Energy Planning in a Big Data Era: A Theme Study of the Residential Sector

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Abstract With a focus on planning for urban energy demand, this chapter re-conceptualizes the general planning process in the big data era based on the improvements that non-linear modeling approaches provide over mainstream traditional linear approaches. First, it demonstrates challenges of conventional linear methodologies in modeling complexities of residential energy demand. Suggesting a non-linear modeling schema to analyzing household energy demand, the paper develops its discussion around repercussions of the use of non-linear modeling in energy policy and planning. Planners and policy-makers are not often equipped with the tools needed to translate complex scientific outcomes into policies. To fill this gap, this chapter proposes modifications to the traditional planning process that will enable planning to benefit from the abundance of data and advances in analytical methodologies in the big data era. The conclusion section introduces short-term implications of the proposed process for energy planning (and planning, in general) in the big data era around three topics of: tool development, data infrastructures, and planning education.

Keywords Energy policy • Residential energy demand • Non-linear modeling • Big data • Planning process

1 Introduction

According to the International Energy Outlook 2013, by 2040, world energy demand will be 56 % higher than its 2010 level, most of which is due to socioeconomic transformations in developing countries (U.S. Energy Information Administration 2013a). This increase is expected to occur despite the existence of several global agreements within the past few decades on significantly reducing greenhouse gases (GHGs) and energy demand (e.g., the Kyoto Protocol, adopted in December 1997 and entered into force in February 2005).

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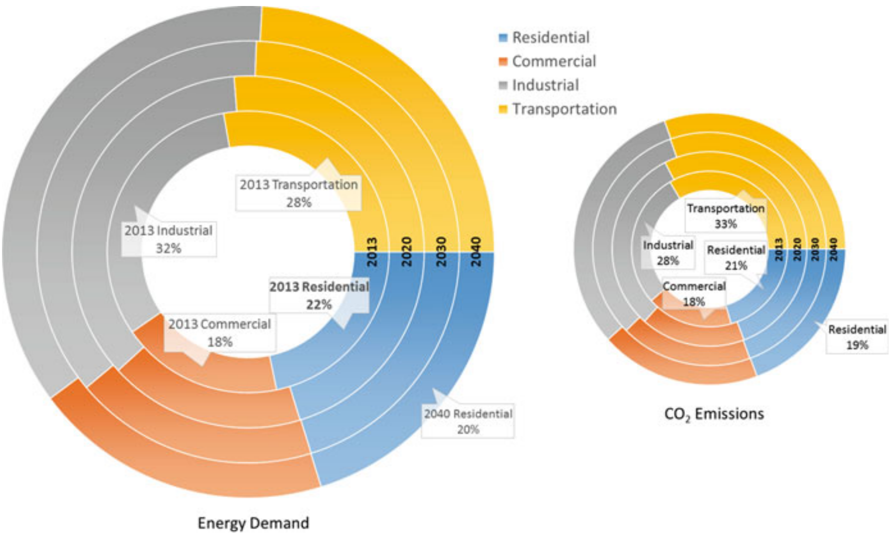

Fig. 1 U.S. energy demand and CO_2 emissions by sector, 2013, 2020, 2030, and 2040. *Data source*: U.S. Energy Information Administration (2013b)

Globally, buildings (residential and commercial) consume about 40 % of total energy (Swan and Ugursal 2009; Roaf et al. 2005; Norman et al. 2006). About 20–30 % of the total energy demand is for residential use. For example, in 2013, 22 % of the energy demand and 21 % of the CO_2 emissions production in the U.S. came from the residential sector (Fig. 1), both of which are expected to slightly diminish in their share to 20 % and 19 %, respectively, due to faster increases in industrial and commercial energy demand (U.S. Energy Information Administration 2013b). Technological improvements are expected to diminish growth rates in residential and transportation energy demand.

