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DOI:
10.1109/ISGTEUROPE.2010.5638967

Document status and date:
Published: 01/01/2010

Document Version:
Publisher's PDF, also known as Version of Record (includes final page, issue and volume numbers)

A methodology for modeling the behavior of electricity prosumers within the smart grid

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Abstract - **Currently, there is a deep discussion going on among the power system society about the architecture of the future system. In practice, the smart grid concept is expected to be applied in various different forms and there will be a need for significant investments in both existing and new infrastructures. In this drastically evolving environment, policy makers and electric utilities are finding themselves in challenging positions to plan and prioritize methodologies and initiatives for future developments. Among others, decentralized power generation is gaining significance in liberalized electricity markets, and small size electricity consumers become also producers (prosumers). The scope of this paper is to map those factors (and their interactions) that influence the load profile, and provide a methodology for modeling the behavior of electricity prosumers. Simulations provide a time and cost effective way to vision the future power system and promote the most efficient solutions. The importance of including the behavior of a large amount of small size prosumers in power system simulations will be outlined, and this concept will be illustrated through an example of modeling car drivers' behavior in order to assess the grid impact of electric vehicles charging in Dutch residential areas.**

Index Terms— **modeling user behavior, prosumer, smart grid, distributed generation, distributed energy resources, power system simulation, mobility data, transport data, electric vehicle.**

I. Introduction

AMONG the power system society, it is commonly assumed that electricity will have a larger share of the overall energy consumption in the future [1], as it can play an important role in de-carbonizing both heating in buildings (heat pumps) and passenger transportation (electric vehicles and plug-in hybrids). While the aggregate demand for electricity is increasing, the part of this aggregate demand that is directly linked to consumers' behaviors is increasing in parallel. Furthermore, decentralized power generation is gaining significance in liberalized electricity markets [2], and small size electricity consumers become also potential producers. Prosumer is a portmanteau derived by combining the word professional (or producer, or provider) with the word consumer. It refers to the evolution of the small size passive consumer towards a more active role in electricity generation and the provision of grid services. In this context, the smart grid concept is reflecting the effort to integrate large amounts of renewable and decentralized energy sources within the current power system without causing additional operational disturbances, while maintaining a proper cost allocation among the stakeholders involved. In this respect, the inclusion of prosumers in the power system operation can be a key aspect.

During the past years, the gradual evolution of the power system allowed electric utilities to compensate for an incremental annual load growth, resulting to an extended and relatively reliable system. The traditional way of sizing new grid infrastructure was governed by peak demand, while balancing load and generation was achieved by controlling large-scale generation units, so as the system frequency range in values close to the nominal operating frequency [3]. Currently, factors such as the aging assets of electricity networks, environmental concerns, and the introduction of novel technologies are introducing new challenges in network planning and management.

A. Purpose of the Paper

In this evolving environment, forecasting the demand for power becomes a much more complex process. Load research and forecasting are integral processes during the planning and operation phases of electric utilities [4]. Decisions about future investments and expansions of the network are mostly based on the accuracy of predictions of both the scale and occurring geographical locations of power demand over different planning horizon periods.

The scope of this paper is to stress the importance of including the behavior of small size prosumers in power system planning. A framework for modeling the behavior of electricity prosumers will be provided. The aim is to map all the factors (and their interactions) that dominate prosumers' behaviors and subsequently shape the system load profile. Following a literature study, an attempt is made in order to bridge the approaches of both policy makers and engineers.

In fact, the smart grid concept is not confined within a certain layout yet, but it is expected that there will be a need for significant future investments in both existing and new electricity network infrastructures. Compared to large scale experiments (which are often expensive), simulations provide a time and cost effective way to vision the future power system and promote the most efficient solutions to be tested in real life conditions. The outcome of this work is expected to provide a useful tool to utilities and policy makers to address the aspects that will form the basis of the future power system.

This work is supported by the E-PRICE project (Price-based Control of Electrical Power Systems) funded by the European Commission's Seventh Framework Programme (Theme ICT for energy efficiency).

