value in the 2019 study (van den Broek et al., 2019), further questioning the result of normative social influences constituting a robust psychological characteristic for predicting energy behavior as suggested by Frederiks et al. (2015). In sum, the role of proposed "psychological" characteristics such as

[1] The theory of planned behavior is one of the most perceived theories of psychological factors influencing energy behavior of occupants within building simulations of energy demand (Delzendeh et al., 2017).

[2] A lack of explanation of why and how the integrated variables from different types of theories influence pro-environmental or energy saving behavior in the specified ways is an important drawback in determining the relative influence of the different variables habit, intention, situation and norm which are discussed as important for energy using behavior but are unclear in their relative contributions.

intentions, habits, values, knowledge and situational factors for influencing energy using behavior seems not well understood and seems to suggest an importance of looking at situational factors when predicting energy using behavior.

As another strand in energy research, Lopes et al. (2012) identify quantitative approaches from engineering and economics focusing on the estimation of energy demand by either top-down approaches or bottom-up approaches. Top-down approaches try to establish a relation between energy use and economic characteristics (e.g., gross domestic product, price indices, income) or technical characteristics (e.g., housing stock characteristics, appliance ownership), while bottom-up approaches use individual end-use or building consumption to predict energy demand for a region, or in micro-scale models try to establish load pattern recognition models (Lopes et al., 2012). One example for a bottom-up approach is described in Stamminger (2011) in which a model of energy and water consumption of laundry and dish washing is build based on characteristics of technical status (i.e., energy efficiency depending on age for washing machine and type of dryer), consumer practices (i.e., consumer segmentation according to characterizations of behavior like average laundry behavior, using tumble dryer, washing dishes by hand etc.) and demographic data (calculations are made for a household size of 2.3 persons). One example for load pattern recognition is the categorization of behavior patterns of occupants in terms of number and location of occupants (Feng, Yan, & Hong, 2015).

Both strands have certain drawbacks when trying to deduce interventions for changing energy using behavior. First, analyzing socio-demographic characteristics as influential on energy behavior without a theoretical assumption of how they influence energy behavior cannot inform theory-based interventions. Second, integrative environmental behavior models (e.g., Stephenson et al., 2010; Wilson & Dowlatabadi, 2007) are an opportunity for theory-based interventions but lack connection to information on for example timing of energy behaviors, which is relevant for describing the consequences of energy using behavior for the energy system, especially, when it comes to describing shifting energy using behavior. Thus, these integrative models tend to insufficiently describe characteristics of energy using behavior. Information on timing of energy using behavior is provided (or at least assumed) by load profiling approaches from bottom-up analyses because it is essential if one aims to describe loads from household end-use consumption. Third, economic and technical macro-level characteristics do not allow a description of individual consumption patterns and typical bottom-up approaches do not incorporate socio-technical influences, specifically behavior (Lopes et al., 2012). For example, a description of variables associated with the results of individual behavior, like the number of occupants in a certain room, does not hold information about the actual behavior patterns. Although the example described for the study by Stamminger (2011) might seem like an example to the contrary, he does not offer a theory for describing behavior, which limits possibilities for deducing interventions for changing behavior. Models of energy using behavior (going beyond a mere predictive purpose like in some engineering applications) should address characteristics that are principally changeable by interventions, which for some socio-demographic characteristics is not the case. Furthermore, models of energy using behavior should pay sufficient attention to describing characteristics of the behavior that is targeted by an intervention, such as timing of energy using behavior, and they should be theory-based.

Lopes et al. (2012) at the time of their review identify one approach that integrates behavior and energy consumption to provide consumer load profiles. It integrates qualitative research on households' behavior with modelling of energy demand. Based on a time-geographic diary approach daily activity patterns in households and electricity measures are combined and connected to household categories. This approach of describing daily activity patterns can principally give insights on how daily activities contribute to energy use but a theoretical analysis of factors influencing the timing of everyday activities is not given. A perspective also considering the timing of energy behavior comes from social practice theory, posing that the timing of energy demand is determined by the order of practices in time: "Time use is along with weather, building characteristics, lifestyle of occupants, habits of occupants, appliance design, appliance control and interdependencies between energy services, a crucial variable for defining energy consumption. It is arguably the most important variable for explaining the timing of energy demand in the household" (Torriti, 2014; p. 8). Both of these approaches are relevant in so far as they combine important characteristics of energy using behavior: timing and associated electrical load.