Most of the growth in global building energy demand is due to socioeconomic changes in developing countries. Since developed countries have greater access to up-to-date technologies, energy demand in the residential buildings is likely to increase at a slower pace in developed counties, with an average of 14 % in developed and 109 % in developing countries (Fig. 2) (U.S. Energy Information Administration 2013a).

Nevertheless, to many consumers, researchers, and policymakers, the energy consumed at homes has become an invisible resource (Brandon and Lewis 1999). A clear understanding of residential energy demand is the key constituent of effective energy policy and planning (Hirst 1980; Brounen et al. 2012). Yet, the residential sector lags behind other sectors on urban energy demand research. Two main reasons explain the uncertainties in household energy demand research and theory, obstructing the clear understanding needed for effective energy policy. First, conventional research has commonly used linear methodologies to analyze

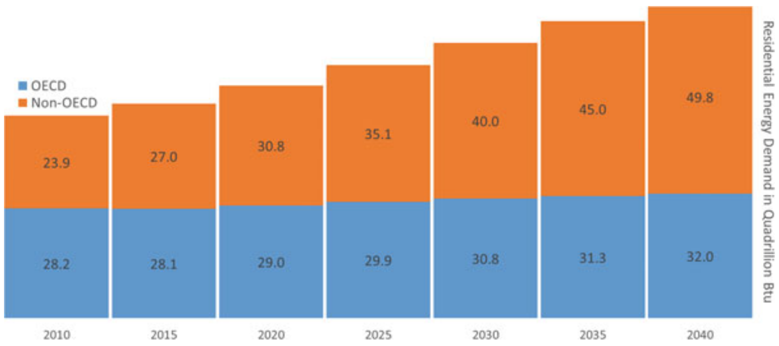

Fig. 2 World residential sector delivered energy demand, 2010–2040. *Data Source*: U.S. Energy Information Administration (2013a)

energy use in the residential sector, failing to account for its complexities. Second, lack of publicly available energy demand data for research has intensified the methodological issues in studying residential energy demand.

2 Problem: Prior Research Underestimated the Human Role

Building energy demand is an outcome of complex socio-technical processes that are driven by human activity. Due to its complexities, investigating the policy implications of behavioral determinants of residential energy demand has received little attention in prior research (Brounen et al. 2012). Traditionally, the debate on residential energy conservation has often overlooked the role of occupants' behaviors by excessively focusing on technical and physical attributes of the housing unit (Brounen et al. 2012; Kavgic et al. 2010; Lutzenhiser 1993; Kriström 2006). Since the early 1990s, energy research and policy have primarily concentrated either on the supply of energy or the efficiency of buildings, overlooking social and behavioral implications of energy demand (Lutzenhiser 1992; Aune 2007; Pérez-Lombard et al. 2008; Lutzenhiser 1994; Brounen et al. 2012). Engineering and economic approaches underestimate the significance of occupant lifestyles and behaviors (Lutzenhiser 1992).

> *"Engineers and other natural scientists continue to usefully develop innovative solutions to the question of 'how we can be more efficient?' However their work does not answer the question 'why are we not more energy-efficient, when clearly it is technically possible for us to be so?'"* (Crosbie 2006, p. 737)

Due to methodological or data deficiencies, even when household characteristics are incorporated in some energy demand studies, only a limited set of socio-demographic attributes are involved (O'Neill and Chen 2002). Moreover, the complexity of the human role in the energy demand process makes meaningful interpretation of modeling results rather difficult, which in turn leads to an ambiguous and limited understanding of the role of socioeconomic and behavioral determinants of residential energy demand. For example, Yu et al. (2011) suggest that because the influence of socioeconomic factors on energy demand are reflected in the effect of occupant behaviors, “there is no need to take them into consideration when identifying the effects of influencing factors” (Yu et al. 2011, p. 1409).

3 Why Has the Role of Human Been Underestimated?

3.1 Linearity vs. Non-linearity

Understanding and theorizing household energy use processes and repercussions are “a far from straightforward matter” (Lutzenhiser 1997, p. 77).