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B. Outline of the Paper

This paper is organized as follows; Section I, provides an introduction on power systems expected developments and a definition of prosumers. In Section II, following a literature study, the background of this study is discussed. Different techniques for load and generation forecasting are presented, while pointing out the inefficiencies of current approaches to capture the uncertainty related with the future power system architecture. Section III, discusses the factors that dominate prosumers' behaviors within the concept of the smart grid, and the interactions with the electrical grid planning are outlined.

In Section IV, a methodology for modeling the behavior of small size electricity prosumers is provided. In Section V, this concept is illustrated through an example of modeling drivers' behavior in order to assess the grid impact of electric vehicles charging in residential areas in the Netherlands [6]. In Section VI, the paper ends with some conclusions.

II. Background

Until now, a passive approach was a common practice while planning the installation of Distributed Energy Resources (DERs), and especially Distributed Generators (DGs). In most of the cases, these devices were installed in stand-alone mode and without considering active management of their operation. In the future, with an increasing number of grid-connected renewable energy generators, this passive approach will most probably lead to under-utilization of grid assets and potential overloading of equipment [10]. However, by aggregating DERs, under the Virtual Power Plant (VPP) concept, and controlling their operation these issues can be overcome and smaller entities can also participate in the energy market [10], [19].

The scope of this section is to point out the main aspects involved in current approaches of load and generation forecasting, while pointing out their inefficiencies to handle the uncertainty involved in the future system architecture.

A. Load forecasting

The system load profile is the result of a dynamic process composed of many individual components. The load profile is influenced by a number of factors, such as devices' operational characteristics, users' behaviors, economic factors, time of the day, day of the week, seasonal factors (i.e. weather), geographic patterns (influenced by weather but also external factors) and random effects. In the past, straight line extrapolations of historical load data served well the load forecasting purpose. However, with the appearance of novel technologies, Demand Side Management (DSM) options, changes in the lifestyle and energy consumption pattern etc., it becomes necessary to use alternative modeling techniques, to capture the effect of factors such as industry developments, environmental concerns, energy regulation, energy prices, per capita income, population segmentation and other variables.

Different methods have been developed for forecasting the demand in the last decades. In [5] the authors classify load forecasting in terms of the planning horizon duration; up to one day for short-term load forecasting (STLF), one day to one year for medium-term load forecasting (MTLF), and one to ten years for long-term load forecasting (LTLF). For the purpose of this work, we extend the long term definition to include also the time period of ten years or more. This is well aligned with the notion of power system planning, since many assets of the grid (generators, power lines etc.) have a lifetime range that exceeds the ten year period.

Most load forecasting techniques (i.e. Multiple Regression, Exponential Smoothing, Iterative Reweighted Least-squares, Adaptive Load Forecasting, Stochastic Time Series, Fuzzy Logic, Neural Networks), make use of historical and time-series data in order to identify and correlate patterns of load and temperature [4]. The implication of utilizing historical load data, within the smart grid concept, is that when referring to certain equipment, measured historical load data are most of the times not available, either because these devices have not yet applied in large scale or are still in the R&D phase. Thus, there is high degree of uncertainty about how these devices will be utilized (and to what extent) in the future.

In [4], it is reported that forecasting methods such as Adaptive Load Forecasting, Stochastic Time Series, and Fuzzy Logic, perform better than classical deterministic models due to their ability to incorporate the intrinsic uncertainty of a process. Still, these models cannot cope with the high uncertainty involved in the future features of the power system, where radical innovations are expected to be integrated within existing infrastructures. Researchers have recognized the fact that, by utilizing time-series methods alone, it is not always possible to predict unique patterns of energy demand in fast developing areas [4].

In [13], the authors argue that unlike STLF, LTLF is mainly affected by economical factors rather than weather predictions. Still, only economical factors are not adequate to represent all the aspects that shape the load profile. Other identified inefficiencies with currently employed forecasting methods are that they do not discriminate between the specificity of individual customers (financial status, motives and needs).

In [14], the authors incorporate in their models variables such as population and per capita gross domestic product, in order to exhibit the relation between population, economic development and demand for power. Still, these average indexes can roughly be considered representative of the diversity among the society. Other techniques utilize a basic classification between the customers served, such as residential, office, commercial or industrial. Still, this type of classification can hardly illustrate the large diversity of customers served in each of these load classes [15].