Wilson and Dowlatabadi (2007) conducted a broad review of different disciplinary models and theories as they are applied to the problem area of residential energy use. Among them, models and theories from traditional and behavioral economics, technology adoption theory, attitude-based decision making, social and environmental psychology and sociology on individual decision making. In conclusion, they appeal to develop more integrated approaches for behavioral research and intervention designs in problems of residential energy use. Even though the approaches differ in aspects such as employed characteristics, assumed relations between characteristics and scope, an overall conceptual difference is whether they use internal constructs to explain and predict behavior or not. Another point of comparison are the discussed problems of explaining a discrepancy between an observed behavior and its prediction. In Wilson's and

Dowlatabadi's (2007) review of traditional and behavioral economic approaches, they identify the 'utility maximization model' with its underlying assumptions of consumers behaving as rational actors maximizing ordered, known, invariant and consistent preferences given certain budget constraints as basis for a broad range of economic theory and practice. Discrete choice modeling and economic-engineering analyses are two applications with relevance for residential energy use (Wilson & Dowlatabadi, 2007). One identified weakness of engineering-economic analyses at an aggregated sectoral or market scale level is their poor characterization of heterogeneous preferences, which is assumed to be one reason why such models fail to close the gap between observed and predicted behavior (Wilson & Dowlatabadi, 2007). Throughout their review, Wilson and Dowlatabadi (2007) take up the point of aggregate analyses neglecting heterogeneity of energy users in terms of variability in energy use behaviors and responses to interventions despite of similarities in socio-demographic characteristics (including building characteristics). This, they identify as one reason for interventions[3] failing to be broadly effective. Hence, next to timing of energy using behavior, associated electrical load and theory-based explanations of energy using behavior which include or maybe even emphasize situational factors, variability of energy using behavior seems important to pay attention to when describing energy using behavior and its potential role in energy research.

2.2 What Does "Renewable" Do to the Energy System: The Mismatch Problem

An integration of large shares of energy from renewable energy sources poses challenges to the energy system because wind power and solar photovoltaic (PV) power are expected to make substantial contributions to a renewable-based energy system (International Energy Agency—IEA, 2014, 2019b). In Germany for example, the net electricity generation for public power supply in the first half of 2019 from wind power made up 25.3% (67.19 TWh of 264.78 TWh total generation from all energy sources) and 9.5% (25.05 TWh) from PV power, which together with the other renewable power sources from water and biomass made up 47.3% of total power generation (Burger, 2019). Electricity from wind and solar PV generation poses a challenge because the variability in availability of wind and sunshine makes it more difficult to balance electricity supply and demand

[3] With interventions the authors (Wilson & Dowlatabadi, 2007) refer to "any of regulation, policy, program, measure, activity, or event that aims to influence behavior." (p. 170)

(IEA, 2014). As the timing of power generation from these two energy sources is variable, they are categorized as variable renewable energy (VRE), highlighting the key issue in terms of integrating them into a less CO_2 emission-intensive energy system. One of the key findings from the IEAs (2014) technical analysis of flexibility options (flexible power plants and consumption units, electricity storage, grid infrastructure and use of DSM) for integrating VRE based on 15 countries (including Germany) is that shares of up to 45% in annual generation can be cost-effectively integrated with a country specific system-wide transformation. So, Germany with about 35% from VRE in the first half of 2019 is coming close to this mark and it could be of importance to improve, expand or make more effective the existing flexibility measures for VRE integration.

The fluctuations in times of power generation due to changing weather and sunlight conditions reduce predictability of power generation. Although variability and uncertainty are not new problems for power systems, it is the increase in supply-side variability and uncertainty that are problematic (IEA, 2014). Variability has typically been an issue on the demand side with possible high load variability within a day between daily peak and minimum demand and uncertainty on the supply side with possible problems such as plant failures or deviations from scheduled production levels (IEA, 2014). With exceptions and in neglect of occurring short term fluctuations on an hour to hour or minute to minute scale which mainly make prediction of solar PV power generation uncertain such as clouds, dust, fog and snow, variability in solar PV power output is mainly driven by regular day and night rhythms and seasonal cycles, while wind power often shows only moderate daily patterns and stronger seasonal patterns (IEA, 2014; Koch, 2012; Schaber, 2013). An example for the described generation patterns from solar PV, wind offshore and wind onshore production units in Germany for a week is shown in *Figure 2.1*. Even though seasonal variations are not shown, the day and night regularity for solar PV can be clearly seen in the repetition of bell-shaped curves, while both wind power generation types have a less regular production pattern in this time frame.

