Human Behavior Considerations in Metrics for Smart Infrastructures

Krishna Kant
George Mason University
kkant@gmu.edu

Abstract—**Smart systems such as physical infrastructures infused with information technology offer a great opportunity for satisfying the customer needs and managing the resources more effectively and efficiently. In this paper, we examine the smart infrastructures in terms of their sustainability potential, which in turn requires a consideration of human aspects. We consider the currently defined metrics for the smart grid and point out the lack of metrics to quantify this aspect. We then present a simple model for smart grid that considers the carbon footprint and energy consumption that would result by accounting for certain aspects of human behavior. Such a model is useful in assessing whether the sustainability objectives are being met and what actions are required in this regard.**

Keywords: Smart Infrastructure, Sustainability, Rebound effect, Carbon footprint, human behavior

I. Introduction

The world we live in is experiencing rapid and likely long-term changes that are already posing difficult sustainability challenges. For example, the increasing population and ongoing migration of populations to mega-cities puts a severe stress on the built infrastructure and the environment. The ongoing efforts to embed information technology into the built infrastructure to make it smart provides a unique opportunity to address this sustainability challenge by promoting efficient use of resources and providing critical services that enhance safety and human well-being. Thus, an important metric to consider for smart infrastructure is sustainability, which requires a thorough understanding of the interactions between built, natural and social systems [9]. In this paper, we would like to make a small beginning by considering the impact of human behavior on the resource usage and the corresponding carbon footprint. We illustrate the considerations involved in doing so, and then propose a simple metric for capturing the resource use efficiency in smart infrastructures.

The organization of the paper is as follows. Section II discusses the role of smart infrastructure in sustainability and points out the need for modeling human behavior. Section III takes the example of smart-grid where metrics are well developed and points out their deficiencies in capturing the human behavior. Section IV then identifies the basic issues that need to be considered in adequately considering the long-term sustainability aspects for smart infrastructures. Section V develops simple equations for characterizing the impact of human behavior on energy consumption and carbon footprint of smart grid and shows some sample results. Finally, section VI concludes the paper.

II. Sustainability and Smart Infrastructure

It is well recognized that the legacy infrastructure, including power grid, transportation infrastructure, vehicles, homes, buildings, factories, etc. can be quite wasteful of resources, and an embedding of intelligence in form of active monitoring, management and coordination of distributed resources could substantially increase the efficiencies. For example, Smart grid enables the integration of many disparate sources of energy from rooftop solar in a home to large electric utility installations. Smart grid can also keep track of energy consumption profiles and thereby direct energy where it is needed and in the process reduce peak generation and storage requirements and hence the ultimate cost to the consumers.

Although the efficient energy use and reduction of waste contribute to sustainability, the smart-grid by itself does not provide any mechanism to reduce consumption of energy. Smart grid only enhances flexibility and lowers cost for the consumer (in terms of avoidance of local storage and ability to sell excess energy back to the utility). Following the well known *Jevon's paradox*[6], or the *rebound effect*, the enhanced flexibility and lower cost will invariably spur the consumer to increase the energy consumption. In particular, if the lowered cost is ploughed back into additional energy purchase, the result could be net increase in peak energy draw, in plant size, and the carbon emissions. Thus, understanding human behavior is crucial to evaluating the long-term sustainability impact of the smart grid [3], [8], [13]. Understanding human behavior is even more important under disaster scenarios to avoid instabilities in the grid and make the most effective use of the surviving infrastructure – although we do not address this aspect in the paper.

Similar arguments hold for other smart infrastructures as well. A smart transportation system can provide congestion alerts, determine optimal routes, help avoid accidents and hazardous conditions, etc. The resultant reduction in fuel consumption and shorter trip to the destination can reduce carbon impact of the trip and make the roads much safer. Nevertheless, the additional infrastructure itself may contribute to additional carbon footprint; the increased travel demand prompted by reduced travel time, less congestion, and safer travel could have an even greater impact.