> *“Household energy consumption is not a physics problem, e.g., with stable principles across time and place, conditions that can be clearly articulated, and laboratory experiments that readily apply to real world.”* (Moezzi and Lutzenhiser 2010, p. 209)

Linear analytical methodologies have been a research standard in understanding domestic energy demand. The assumption of linearity—where the dependent variable is a linear function of independent variables—and the difficulty of ascertaining any causal interpretations (i.e. the correlation vs. causation dilemma) are major downsides of traditional methodologies, such as ordinary multivariate regression models (Kelly 2011). As a consequence of the predominant assumption of linearity in energy demand research, “the present [conventional] energy policy still conveys a ‘linear’ understanding of the implementation of technology” (Aune 2007, p. 5463), while linear models cannot explain the complexities of household-level energy consumption (Kelly 2011). For better energy policies, a better understanding of the complexities of its use is needed (Aune 2007; Swan and Ugursal 2009; Hirst 1980).

3.2 Lack of Publicly Available Data

A major problem in residential energy demand research is that “the data do not stand up to close scrutiny” (Kriström 2006, p. 96). Methodological approaches lag behind theoretical advances, partly because data used for quantitative analysis often do not include the necessary socio-demographic, cultural, and economic information (Crosbie 2006). In addition, the absence of publicly available high-resolution energy demand data has hindered development of effective energy research and policy (Min et al. 2010; Kavgic et al. 2010; Pérez-Lombard et al. 2008; Lutzenhiser et al. 2010; Hirst 1980).

Even though relevant data are being regularly collected by different organizations, such data sources do not often become publicly known (Hirst 1980).

Conventional wisdom and modeling practices of energy demand are often based on "averages" derived from aggregated data (e.g. average energy demand of an appliance, a housing type, a car, etc.), which do not explicitly reflect human choice of housing and other energy consumptive goods (Lutzenhiser and Lutzenhiser 2006).

4 Non-linear Modeling

Like most urban phenomena, residential energy demand is an "outcome" of a set of complex interactions between multiple physical and behavioral factors. In complex systems, the multiplicity of causal links form a more complicated identity for the system than a single chain, encompassing an 'intricate' graph of causal networks (MacKay 2008; Phillips 2003). One main approach to modeling non-linearity is to decompose the linearity assumptions into a set of simultaneous linear sub-systems with explicit error estimates. Figure 3 illustrates one dimension of the difference between linear and non-linear approaches. A linear approach often considers the outcome as a "dependent" variable that correlates with a set of "independent" variables, which in turn, may correlate with each other as well. Clear examples of linear models are various types of multivariate regression models. In a non-linear approach, however, the outcome is the result of a set of cause-and-effect interactions between the predictor variables. This means that if one of the predictor variables changes, it will be unrealistic to assume that other variables would hold constant (a "gold standard" in reporting regression results)—with the exception of totally exogenous variables.