As typical times of higher consumption often do not coincide with higher availability of power and times of lower power generation often do not coincide with times of lower demand, the result is a mismatch between time of power generation and demand. This can be seen for example when comparing the solar PV and wind power generation curves from *Figure 2.1* and the total load[4] for Germany as displayed in *Figure 2.2* for solar PV for one day (and coming to it

[4] Total Load is defined in the online glossary from the ENTSO-E: "Total load, including losses without power used for energy storage, means a load equal to generation and any imports

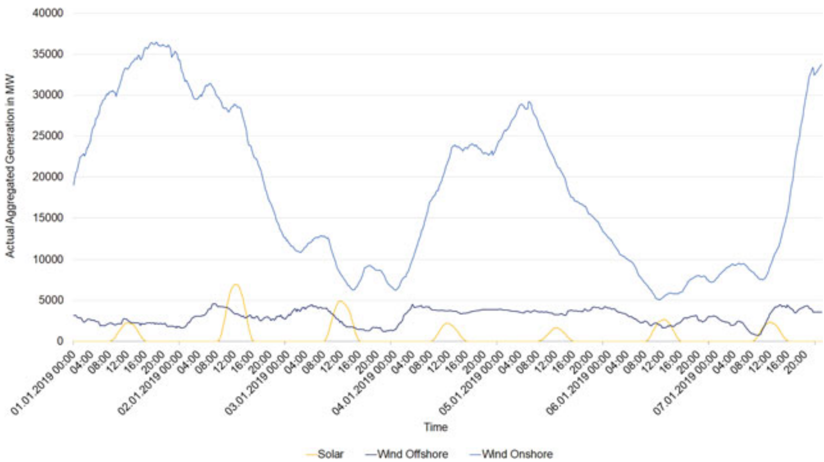

Figure 2.1 Actual generated production from wind and solar energy sources aggregated for Germany for the first week in January 2019. Own representation, data source (ENTSO-E Transparency Platform, 2019a, 2019b) available at https://transparency.entsoe.eu/dashboard/show

later in the text in *Figure* 2.4 for wind offshore and wind onshore for a month). As can be seen exemplarily in *Figure* 2.2, due to the regular pattern of solar PV generation, outside a time period between approximately 08:30 and 16:30, demand is not matched by a possibility to supply power from solar PV.

Looking at the timely discrepancy on a less aggregated load level, one can also compare the timely generation pattern of solar PV to a standardized load profile for households as described for Germany by the Bundesverband der Energie- und Wasserwirtschaft (BDEW). An example for assumed typical household load profiles for a winter weekday, Saturday and Sunday are displayed in *Figure* 2.3. In these rough aggregated estimates, typical time periods of high demand for German households on such days are assumed to be towards midday, which matches well with the solar PV pattern, however the assumed evening peak at around 20:00 is not matched, as well as an earlier rise in demand on a winter weekday. This shows that in some respect solar PV has an opportune correlation with electricity demand. For wind power output the relationship between power output and load is described as weaker and also dependent on location (IEA, 2014). While onshore

deducting any exports and power used for energy storage." (ENTSO-E, 2018) Retrieved from https://docstore.entsoe.eu/data/data-portal/glossary/Pages/home.aspx (accessed 04.12.2019).

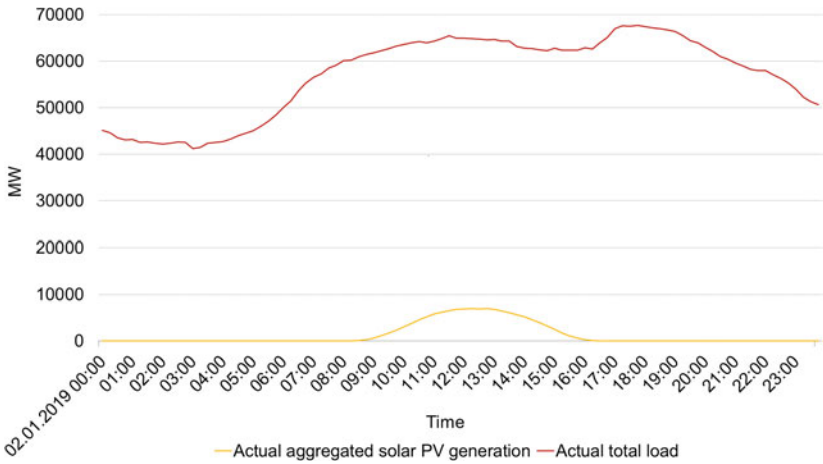

Figure 2.2 Comparison of actual aggregated generation from solar PV units and actual total load for Germany for January 2nd 2019. Own representation, data source (ENTSO-E Transparency Platform, 2019a, 2019b) available at https://transparency.entsoe.eu/dashboard/show

generation is often greatest during night time hours, offshore generation is often greater during the day[5] (IEA, 2014).

In *Figure 2.4* the discrepancies in timing of energy demand and supply are displayed exemplarily for the month of January in 2019 for wind onshore and offshore generation. On this timescale it is not possible to see the mismatch on an hour to hour basis but it shows that times of higher or lower production do not always correspond to times of higher or lower demand and it further gives an impression of monthly variability in wind power generation.