Forecasting load demand is a complex process that combines art with engineering; apart from scientific and technical knowledge it requires acquiring an insight into the way individuals express their needs, which consequently shape their demand for energy. Even though there is a wide range of tools for performing load research and demand side management, a key aspect in this process is the knowledge about the electricity consumer needs, and an understanding of the way individuals use electricity.

B. Generation forecasting

A main advantage of integrating decentralized generators in the current system is the potential energy loss reduction in the electricity network by reducing transportation losses [16]. In the future, this approach might also contribute to significantly less need for transmitting power over long distances. However, the incorporation of DGs, especially in the form of intermittent renewable energy technologies (i.e. wind-turbines and photovoltaic modules) complicates the operation and planning of power systems.

A supportive tool in this process is the employment of generation forecasting techniques. The accurate forecasting of power derived from renewable energy sources is essential for the power system's operation. Renewable energy generation forecasting is mainly a function of time of the day, season of the year, spatial characteristics and local weather. Compared to energy derived from the sun, wind is considered as one of the most difficult meteorological phenomena to forecast [13]. In addition, wind characteristics in off-shore or open space locations are significantly different than those within urban environments, where turbulence is a dominant effect affecting the output of small scale wind turbines. In [13], a comparison of various wind forecasting approaches is included.

III. Modeling Methodology

Herewith, we propose a hybrid approach for modeling the load profile in order to support decisions of policy makers and engineers, especially for long term planning. This approach consists of a combination of deterministic (devices' operation), probabilistic (user groups, user behavior) and stochastic models (weather and external parameters). The main advantages in this approach are that the planner can incorporate deterministic models of both power generating and consuming devices, and define (in the preferred degree of detail) user groups, users' behaviors, market influences and other interactions (depending on the study objectives). A modeling methodology should be defined as a function of the study objectives (goals), data availability (statistical, survey, measurement data or a combination of the aforementioned), user groups' definition (customer segmentation, target user groups) and the study boundaries (degree of detail required, limitations and hypotheses). The definition of user groups is crucial for an efficient allocation of the costs related to the processes of generation, transmission, and distribution of electrical energy. Identification of similar consumption patterns among different groups of consumers (i.e. residential, office, commercial, industrial) can support an efficient cost allocation and prevent the problem of double counting [28].

The scope of this section is to point out the main aspects involved within the interaction of small size prosumers with the electrical grid. During this effort, emphasis is given in both technical and social aspects. The authors acknowledge that there is a gap between the practices of engineers and policy makers while pursuing societal change. Even though they often share the same objectives, in many cases the linkage between the consumer and aspects related to technology, regulation and markets, is not addressed adequately.

Figure 1, illustrates the components involved in the proposed methodology, and which represent the interactions between the user (prosumer) and the electrical grid (power system physical layer). These components are explicitly described in the following sub-sections.

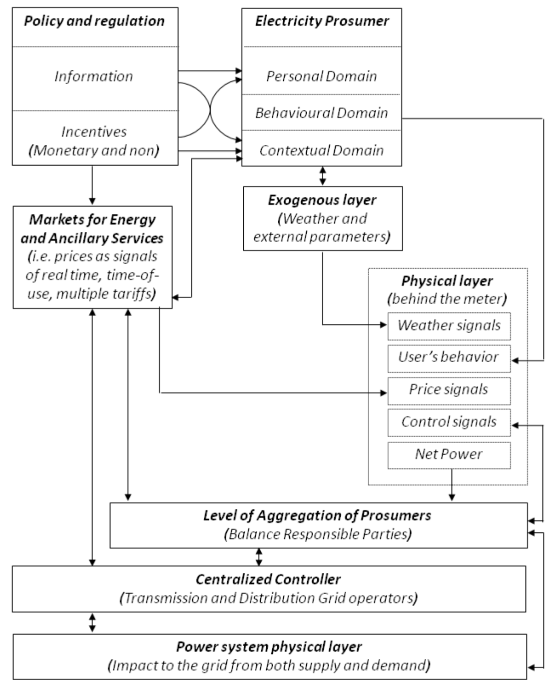

Fig. 1. Mapping the factors that dominate prosumers' behaviors, and their interaction with the electrical grid.