Smart buildings and homes provide an interesting example of infrastructure where the main objective of the intelligence is to reduce consumption of resources such as energy or water. While turning off cooling/heating/lighting in unoccupied areas

 ISBN: 978-1-61208-225-7

can surely reduce energy consumption substantially, this applies only to buildings with low occupancies and highly granular controls. In other instances, the automated control could well result in higher energy consumption than a conscious manual control by the occupants. Once again, understanding human behavior and accounting it in the evaluation is crucial for assessing the overall benefit.

III. CURRENT METRICS AND THEIR DEFICIENCIES

Since smart grid has been advocated as a significant improvement over the existing and well entrenched power grid of yesterday, the issue of metrics to quantify the cost-benefit trade-off of the smart grid has been a topic of substantial current interest. In particular, the investment grants and demonstration projects funded by US Department of Energy (DOE) and Electric Power Research Institute (EPRI) have required evaluation of the projects along a variety of metrics that they have defined. In the following, we review these and related metrics and point out their deficiencies from the sustainability perspective. Similar observations can be made about other infrastructures as well.

The DOE analytical framework for smart-grid [1] establishes around 25 benefit metrics. These relate to costs, loading of different components, reliability, power quality, losses, power factor control, etc. A few of the metrics also relate to sustainability and concern capacity deferral and emission reduction due to smart energy management and integration of distributed renewable energy.

There are several other evaluation attempts for smart grid in the literature. In particular, Faruqui [4] shows the advantages of reduction in peak energy production, energy efficiency and distributed generation. Miller [10] provides a conceptual framework with multiple metrics under the broad categories of system efficiency, economic issues, reliability, security, environmental issues and safety. There are several other metric related studies, as summarized in the EPRI document [2]. Most of these metrics are effectively similar in nature, and they all lack consideration of long-term sustainability issues and a detailed understanding of the human behavior.

IV. UNDERSTANDING HUMAN BEHAVIOR

In understanding human behavior relevant to resource use, we need to address the following aspects of smart infrastructures: demand shaping mechanisms, extent of customer compliance with behavior monitoring, social influence, and behavior shifting over time. In the following subsections, we explain these and discuss how we plan to account for them. It is important to note here that although there is a rich literature to understand human behavior at a more detailed and elemental level (cultural, social, cognitive, and psychological) [11], our interests are at a higher level here. The more detailed models could presumably be used in deriving some of the parameters that we desired here.

A. Demand Shaping

Demand shaping refers to user's response to non-coercive mechanisms designed to influence the resource usage. (We only consider non-coercive mechanisms since the main issue with coercive mechanisms is compliance, which is covered in the next subsection.) The most common example of demand shaping is demand sensitive pricing. Another common example is to provide appropriate feedback to the user on its resource consumption. We discuss these in the following.

Demand shaping via dynamic pricing is a well known mechanism that is already being used to some extent in the current power grid. Studies show a 50% increase in price reduces household energy demand by only 11-15% and the tripling of price reduces consumption by 29-36% [13]. While pricing is an effective tool for smoothing out short-term demand variations, the rate regulations often come in the way of using it as a longer-term demand shaping mechanism. For example, while a utility can charge more during peak consumption periods, it often cannot raise the rate uniformly over long periods. As distributed generation takes hold, where the consumer generates its own energy, there is less role for pricing based behavior change.

Providing energy use feedback to user is a well known technique for influencing energy consumption behavior. It is important to note that feedback is not simply about providing information – the form in which the information is provided, the way it is presented, and how it is reinforced are crucial to making an impact on the energy consumption. The granularity of feedback is also critical – making a customer aware of using too much energy on hot water is far more useful and actionable than simply providing the overall increase in energy usage. It is also important to note that a feedback with the intent of decreasing energy consumption could sometimes have an opposite impact. This happens when the user determines that its consumption is lower than its peers or the effort to reduce consumption did not really make much difference to the energy bill. Experiments show that feedback can result in change in energy consumption from -5% to +20% [3].