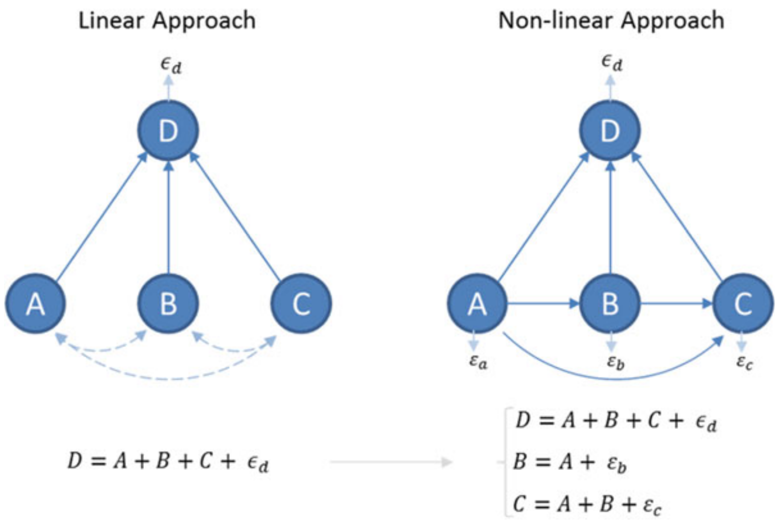

Fig. 3 Comparing linear and non-linear modeling approaches

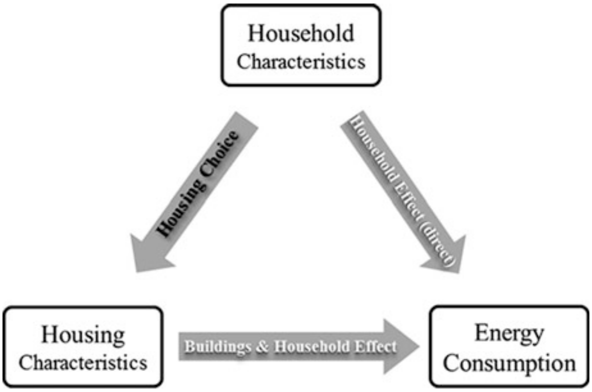

Fig. 4 A non-linear conceptual model of the impact of the household and the housing unit on energy demand. *Source*: Estiri (2014a)

This difference in the two approaches can be game changing, as the non-linear approach can reveal an often hidden facet of effects on the outcome, the "indirect" effects. Research has shown that, for example, linear approaches significantly underestimate the role of household characteristics on energy demand in residential buildings, as compared with the role of housing characteristics (Estiri 2014b; Estiri 2014a). This underestimation has formed the conventional understanding on residential energy and guided current policies that are "too" focused on improving buildings' energy efficiency.

Figure 4 illustrates a non-linear conceptualization of the energy demand at the residential sector. According to the figure, households have a direct effect on energy use through their appliance use behaviors. Housing characteristics, such as size, quality, and density also influence energy use directly. Household characteristics, however, influence the characteristics of the housing unit significantly—which is labeled as housing choice. In addition to their direct effect, through the housing choice, households have an indirect effect on energy demand, which has been dismissed with the use of linear methodologies, and so, overlooked in conventional thinking and current policies.

5 A Proposed Non-linear Modeling Schema

Energy use in the residential sector is a function of local climate, the housing unit, energy markets, and household characteristics and behaviors. A conventional linear approach to household energy use correlates all of the predictors to the dependent variable (Fig. 5). Figure 6, instead, illustrates a non-linear model that incorporates multiple interactions between individual determinants of energy demand at the residential sector. Results of the non-linear model will be of more use for energy policy.

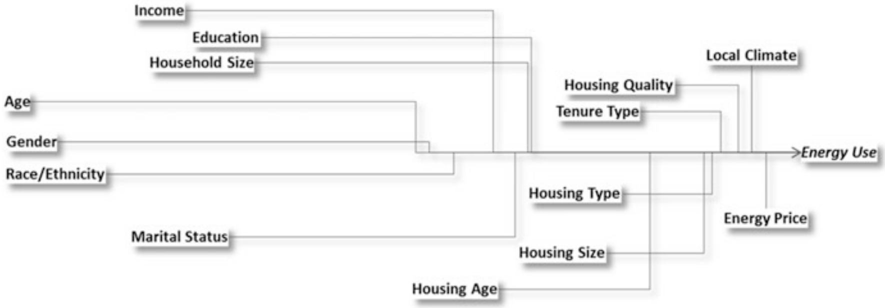

Fig. 5 Graphical model based on the linear approach. All predictors correlate with the dependent variable, while mediations and interactions among variables are neglected