According to the IEA (2014) an increasing share of VRE integration results in an increase in magnitude and frequency of changes in residual (or net) load, which is the difference between power demand and VRE generation output and an energy system must have enough flexible resources or possibilities to accommodate these variations. In the future, these variations can pose a problem in terms of an excess in electricity supply as well as a problem in terms of a deficit in electricity supply from VRE compared to demand and the range of residual load

[5] Using the different regularities in PV, wind onshore and offshore generation to design a well-matched energy mix for meeting demand side variations is another relevant approach to lessen the mismatch problem.

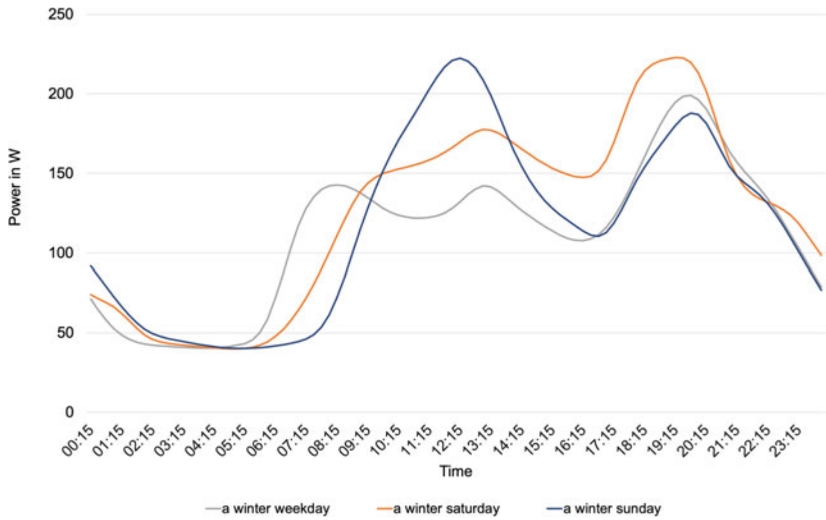

Figure 2.3 Standard household load profile for exemplary winter type days. Own representation, data source (Bundesverband der Energie- und Wasserwirtschaft (BDEW), 2017) retrieved from https://www.bdew.de/energie/standardlastprofile-strom/

changes within one and two hour time spans that need to be addressed will be larger (Steurer, 2017). Based on a future energy scenario from Schlesinger et al. (2014), Steurer (2017) describes an increase in residual load changes for an 80% VRE integration in Germany between two consecutive hours from − 11200 MW/h in negative and + 8400 MW/h in positive direction in 2014 to changes of − 18200 MW/h and + 19100 MW/h for a situation with 80% VRE.

The increase in uncertainty on the supply side concerning time of power generation compared to none VRE power plants and the increase in frequency and magnitude of non-matching generation and demand makes it more difficult to design an energy system which is still reliable, cost-effective and meets power demand because it requires more flexibility in the power system (IEA, 2014). The increased amount of distributed generation units from large suppliers and distributed energy resources from active customers or prosumers add to the difficulties in the energy system on the side of the transmission and distribution grid and there are further aspects such as location constraints and providing other services to the grid than load balancing that are important aspects to consider when integrating increasing shares of VRE into an energy system (e.g., IEA, 2014; Schaber, 2013) beyond the here focused mismatch challenge.

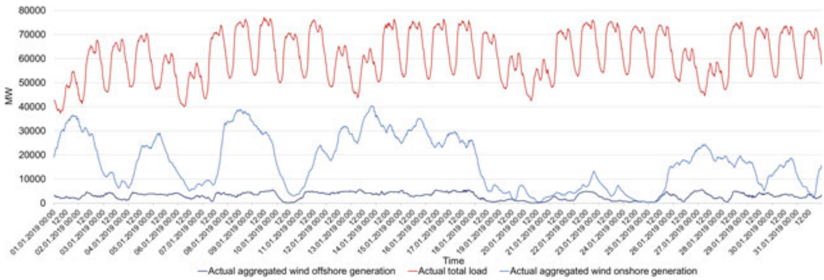

Figure 2.4 Comparison of actual aggregated generation from wind offshore and onshore units and actual total load for Germany for January 2019. Own representation, data source (ENTSO-E Transparency Platform, 2019a, 2019b) available at https://transparency.entsoe.eu/dashboard/show

The main idea for making integration of large shares of VRE possible is to increase the flexibility of the power system. The IEA (2014, p. 23) gives the following description: "In its widest sense, power system flexibility describes the extent to which a power system can adapt the patterns of electricity generation and consumption in order to maintain the balance between supply and demand in a cost-effective manner. In a narrower sense, the flexibility of a power system refers to the extent to which generation or demand can be increased or reduced over a timescale ranging from a few minutes to several hours in response to variability, expected or otherwise." This encompasses on the supply side measures such as grid reinforcement and extension to allow for an increased exchange between regions, energy storage, integration with other sectors using conversion technologies, importing or exporting electricity, increasing dispatchable[6] units from renewable energy sources with short ramping times and on the demand side measures such as DSM (IEA, 2014; Schaber, 2013; Schwabeneder et al., 2019; Steurer, 2017).