A. The Electricity Prosumer

Research on individual behavior reveals great variety, both in the relevant behaviors and in the factors that influence them [7], [8]. In order to handle this variety, the author in [7], categorized the phenomena that affect the envisaged impact of individuals between three domains; the personal, behavioral, and contextual domains.

1) Personal Domain: In this domain are individuals' basic values, beliefs, and various other cognitions, motives, and feelings [7]. Theories such as the Value-Belief-Norm (VBN) have been developed in order to show how the elements of the personal domain interact and affect individual's behavior [29]. Other theories of the personal domain that have been applied with success to environmentally relevant behavior are the Theory of Reasoned Action [30], and the Theory of Planned Behavior [31]. A summary of behavioral change models and theories can be found in [22].

2) Behavioral Domain: From a predictive perspective, a possible occurring behavior is dependent on both the personal and contextual domains [7], [8]. With respect to modeling the behavior of prosumers, this can be interpreted through variables that capture the level of commitment of individuals (i.e. to own and operate a DER), the levels of DER penetration among population (as a percentage), and variables that captures the flexibility of prosumers to adjust their demand for power (to shift their demand to off-peak hours).

3) Contextual Domain: The contextual domain influences the behavioral domain through a wide range of attributes [7], such as the individual's background (socio-cultural demographics, financial, educational, religion), the individual's current status (urban or rural residential environment, ownership of vehicles and devices), the social context (available infrastructures, policy and regulation), the economic context (individual's income, availability and prices for commodities and services) and other aspects (weather and external parameters).

B. Policy and Regulation

According to the authors in [18], many studies confirm that human forecasts are often flawed and biased. Changing consumer behavior can make a significant difference to the environment and consumer research can help engineers and policy makers to understand this behavior, and to influence it in a positive direction (i.e. to make demand for electricity more price elastic) [7], [8].

Policy makers and regulators can influence individuals' behaviors mainly by the use of interventions (information, incentives, institutional support) in the personal and contextual domain. Information or education is an intervention in the personal domain and incentives of various kinds (monetary and non-monetary) are interventions in the contextual domain. Under some conditions, policy interventions in the personal domain have interactive effects with policies aimed at context [7], [8]. Furthermore, the effectiveness of those interventions depend strongly on the target group (i.e. particular behavior) and the planning horizon, since their long-term effects might be different (or even opposite) from the short-term effects.

In general, consumers do not have the same motivations, understanding or technology awareness as producers, and interventions are most effective when designed from the consumer's perspective (or when the consumer is engaged in the design process) [7], [8]. Since it is often impractical to undertake an analysis for each individual consumer, it is crucial to recognize the importance of contextual, personal and behavioral aspects (and interventions), in order to understand the interaction of prosumers with the electrical grid. For example, many researchers have developed deterministic models of devices (i.e. smart appliances, electric vehicles) [12], [36], but most of these studies miss the interaction with the user. In the proposed methodology an important input parameter is the user behavior.

C. Energy Markets

The interactions between the user and energy markets consist of all kinds of commercial agreements between power system participants (such as bilateral contracts, forward markets, real-time markets, power exchanges). The author in [32], points out that wholesale and retail electricity markets are inherently incomplete and imperfectly transparent due to two main characteristics of electrical power; power is a flow of energy that cannot be monitored perfectly, and storing large amounts of electrical energy is involving high costs.

Currently, the notion of using price signals to control the electrical power system is gaining significance. The idea of price-based control of the power system is mainly based on the work of Schweppe and his co-workers [33], [34]. Price signals can be an effective tool in the effort to shape the behavior of grid-connected entities (through the use of a dynamic feedback). Price signals can be in the form of multiple levels of tariffs reflecting the time-of-use, and real time price signals.

D. The physical layer behind the meter

In the proposed methodology, a main component refers to the physical layer behind the energy meter. Four inputs are defined for this component (weather signals, user's behavior, price signals, and control signals) while the output is the 'net power' (which refers to the actual measured and scheduled power; load or generation). This component (See figure 2) is described in more detail in section IV.