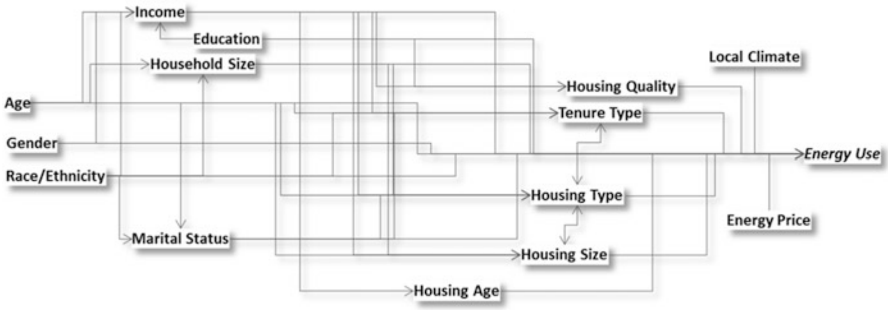

Fig. 6 Proposed graphical model based on a non-linear approach. Predictors impact both: the outcome variable and other variables

The recommended graphical model (Fig. 6) can be operationalized in form of 10 simultaneous equations with 69 parameters to be estimated, as represented in the following form:

$$\overbrace{\begin{vmatrix} \textit{Energy Use} \\ \textit{Income} \\ \textit{Education} \\ \textit{Household Size} \\ \textit{Marital Status} \\ \textit{Housing Age} \\ \textit{Housing Size} \\ \textit{Housing Type} \\ \textit{Tenure Type} \\ \textit{Housing Quality} \end{vmatrix}}^{\text{Variable Estimates}} = \overbrace{\begin{vmatrix} \beta_1 & \beta_2 & \beta_3 & \beta_4 & \beta_5 & \beta_6 & \beta_7 & \beta_8 & \beta_9 & \beta_{10} & \beta_{11} & \beta_{12} & \beta_{14} \\ \beta_{15} & \beta_{16} & \beta_{17} & 0 & \beta_{18} & 0 & \beta_{19} & 0 & 0 & 0 & 0 & 0 & 0 \\ \beta_{20} & \beta_{21} & \beta_{22} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \beta_{23} & \beta_{24} & \beta_{25} & \beta_{26} & \beta_{27} & 0 & \beta_{28} & 0 & 0 & 0 & 0 & 0 & 0 \\ \beta_{29} & \beta_{30} & 0 & 0 & \beta_{31} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \beta_{32} & 0 & \beta_{33} & \beta_{34} & \beta_{35} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \beta_{36} & 0 & \beta_{37} & \beta_{38} & \beta_{39} & \beta_{40} & 0 & 0 & 0 & \beta_{41} & 0 & 0 & 0 \\ \beta_{42} & 0 & \beta_{43} & \beta_{44} & \beta_{45} & \beta_{46} & \beta_{47} & 0 & \beta_{48} & 0 & \beta_{49} & 0 & 0 \\ \beta_{50} & 0 & \beta_{51} & \beta_{52} & \beta_{53} & 0 & \beta_{54} & 0 & \beta_{55} & 0 & 0 & 0 & 0 \\ \beta_{56} & 0 & \beta_{57} & \beta_{58} & \beta_{59} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{vmatrix}}^{\text{Estimated Regression/Effect Coefficients}} \times \overbrace{\begin{vmatrix} \textit{Age} \\ \textit{Gender} \\ \textit{RaceEthnicity} \\ \textit{Income} \\ \textit{Education} \\ \textit{Household Size} \\ \textit{Marital Status} \\ \textit{Housing Age} \\ \textit{Housing Size} \\ \textit{Housing Type} \\ \textit{Tenure Type} \\ \textit{Housing Quality} \\ \textit{Energy Price} \\ \textit{Local Climate} \end{vmatrix}}^{\text{Variables (data)}} + \overbrace{\begin{vmatrix} \epsilon_1 \\ \epsilon_2 \\ \epsilon_3 \\ \epsilon_4 \\ \epsilon_5 \\ \epsilon_6 \\ \epsilon_7 \\ \epsilon_8 \\ \epsilon_9 \\ \epsilon_{10} \end{vmatrix}}^{\text{Residuals}}$$

There are five exogenous variables in this model: age, gender, race/ethnicity, local climate, and energy price. All housing-related characteristics can be predicted with household characteristics (which can be improved by adding other influential variables). The parameters in these simultaneous equations can be estimated using a variety of software packages. How the estimated parameters can be used in planning and policy is yet another challenge.