[6] Compared to generation units which can be controlled in their power generation capacity (dispatchable sources of electricity), wind and solar PV power cannot be controlled in their timing by an operator. They are non-dispatchable without additional measures such as storage units and thus cannot be used equally well to match demand (IEA, 2014).

DSM[7] aims at making demand more flexible by shifting it in time to match supply, which in case of high shares of VRE will mean shifting demand to times of high VRE generation and away from times of low VRE generation. The residential sector makes up only about 25% of net electric energy consumption thus limiting the potential impact of DSM to provide system services such as load balancing on different aggregation levels of the grid. However, if one assumes that it could be one enabling factor for providing more power system flexibility, the important question from a behavioral perspective is in what way energy using behavior can contribute to mitigating the mismatch challenge.

2.3 What can Energy Using Behavior Do to Mitigate the Challenge of Variable Renewable Energy Integration

Integrating up to 100% VRE in the energy system comes with increasing challenges in dealing with mismatches between energy supply and demand. Looking from the demand side, this problem goes in two directions: What to do with excess electricity from supply? And what to do with a deficit in electricity supply? When looking at the role of energy using behaviors this boils down to two broad questions: How can energy using behavior be either reduced or how can it be shifted in time? In case of reducing energy consumption, one would look towards descriptions of behavior referenced under the categories of energy efficiency and energy conservation (or saving or curtailment) behavior to specify the target behavior. In case of shifting energy using behavior in time, one would look towards descriptions of behavior referenced under the category of energy flexibility behavior. While the term flexibility in connection with energy using behavior is often used more broadly to include every type of behavior that can provide flexibility on the energy system level, i.e., also efficiency and conservation behavior as well as options of supplying energy or providing operating reserves, it seems useful to restrict the meaning to referring to shifting energy using (i.e., demand)

[7] DSM is sometimes referred to as demand side integration (DSI) as a synonym, for example in the study "Demand Side Integration—Lastverschiebungspotentiale in Deutschland" (Apel et al., 2012). Sometimes DSI is described as combining activities of energy efficiency and DSM and activities of DR (e.g., IEA, 2014) and sometimes DSM is used as term for describing energy efficiency and DR strategies (e.g., Dranka & Ferreira, 2019). Here the term DSM and DR will be used in the sense of the last categorization system in which DSM is a supra-category including the two subcategories of energy efficiency and DR strategies.

behavior in time because it addresses the mismatch problem most specifically and suitably from a behavioral perspective.

Reducing the overall energy consumption by increasing energy efficiency or energy conservation behaviors would result in a reduced base load demand but it does not accommodate the problem of excess in electricity supply (Nordic Council of Ministers, 2017). This can be described exemplary by a schematic illustration as displayed in *Figure 2.5*. Given the two possible mismatch situations, one of excess in supply and one of deficit in supply, reducing the overall electricity consumption will only help mitigating the mismatch problem in some cases. Reducing the overall load for a prototypical German household load curve (BDEW, 2017) will only result in lessening the mismatch problem in situations where there is a deficit in power supply from VRE and the difference in load between supply and demand is smaller compared to the unchanged (i.e., typical household) load demand (green arrows are shorter than black arrows). In a situation with a surplus or excess in electricity supply from VRE, which can be expected to occur with high shares of VRE, reducing the base load will rather increase the discrepancies if the overall energy and power supply is not changed. Even though such an overall reduction of energy supplied and consumed is an important sustainability goal, it cannot help address the specific problem of mismatch. This becomes even more evident when highlighting the time scale. Both, energy conservation behavior, which reduces energy using behavior by permanently changing aspects of energy consumption patterns, and energy efficiency behavior, which reduces load associated with energy using behavior by a permanent change in housing stock, target a permanent behavior change leaving other characteristics of the behavior pattern unchanged or fixed, while what is needed for mitigating the mismatch problem is flexibility in energy using behavior.