Voluntary demand shaping depends on the choices made by the user, and an understanding of how users react to such mechanisms can improve predictability and ultimately the design of the mechanisms. Unfortunately, humans cannot be modeled as rational actors that simply maximize their utilities, even though a lot of pricing driven models assume this to be the case [12]. Users are often influenced by a host of factors, many of which may be ephemeral. For example, the adoption of an energy conservation idea or technique by an individual could depend on such diverse things as mood or emotional state, the way the idea is presented, prevalent social and cultural norms, ease of understanding the benefits, novelty, etc. [13].

B. User Compliance

The operation of a smart infrastructure involves collection of a variety of data about the way customers use it and often generates advisory data to enable them to make better choices. User compliance in terms of both accurately providing the requested data (input side) and following the advisory (output side) is crucial for smooth operation and resource efficiency of the entire system.

Let use start with the input side. A significant advantage over of smart grid over the current power grid is the active monitoring of the energy demand that allows a better management of the flow of energy and hence less conservative sizing of the facilities. However, the key question is whether the customer would feel comfortable with the active monitoring and what kind of data he/she will allow to be collected? The granularity of data collection acceptable to the user affects the advantage that can be derived from it. For example, if the customer is unwilling to allow individual monitoring of major energy consuming systems in a home/building, it is not possible to generate customized strategies for reducing the energy consumption. Similar comments apply to other smart infrastructures. In the smart transportation system context, if the drivers are unwilling to share their destinations and planned routes, the system cannot derive very accurate information about expected delays and future congestion.

There is a similar compliance issue on the output side. If a smart transportation system provides drivers feedback regarding the desirable routes or routes to avoid, but such feedback is ignored, the system will not be able to do a good job of managing delays and congestion irrespective of how much information it collects or how good an analysis job it does. In fact, erratic compliance could occasionally lead to traffic and congestion that is much worse than the one without any intelligent monitoring. Similarly, if the smart grid generates sound advice on how to smooth out the energy consumption profile w/o sacrificing comfort, and the advice is poorly used, it could lead to worse supply-demand mismatches.

Another area where compliance is an issue are legal mechanisms that prohibit wasteful use or mandate frugal use of resources. However, such mechanisms are normally viable only in cases of extreme resource shortages which we do not consider here.

C. Social Influence

An individual's behavior is often driven by the behavior of others around it, either in form of imitation/conformance or as a contrarian. For example, a driver that sees a lot of other people exiting the road may either also decide to exit (conformance or herd behavior) or decide to stay (to potentially benefit from the herd behavior exhibited by others). Similarly, people may imitate or contradict other people in their neighborhood in terms of energy or water use.

The characterization of social influence is itself a challenging problem but has been studied extensively particularly in the context of "herding behavior" that is routinely seen in complex adaptive systems such as investing, driving/walking, emergency evacuation, etc. [14]. As with other parameters, devising general model for it is extremely difficult. Even a direct measurement could be somewhat challenging since it may not be clear if the observed behavior represents herding or something else.

The social influence can be exploited to nudge people towards sustainability, though it could also prove ineffective. For example, if home-owner is simply provided data about the energy consumption of other similar homes in the neighborhood, the effect is likely to be conformance rather than reduction in energy consumption. In particular, those with high energy consumption may reduce it, but those on the lower end may increase their consumption. However, creative mechanisms for feedback and positive reinforcement could help lower the consumption on the higher end without raising the lower end.

D. Behavior Shifting

This aspect directly relates to the long-term shift in the resource usage that may be triggered by the smart infrastructure itself. The qualification here is essential since we do not want to include influence of other extraneous factors such as rising incomes of the population served by the smart infrastructure. Thus the primary mechanism for behavior change considered here is the rebound effect. This is likely to be mostly cost driven – the lower cost brought about by improved efficiencies and ability of customer to sell power to utilities could make them gradually increase their consumption. However, other factors may also play a role. For example, the "feel good" emotion about locally harvested renewable power may make people more comfortable with increasing their energy consumption. Generally, such behavior shifting will have a long time constant. It is generally very difficult to characterize since the impact depends on a large variety of poorly understood human behavior issues; therefore, we merely illustrate it here without making any claims regarding the definitiveness of our assumptions.