6 Scientists, Planners, and Complex Modeling Outcomes

"For the theory-practice iteration to work, the scientist must be, as it were, mentally ambidextrous; fascinated equally on the one hand by possible meanings, theories, and tentative models to be induced from data and the practical reality of the real world, and on the other with the factual implications deducible from tentative theories, models and hypotheses." (Box 1976, p. 792)

The better we—as individuals, planners, policy-makers—process complexities, the better decisions we'll make. Future policies need to be smarter by taking more complexities into account. With the current growing computational capacities, it is quite feasible to estimate such complex models—models can be connected to and estimated using live data, as well. Further, modern analytical algorithms can easily handle more complex models (models with increasing number or parameters). Clearly, we won't be short of tools and technologies to model more and more complexities.

However, as the models get more complicated—and ideally produce more realistic explanations for energy demand—translation of their results for policy and planning will become harder. Planners and policy-makers are not equipped with the required skillset to understand and interpret sophisticated modeling outcomes. Their strengths are in developing policies and plans that operationalize community goals. I suggest, in a big data era, planning can benefit from the abundance of data—of varying types—and the advances in computational and analytical techniques through a planning process that is accordingly modified.

7 A Modified Planning Process

The traditional planning process is not capable of directly incorporating complex scientific outcomes into policy development. The three primary steps in traditional planning process are: (1) gathering data; (2) transforming data into information; and (3) setting goals and objectives. Policies often follow explicit goals arrived at as the fourth step in the traditional planning process. There seems to be a missing link to connect complex modeling outcomes with the production of policy; perhaps an interface that can help planners and policy-makers set explicit goals for their respective communities.

The planning process needs modification to adapt to and benefit from this new big data era, with the abundance of data and growing advances in computer

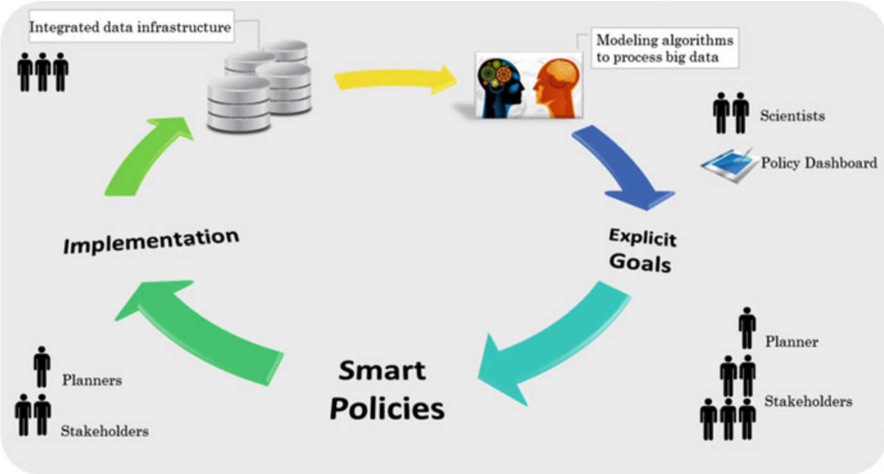

Fig. 7 The proposed modified planning process for the big data era

analytics. What is required for the outcomes of advanced complex modeling to be used in planning and policy is a paradigm shift in planning practice: a modified planning process (Fig. 7).

As I mentioned earlier, the traditional planning process often begins with data gathering. I also discussed that data unavailability is an important issue that has hindered the advancement of residential energy demand research and policy. Local utility companies are concerned about privacy issues. In addition, energy data needs to be connected to population, market, and climate data in a standardized way, to become useful for research and policy purposes.