Likewise, the concept of reducing energy consumption behavior specifically at times of high peak demand without compensation at other times also deals only with one part of the mismatch problem as it does not address the problem of excess production either (i.e., Nordic Council of Ministers, 2017). Furthermore, applying this concept referred to as load shedding (reducing consumption without compensation at other times) as practiced for larger industrial consumers for non-critical loads (e.g., IEA, 2014; Klobasa, 2010; Nordic Council of Ministers, 2017) to residential users seems less appropriate. For most common energy using behaviors on the household level with larger loads such as using a dishwasher, washing machine and tumble dryer it seems unreasonable to assume that the behavior associated with the load shed will not be performed at a later time because the function provided by an appliance such as clean and dry laundry will still be needed. This is not to say that it is in principle not possible to reduce

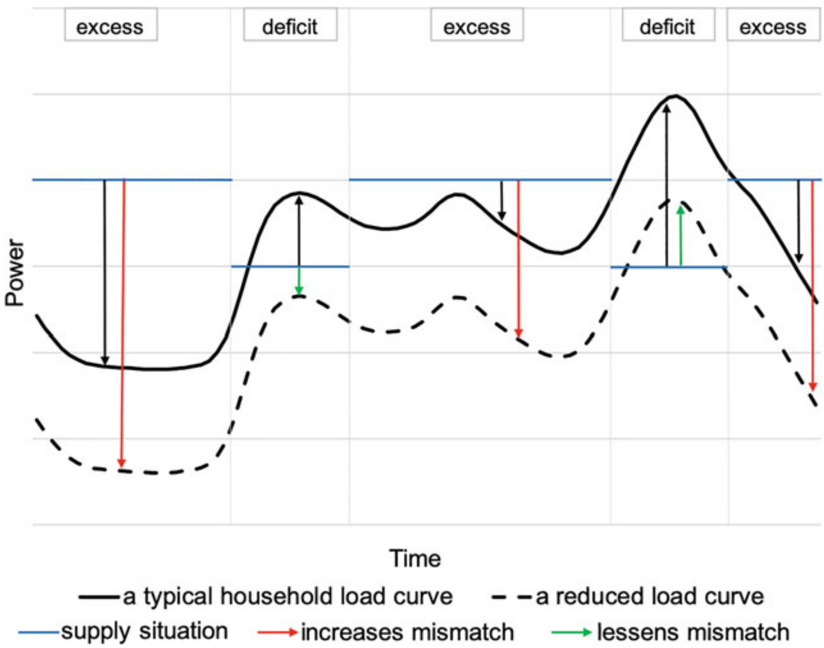

Figure 2.5 Illustration of the effect of reducing base load for mitigating the mismatch problem (own diagram)

consumption at certain times without later compensation, only that it seems a less appropriate description than for large industrial processes which once load is shed cannot increase production due to other restrictions at later times. The key difference in the load shedding concept compared to load shifting is that of no compensation. In the case of applying this idea to household energy using behavior the aspect of no compensation would also not hold because when not performing the appliance using behavior at a certain time without performing it at a later time there is an alternative behavior that does not require electricity for running an appliance like washing dishes or doing laundry per hand and hanging laundry out to dry. Thus, there is a possible way of compensation even though it does not require compensation on a level of energy consumption. So, while load shedding is a possibility to cut off high peaks and by this can importantly help to prevent critical events in an energy system such as black-outs, when employed in the industrial sector, it cannot fully address the mismatch challenge and cannot be applied well to the residential sector.

The third discussed possibility in which behavior can mitigate the mismatch problem is by shifting the timing of energy using behavior in time without reducing the overall amount of energy consumption and without compensation by increasing alternative behaviors. This option can address both, the problem of excess and deficit in supply and can thus help alleviate intra-day and intra-hour fluctuations in power supply (Nordic Council of Ministers, 2017). The idea of this load shifting concept is displayed in *Figure 2.6*. By shifting load backwards or forwards in time from high demand and low VRE generation time points to times of excess of VRE generation the discrepancy between supply and demand can be lessened. In principle, this approach allows for addressing variability in generation quickly and repeatedly, as the idea is not to incur a permanent change from one relatively fixed behavior pattern to another relatively fixed behavior pattern but instead to incur an occasional change of a behavior pattern depending on the momentary supply situation. Even though this generally supposed concept for load shifting addresses the mismatch problem suitably as it deals with problems of excess as well as deficit in VRE supply compared to demand, the assumption for what to change in behavior as generally supposed as part of load shifting and DSM and DR proposals is only one possibility. Another possibility for mitigating the mismatch problem by load shifting would be to not occasionally disrupt a relatively fix behavior pattern, but instead, shift load by making behavioral patterns more variable (i.e., more flexible overall) and by this more evenly distributed across time to decrease the occurrences of large changes in residual loads and to make it possibly easier to shift load by DR strategies.