Wang [13] contains a wealth of information regarding the behavioral impact on energy consumption. It also quotes data from 20 different studies to quantify the magnitude of the rebound effect in the context of energy use for various purposes. The high variability in the estimates in these studies (not included here for brevity) reflects the difficulty in ascertaining the impact of human behavior.

E. Human Behavior Centric Efficiency Metric

In this section, we propose a new metric that accounts for the influence of the above factors with respect to resource consumption and hence sustainability. The goal of the metric is to quantify to what extent human factors can increase or decrease the resource consumption (or its carbon footprint). The metric thus provides an estimate of what can be achieved by putting more effort into influencing human behavior.

Let R_0 denote the baseline resource consumption and R_x the modified resource consumption due to influence x where x takes the following values:

- $x = pf$: Influence of private feedback to customer on his/her resource consumption. Here, "private" means that a user receives data on his own consumption, and not that of others.
- $x = si$: Influence of feedback that compares a customer's resource consumption against that of his/her peers.
- $x = bs$: Influence of long-term behavior shifting (primarily rebound effect).

The three factors above have been defined in such a way that they are reasonably independent of one another. It must

 ISBN: 978-1-61208-225-7

be acknowledged, however, that seemingly independent human behavior factors could be related in complex ways; therefore, one cannot claim complete independence. For example, it is possible that the extent of behavior shift depends on how much resource reduction we start out with. Nevertheless, we assume independence for simplicity.

Let us now define the metric γ_x as R_x/R_0 which gives the fractional resource consumption relative to the baseline. Furthermore, by exploiting the independence assumption, we also define total metric γ_t as follows:

$$\gamma_t = \gamma_{pf}\gamma_{si}\gamma_{bs} \tag{1}$$

The combined metric γ_t allows us to assess the net advantage resulting from the behavioral aspects, with $\gamma < 1$ being desirable. All 3 individual factors, and hence γ_t will typically vary with time, and may or may not settle to a long-term value. For example, γ_{pf} may go down slowly over months as consumers begin to react to feedback and then settle, go down initially and then creep up (initial enthusiasm for conservation that wanes over time), or show other more complex behavior. Thus a periodic assessment of the γ_t metric may be in order, with the intent that whenever it tends to inch up significantly, new mechanisms can be tried to drive it down. From a modeling perspective, we may be interested in predicted range for γ_t over the long term either with or without corrective actions.

The influence of feedback can be attributed to 3 different factors: (a) The granularity of usage data provided by the customer, (b) the granularity of feedback provided to the customer, and (c) the customer compliance, which in turn depends on the quality and effectiveness of the feedback. We optimistically assume that (b) is not an issue; i.e., the system always attempts to generate as granular a feedback as the monitored data would allow. The user provided data granularity may be limited due to a variety of factors including technological, regulatory, or customer choice. Even the technological factors could be a significant barrier since putting meters or sensors at multiple points could be expensive or impractical. In this regard, a significant amount of work exists on "signature analysis" to identify components of resource consumption [5]; however, such measurements are prone to errors. In view of this, it is not useful to determine γ_{pf} as a function of some measure of granularity; instead, it suffices to estimate typical values of γ_{pf} under a couple of scenarios and best presentational practices.

The metrics γ_x and γ_t can also be defined relative to carbon footprint instead of resource consumption. We denote these alternate versions as Γ_x and Γ_t respectively. The main advantage of considering these is their ability to distinguish between various technologies in terms of sustainability (e.g., renewable vs. fossil fuel based energy conversion). Note that the carbon footprint comes not only from the direct use of the resource (e.g., use of gasoline in the car) but also from the machinery (e.g., the car itself) and the associated infrastructure/operations (e.g., extraction and transportation of materials and fuel). A comprehensive accounting of all components of the carbon footprint is beyond the scope of this paper. Instead, we assume that for a given technology, the carbon footprint can be related to the resource use via a known constant factor.