E. Others

Other components involved in the proposed methodology are the exogenous layer (weather and external parameters), the level of aggregation (for instance under Balance Responsible Parties - BRPs), which is constrained by time and spatial constraints, the centralized controllers (grid operators) and the power system physical layer (the electrical grid). An idea that enables controlled inclusion of large amounts of DERs is to introduce aggregators as mediators between electric utilities and end-users. An aggregator can be a BRP that collects and operates an amount of small decentralized generation units as Virtual Power Plants (VPPs). The VPP concept provides the means for active management of DERs, in a similar way that large scale conventional power plants are currently operating [19]. A main advantage of aggregating DERs is the potential improvement in forecasting accuracy. According to [23], for a large group of dwellings, the spikiness of the demand is smoothed due to the diversity of behaviors among the consumers.

IV. The Interaction Between The User And The Grid

As illustrated in Figure 1, the proposed methodology defines four inputs and one output for the physical layer behind the meter. Figure 2, illustrates this physical layer, and shows both the inputs and output. According to this figure, the user interacts with a device through an interface. The devices in return will provide services to the user (benefits of the user). Devices include both power generators and loads. The output of those devices (power supply or demand) is dependent on inputs defined by the user (requirements), weather signals, and control signals. Energy storage devices and decentralized controllers are not excluded from this architecture. However, energy storage devices are available for a relatively high cost, which reflects manufacturing and recycling costs [17]. Thus, in this work, the focus is not on energy storage solutions (without excluding them) but on identifying the synergies between electricity supply and demand, in order to support the power system planning.

The output of this component is the 'net power', which refers to the actual measured (at the point of connection of smart metering devices) and scheduled power (load or generation), and consists of the sum of power supply and demand (both measured and predicted).

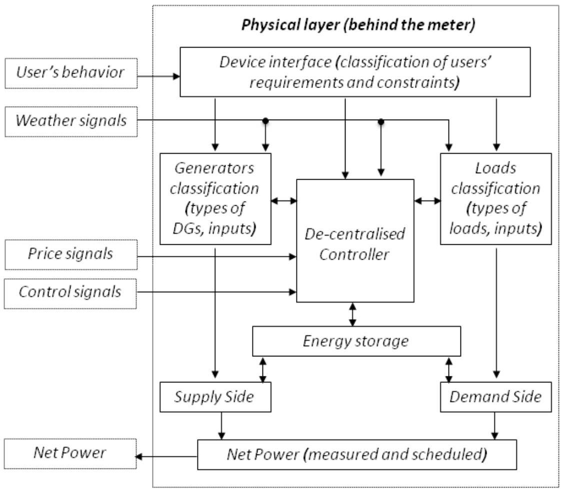

Fig. 2. Break down the physical layer (behind the meter)

Electrical loads can be classified in many ways such as residential, commercial, industrial, and municipal loads, or can be classified in terms of predictability. For example some domestic loads can be considered predictable when the users are not present (i.e. in unoccupied buildings) or are not active (i.e. sleeping hours), such as cyclic loads from refrigerators, and standby equipment. Other domestic loads can be characterized as semi- or non-predictable, depending on the occupancy, the regular or irregular behavior of the users, and external parameters (i.e. seasonal weather variations, availability of natural lighting) [23]. In [25], the authors followed an end-use approach and incorporated in their model an availability function which determines the probability that a dwelling is occupied, and a function which represents the probability for a particular appliance to be used. However, such models are dependent on the availability of social data which are not always available. Another approach for modeling the behavior of users is to combine interviews with modeling for end-use [27].

The diversity among different households' energy requirements are resulting mostly from variations in the micro-level (i.e. individuals behaviors and needs, time-schedules etc.). In [9], the authors point out that studies in the U.S., the Netherlands and the U.K. show that 26-36% of domestic energy end-use variations is due to the behavior of the residents. Furthermore, domestic energy demand for a specific household is a function of the behavior of all the inhabitants (i.e. a single person, a couple or a multi-member family). In [24], electrical load profiles are modeled at the level of an individual consumer in order to represent the diversity of demand that exists within a group. The stochastic model incorporates random elements that represents the diversity between consumers (occupant behavior, appliance ownership and scale of their demand), and weather variations.