In sum, while more energy conservation and efficiency behavior thus might help with VRE integration when VRE output is low, at times of high VRE output and high shares of VRE in the energy system those types of energy behaviors cannot help in mitigating the mismatch problem. Even though from an environmental point of view an overall reduction in power consumption is always a worthy goal, for the specific mismatch problem resulting from integrating increasing amounts from VRE into the electricity system, analyzing the shifting of energy using behavior is more appropriate and will be referred to as energy flexibility behavior.

Results which address the potentials and barriers of energy flexibility behavior for mitigating the mismatch problem as part of DSM approaches often regard it in terms of evaluating the potential of variable power tariffs as part of different strategies in DR (e.g., Dranka & Ferreira, 2019). Although different definitions of DR exist, a common theme is, that it reflects electricity demand, which is responsive (flexible) to economic signals (Eid, Koliou, Valles, Reneses, & Hakvoort, 2016).

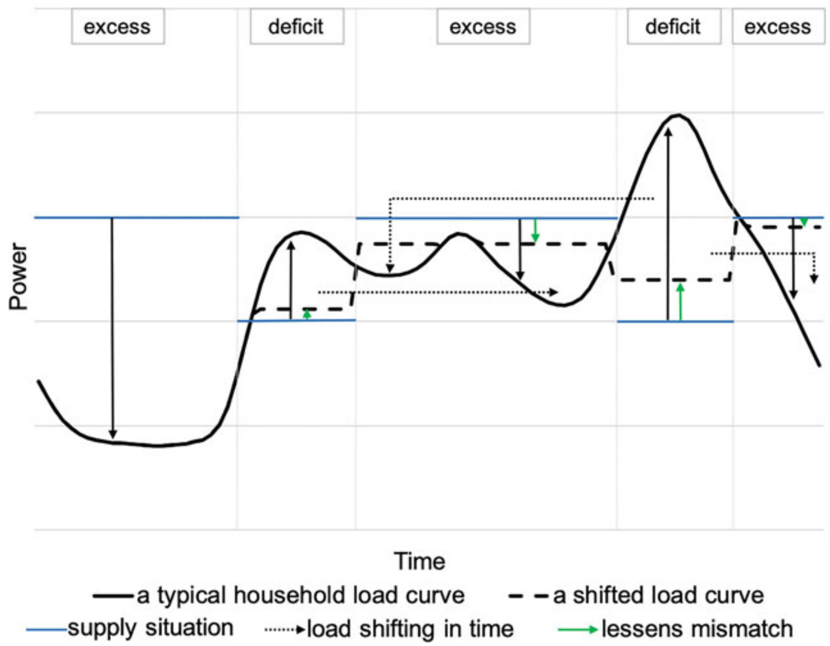

Figure 2.6 Illustration of the effect of shifting load in time for mitigating the mismatch problem. (Own diagram)

An example of such a definition is: “Demand response (DR) can be defined as the changes users make in their electric energy use compared to their usual consumption patterns, as a response to the electricity prices or the payment of incentives that induce low consumption on highly-priced timeslots set by the market or even to maintain a certain stability in the network.” (Arias, Rivas, Santamaria, & Hernandez, 2018, p. 1). The estimated potential for peak load reduction from applying variable power tariffs varies greatly between 1.6% and 44% (M. Maier, 2018). Effects of other interventions for increasing “user flexibility”, like providing information and feedback are also estimated to be small in their effect, lying between 5% to 15% (Schuitema et al., 2017). According to Schuitema et al. (2017), studies on shifting loads by introducing time-of-use tariffs realize an energy shift from consumption peak times to off-peak times by approximately 8%. A qualitative study (J. Pierce, Schiano, & Paulos, 2010) on people’s daily interactions with energy-consuming products and systems (including shifting behavior) emphasizes a general inflexibility in respondents' willingness to change their interactions with a wide variety of everyday energy consumption products. Taking behavioral limitations such as these into account as well as maybe not yet addressed opportunities for increasing variability in energy flexibility behavior when trying to find solutions for the mismatch problem in order to design a more sustainable energy system seems very important. Because otherwise, analyzes of technical and economic DR potentials as mostly done in simulation studies might be too unrealistic (e.g., Dranka & Ferreira, 2019; Nolan & O'Malley, 2015) and possible explanations for large variations in peak load reduction might be overlooked as well as further potential for increasing energy using flexibility.