The first step in this proposed planning process is a data collection and integration infrastructure comprised of energy, population, market, regulations, and climate data. There are various examples of federated data sharing infrastructures in health services that were developed using appropriate data governance and information architecture. Given that the bars for privacy are often set very high for health data, it should be feasible to develop similar data infrastructures for energy policy and research. Establishment of such integrated data infrastructures will require both technical and human components. Clearly, we will be needing data centers that can host the data, as well as cloud-based data sharing and querying technologies. But, technologies are only useful once the data is available—the foundation for data collection and integration are built. Here is where human role becomes important. To build a consensus among the data owners (utility companies, households, government or local agencies) multiple rounds of negotiations are conceivable. There also needs to be proper data governance in place before data can be collected, integrated, and shared with policy researchers.

New technologies (e.g., cloud computing, etc.) have made it easier to share and store data. Computer processing and analytics are also advancing rapidly, making it possible to process more data and complexities, faster and more efficiently (in its statistical denotation). There are several modern analytical approaches that can analyze more complexities, and can provide simulations. I suggest that the traditional analysis in planning process (step 2) should be enhanced/replaced by incorporating advanced modeling algorithms that are trainable and connected to live data. This process involves scientific discoveries.

Yet, planners and policy-makers should not be expected to be able to utilize complex modeling results directly into planning and policy-making. The findings of such analyses and simulations need to be made explicit via a policy interface. Using the policy interface, planners and policy-makers would be able: (1) to explicitly monitor the effects of various variables on energy demand and results of a simulated intervention, and (2) to modify the analytical algorithms, if needed, to improve the outcomes. The interface should provide explicit goals for planners and policy-makers, making it easier to reach conclusions and assumptions.

From the explicit goals, designing smart policies is only a function of the planners'/policy-makers' innovativeness in finding the best ways (i.e., smartest policies) for their respective localities to achieve their goals. Smart policies are context-dependent and need to be designed in close cooperation with local stakeholders, as all "good" policies are supposed to. For example, if reducing the impact of income on housing size by X% is the goal, then changes in property taxes might be the best option in one region, while in another region changes in design codes could be the solution. Once smart policies are implemented, the results will be captured in the data infrastructure and used for further re-iterations of the planning process.

8 Conclusion

This chapter built upon a new approach to energy policy research: accounting for more complexities of the energy demand process can improve conventional understanding and produce results that are useful for policy. I suggested that in order for planners and policy makers to benefit from the incorporation of complex modeling practices and the abundance of data, modifications are essential in the traditional planning process. More elaborations around the proposed modified planning process will require further work and collaborations within the urban planning and big data communities. Regarding the modified planning process, in the short-run, three areas of further research can be highlighted.

First is developing prototype policy interfaces. The non-linear modeling that I proposed in this work can be operationalized and estimated using a variety of software packages. More important, however, is the integration of the proposed non-linear model into the corresponding policy interface. More work needs to be done in this area using different methodologies, as well as developing more complex algorithms to understand more of the complexities in energy use in the residential sector—and perhaps, in other sectors.

Without integrated data it will be impossible to understand the complexities of energy use patterns—or any other urban phenomenon. Therefore, it is important to invest on city- and/or region-wide initiatives to securely collect and integrate data from different organizations. As the second area of future work, although establishing such initiatives and preparing the required socio-technical data infrastructure may not be a direct task for planners (for the time being), it certainly will be within the scope of work for local governments and planning / urban studies scholars.

Finally, the proposed modifications to the planning process have important implications for planning education. It will be crucial for planning practitioners or scholars in the big data era to be able to effectively play a role across one or more steps of the proposed planning process. When there is an abundance of data, planning education needs to incorporate more hands-on methodological training for planners in order to familiarize them with [at least] basic concepts of using data and data interfaces smartly. There also needs to be training around developing data architectures and infrastructures, especially for planning scholars to integrate urban data. Training options will also be helpful for planners to understand the required governance and negotiations related to obtaining and maintenance of data.

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