Depending on the study objectives, electrical loads can be further classified as weather-insensitive and weather-sensitive. Furthermore, weather is a function of seasonal and geographical characteristics. In [20], the historical relationship between the load and temperature for a given season, day type and hour of the day, is discussed.

Loads can also be characterized as critical (loads which is difficult or impossible to be displaced without creating a sense of discomfort to the consumers) or non-critical. The operation of a refrigerator can be considered non-critical for a user (as long as the inside temperature is ranging within acceptable limits). The operation of other loads can be dependent on seasonal parameters (i.e. air-conditioning/cooling systems in south European countries during the summer) or weekly patterns (equipment used in recreational activities during weekends or holidays). Finally, other loads are dependent on the time of the day (i.e. domestic lighting during the night hours or commercial loads during shopping hours).

V. Case Study

In order to provide an insight into the possibilities of including the individual's behavior in system simulations, the concept will be illustrated through an example of modeling car drivers' behavior to assess the grid impact of electric vehicles (EVs) charging in Dutch residential areas, as discussed in [6].

A. Scenario Definition

For this study, two different scenarios are utilized, the baseline and the scenario of uncontrolled charging. The baseline scenario consists of the reference scenario and describes the situation prior to the introduction of electric vehicles (only conventional residential loads are considered). For the scenario of uncontrolled charging, it is assumed that electric vehicle (EV) users plug-in the chargers to their vehicles' batteries when they return at home. The charging process starts with no delay and the grid operator has no control over the process. In addition, it is assumed that EV users plug their vehicle whenever they return at home regardless the incentive tariff. This approach allows the identification of possible bottlenecks in the system and provides an indicator of when these bottlenecks might occur. Furthermore, it is assumed that the vehicles batteries are getting recharged when the vehicles are plugged in the outlets of the owners' households. Since there is a lack of charging stations installed in public locations, domestic charging will be the most obvious way for early adopters of electric vehicles to recharge their vehicles' batteries in the short term future.

B. Study Boundaries

In practice, there is variety of constraints that affect the behavior of an individual. For example, when looking to EV users, someone may drive to work because public transportation is unavailable or inefficient (in terms of costs and time), or because of other contextual conditions. Another individual may use public transport because of specific constraints, such as financial inability to maintain a private vehicle or lack of parking space near the working location.

Since there is scarcity of available data about the use of electric vehicles, this study incorporated data about the use of conventional vehicles. The main assumption underlying the construction of drivers' profiles is that EV drivers will use their vehicles in a similar way they are using conventional internal combustion engine vehicles and will demand the same level of driving convenience.

C. Data Availability

In order to represent the power load profile of a low voltage (LV) distribution grid, it is important to represent the demand at the level of the individual household connection. In this respect, models that incorporate end-use demand and occupant behavior [25], [26] are ideal, provided that behavioral data are available. For this study, drivers' profiles were constructed, for simulation purposes, based on data from the 2007 mobility research of the Netherlands (MON) [21]. The database of MON provides information for researchers and policy makers in the field of mobility and transport of the Dutch population. Acquisition and access to the database of MON is possible by request to the Ministry of Transport, Public Works and Water Management [21].

D. Defining User Groups and Data Process

In order to define user groups for simulation purposes, the data records of MON [21] were filtered in order to meet the profile of an active driver, according to the following criteria: persons of 18 years old and more, who own driver's license, who own a car, and are the main users of this car. The resulted drivers' samples were allocated between nine different motives of mobility which are defined in [21]. Figure 3, illustrates the distribution of the drivers' samples as a percentage for all mobility motives. For this study, the simulated drivers were allocated, between the nine user groups, according to this distribution. Then, average figures such as average vehicle speed, travel time duration and activity time duration (i.e. 'work', 'shopping', 'visit', etc.) were calculated (per car driver per day) for all user groups and the results are illustrated in figure 4.