2.4 What to Look at When Shifting Household Appliance Loads by Behavioral Means

If one focusses on shifting energy using behavior in time to better fit fluctuations in VRE generation and supply in the residential sector one can target the using of electrical heating and cooling appliances, using of different types of electrical appliances from hairdryer to washing machine and with the aim of increasing using of alternative energy sources for individual mobility also the use of electric vehicles and their charging at home. All of these behaviors could be a target for shifting energy using behavior because all are associated with generating load on the household level. With regards to expected potential for DR, Dranka and Ferreira (2019) summarize the following processes as relevant on the residential level: air-conditioning, washing machines, tumble dryers, dishwashers, water heaters, refrigerators and freezers as well as heating systems and electric boilers. As energy using behaviors having to do with body temperature regulation can be understood as a distinguishable group of behavior (e.g., van Raaij & Verhallen, 1983) and electric vehicles are not that common in German households as of yet, this analysis will focus on analyzing the other types of appliance using behaviors.

First, such an analysis of appliance using behavior needs to describe the timely distribution of behavior because using an electrical appliance at a certain time is what results in the timing of electrical load on the demand side and is the target for what needs to be shifted. The problem of accommodating peak demand in times of low VRE generation or reducing excess generation in times of low demand arise from the perspective of the demand side, when many people simultaneously use or do not use household appliances. Thus, it is important to describe similarities between the timely distribution of appliance using behavior of different people (i.e., describe behavioral patterns) because it shows at what times electrical loads might occur simultaneously throughout a day leading to low or high demand in the power system at specific times from the residential sector and thus inform potential problems of peak demand or excess generation.

Second, the question of where appliance using behavior can be shifted to depends on the possibilities for performing that behavior at other times. Looking at the timely distribution of behavior, possibilities for showing a behavior exist if a certain behavior is shown at a certain time and the possibility to show a behavior at a certain time can be assumed to be higher if a behavior is shown more often at that time. Thus, looking at the variability of appliance using behavior is an important aspect of shifting loads from appliances in households. Information on variability of appliance using behavior could in principle come from two sources.

One could look for variability in behavior of individuals over a longer time period or one could look at variability in behavior between individuals over a shorter and same time period. Analyzing how timely distributions of individual behavior changes over a longer time (like for instance a time period of a year) shows how variable different appliance using behaviors are in their intra-day timely distribution. The differences in variability of different appliance using behaviors could then be used as an indicator for possibilities to shift different appliance using behaviors because they are more or less variable in their timing. What is difficult when analyzing variability in this way is to determine where to cut time in order to describe variability and what variability in behavior depends on. For example, if a time period such as one year has been chosen for analyzing variability, one can look for differences in daily, weekly, seasonal, or other time cutting patterns. But what is the most appropriate cut to inform intra-hour variability and what it depends on? If a way of cutting time periods has been identified which covaries with variability, a meaningful way to describe variability in appliance using behavior has probably been found but a drawback might be that knowing how variability changes between different time periods cannot help to inform possibilities for increasing shifting possibilities because it is unfeasible to change time. The way in which one looks at possibilities for shifting appliance using behavior should thus not only allow to describe the timely distribution of behavior and its variability but also describe variability in a way that points towards possibilities for increasing shifting possibilities.

One could also analyze variability in appliance using behavior by looking at changing frequencies of appliance using behavior within a day from many individuals. Then, changes in frequencies over the course of a day can be seen as assessing variability because changes occur if people perform behaviors at certain times more often than at other times indicating different timing possibilities for showing a behavior. Analyzing variability of appliance using behavior based on different behavioral patterns could thus inform opportunities and limits for shifting appliance behavior. In this case, ways of increasing possibilities to shifting appliance using behavior have not been pointed out either.

Third, when looking at possibilities to shifting appliance using behavior by behavioral means, one needs to consider the difficulty or effort for changing the timing of a behavior if one assumes that the timely distribution of behavior is not random. In this case, the variability in timely distribution of behavior could also be relevant for describing difficulties of shifting different appliance using behaviors because depending on the shifting possibilities it can be assumed that shifting behavior to some time points is relatively more easy or difficult or equally so than shifting it to other time points.

When addressing the specific problem of alleviating intra-hour and intra-day fluctuations in power supply by providing flexibility from the residential sector, it is suggested to identify possibilities for and difficulties in shifting appliance using behavior in time by analyzing variability in energy using behavior and effort for shifting behavior. However, the link from describing variability in energy using behavior to deducing ideas for interventions is still missing. To form this link, assumptions must be made on what relates to variability in energy using behavior and what in these relationships can be changed by interventions. As could be seen by the given brief and skewed overview of different energy behavior models in energy research, the ideas, concepts, models and theories on how to look at relationships having to do with energy behavior are diverse. Here, a behavior analytical approach is applied, which is thought to be worth pursuing because it is theoretically consistent and surprisingly a rarely taken perspective within energy research, especially within environmental psychology and it is thought to be suitable to address some of the discussed shortcomings (i.e., neglect of situational / contextual factors, neglect of variability between individuals, neglect of theory-based interventions, neglect of time) in analyzing energy using behavior.