Two main parameters involved in the process of modeling drivers' behaviors are *displacements* per driver per day, and *average number of kilometers driven* per driver per day. A displacement refers to a travel (or part of a travel) to a destination for a specific purpose, as well as to the travel from this destination back to the arrival location. In 2007, the average number of displacements per car driver was 0.99. In the data of [21], it can be observed that the average number of displacements per car driver per day from 2000 to 2007 do not vary significantly through the years. For this study it was assumed that the average number of displacements per car driver per day is equal to one. In [21], the average number of kilometers driven per car driver per day in the Netherlands is included, from 2000 to 2007, and what can be observed is an annual growth of 0.7 % between those years. Assuming the same rate of growth until the projected year 2010, the corresponding figure is 19.73 km per car driver per day, and this figure was incorporated in this study. During the process of modeling drivers' behaviors instead of making use of average values of displacements and driven distances, the data from [21] were incorporated as corresponding percentages (%) and it was assumed that the simulated drivers follow these statistical distributions. For example, figure 5 illustrates how the average number of displacements and driven distances per day by car are distributed (as percentages) during the hours of a day. Figure 5 refers to all mobility motives while other available data in [21] refer also to specific mobility motives ('from and to work', 'visit / overnight' and 'shopping purposes'). Displacements were allocated in pairs, one to the final destination (i.e. work location) and one back to the initial location (i.e. home) and it was assumed that for its pair, both displacements occur in the same day. In addition, it was assumed that the driven distance and travel duration are approximately the same during both displacements.

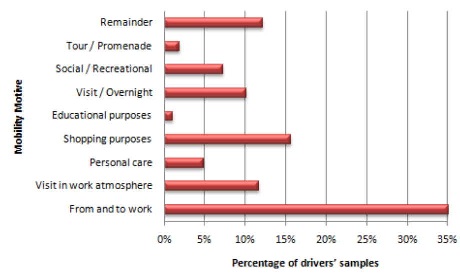

Fig. 3. Percentage of drivers' samples per mobility motive [21]

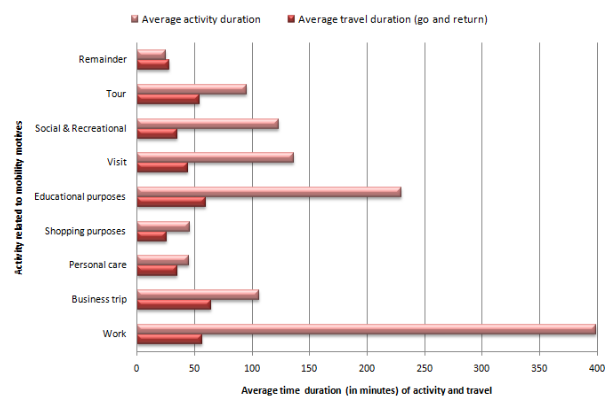

Fig. 4. Average time duration of travel and activity (in minutes) per car driver per day related to the mobility motives, based on drivers' samples [21]

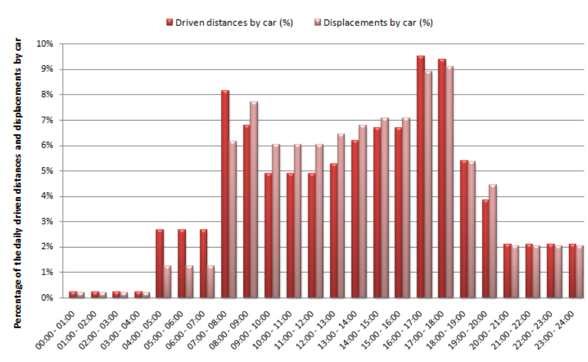

Fig. 5. Density of displacements and driven distances (%) by car per day and hours of the day for all motives of mobility [21]

The data presented above, were combined in order to simulate the behaviors of electric vehicle drivers. Statistical distributions about average number of displacements and driven distances per driver were constructed for all user groups and for each day of a week. The statistical data where utilized in combination with a random function (with a specific variance) in order to incorporate the uncertain variation in the behavior of individuals (among a user group).

Then, time schedules were constructed for a number of simulated drivers, based on these data. These schedules show how the availability of electric vehicles varies over space (parked in the household location or elsewhere), and as a function of time (through the hours of a day and through the days of a week). The aim is to define at what time the simulated EV users return at the household location and plug-in their vehicles for charging purposes. These schedules are utilized as input files in the deterministic model of the charging process. The result is charging power profiles for each household that possess an electric vehicle (for the scenario of uncontrolled charging).

Then for different projections about the number of electric vehicles, as a percentage of the total households in the investigated area (ranging from 0% to 100%), the total energy content that fulfils the energy need of simulated drivers for re-charging their vehicles' batteries is calculated (per five minutes intervals). These results, as well as actual power measurements from the households, are utilized as input files for the model of the investigated low voltage (LV) grid. The integrated model was made by superimposing charging power profiles to actual measurements from residential loads. The calculations with the model resulted in detailed daily loading profiles for the 3-phases of the LV grid (See figure 6) for both the baseline and the uncontrolled charging scenarios.

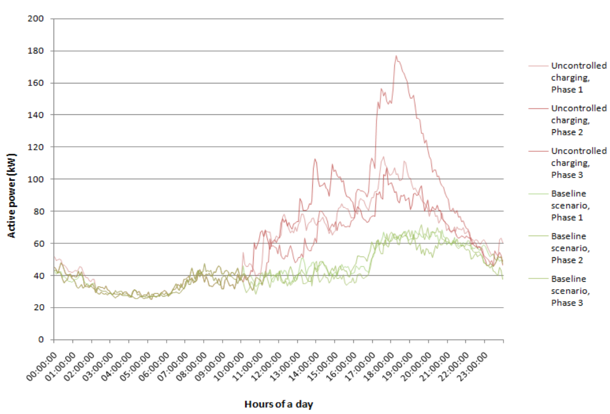

Fig. 6. Transformer's 3-phase active power load during one day, for both scenarios and assuming that each household possess an electric vehicle [6]

E. Results and discussion

Overall, looking to all mobility motives (Figure 5), most of the displacements from a location to home occur at the conclusion of the day, between 17:00 and 19:00 hours. This is also the time that most of the demand for power occurs in typical distribution grids that supply residential loads in the Netherlands [6]. If the EV users initiate the charging process at that time, the result will be a high aggregate load during those hours that contributes to increased energy losses and possible overloading of equipment (See figure 6). This finding is the result of the effort to correlate displacements from and to home and was made possible by incorporating data which are illustrated in figure 4, such as travel time duration and activity time duration By defining the time of the first displacement (from the household to the destination) of the day and counting in traveling time and activity duration, then the time of the displacement from the initial destination to home can be estimated. Furthermore, by looking to figures 3 and 5, it is important to highlight that the category of commuters (from and to work) is the dominant among passenger vehicles users. The characteristics of this specific group (driven distances, displacements, schedules) indicate that it would be beneficial if part of the demand for charging power could be derived while the EVs are parked at the working location. This approach could curtail the power demand from residential areas during afternoon hours. These findings suggest that with the prospect of an increasing number of EVs on the road, there will be an increasing need for communication between electric vehicles and utilities [6], [35]. However, with incremental improvements, policy makers and engineers can provide effective and economically efficient solutions to accommodate electric transportation in the short to medium term future.

VI. Conclusions

The scope of this work was to highlight the importance of including the behavior of large amount of small size prosumers in power system planning. A framework for modeling the behavior of small size electricity prosumers is provided. This framework involves the classification of users among different groups and considers users' behavior as an important input parameter. The added value of this approach is illustrated though an example of modeling car drivers' behavior in order to assess the grid impact of electric vehicles charging in Dutch residential areas. The proposed methodology creates an insight of how different user groups demand power for charging purposes, and provides knowledge about the way individuals use electricity.

VII. Acknowledgment

The authors acknowledge Enexis B.V. for the provision of technical and measurement data, and the Dutch Ministry of Transport, Public Works and Water Management for the provision of mobility and transport data.

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Wil L. Kling received his M.Sc. degree in electrical engineering from the Technical University of Eindhoven in 1978. Since 1993 he has been a (part-time) professor in the Department of Electrical Engineering at Delft University of Technology, in the field of Power Systems Engineering. Since 2008, he is a full-time professor at Eindhoven University of Technology where he is leading research programs on distributed generation, integration of wind power, network concepts and reliability. Prof. Kling is involved in scientific organisations such as CIGRE and the IEEE. As Netherlands' representative, he is a member of CIGRE Study Committee C6 Distribution Systems and Dispersed Generation, and the Administrative Council of CIGRE.