V. Efficiency Metric for Smart Grid

In this section we focus specifically on the smart grid and address the question of under what conditions does smart grid lead to decrease in the energy consumption and the carbon footprint? In particular, we compare the sustainability advantages of integrating distributed renewable power generation by customers into the smart-grid vs. the traditional model of central utility based power distributed to the customers.[1] Our analysis here is rather simple and is only meant to illustrate the usefulness of the efficiency metric defined above. It is possible to take this analysis much further, but that is beyond the scope of this paper.

Let us assume that a smart grid serves a community of N homogeneous customers, each of which consumes R_c units and generates renewable energy G_c, at the cost of η_c dollars/unit (or KWHr). Of this, a fraction α is sold to the utility company at the cost of η_{cu} dollars/unit and the rest is consumed locally. Note that α is intended to be simply a long-term average fraction. Depending on the variability of the demand, the actual energy exported to the utility will vary with time.

Let G_u denote the required generation capacity of the utility. We assume that G_u is just enough to satisfy the demands of all N customers if they do not generate any energy on their own. The generated amount also includes excess to account for the transmission and distribution (T&D) losses. Thus, if f_L is the T&D loss fraction, we have:

$$G_u = NR_c/(1 - f_L) \tag{2}$$

Let R'_c denote the energy consumption of each customer under distributed generation. If there is no behavior change, $R'_c = R_c$, otherwise, the two could be different. Let G'_u denote the central generation requirements in this case. It is easy to see that:

$$G'_u = N[R'_c - G_c(1 - \alpha f_L)]/(1 - f_L) \tag{3}$$

Here, $R'_c - G_c$ is the amount of energy that the customer needs from the utility. Furthermore, since the customer feeds αG_c energy to the utility (to be recycled back to same or different customer), a fraction f_L of this is lost and needs to be generated centrally. Finally, all power generated by the central utility must be further bumped up by the factor $1/(1 - f_L0)$ to account for forward T&D losses.

We assume that the utility company generates energy from non-renewable sources and sells it at the cost of η_{uc}. It is assumed that $\eta_{cu} < \eta_{uc}$, i.e., the customer receives less from utility than utility's energy selling rate. (Although currently there are instances where the utilities pay more to customers than their selling rate, this is an unsustainable model in the long run.) Generally, one would expect that $\eta_c > \eta_{uc}$, i.e., small distributed generation is more expensive than the centralized generation if the up-front, leasing or maintenance

[1] In what follows, distributed generation is used as a codeword to refer to smart-grid, whereas centralized-only generation is used to refer to the conventional grid.

costs of the infrastructure are also taken into account. With centralized generation, the energy price paid by a customer, P_c is given by:

$$P_c = R_c \eta_{uc} \tag{4}$$

With distributed generation, it changes to:

$$P'_c = [R'_c - G_c(1 - \alpha f_L)]\eta_{uc} + G_c[\eta_c - \alpha(1 - f_L)\eta_{cu}] \tag{5}$$

where the first term represents the cost of buying energy from the utility, second term the cost of generating it locally, and third term is the discount for selling energy to the utility. Note that in the first term, the customer must buy back the energy it sells to the utility at the regular rate. Also, just like the customer, the utility pays for only the energy it sees on its end. Thus, even though the customer sells $G_c\alpha$, the utility only sees a fraction $(1 - f_L)$ of this.

It is important to note here that it is not so much the actual cost η_c, but rather the customer perceived cost, say η'_c that matters. As in many other contexts of do-it-yourself scenarios, the customer often tends to ignore the fixed initial investment and regular maintenance costs and only considers the running cost. For example, when considering the cost of driving vs. taking public transport, people often only consider the fuel cost of driving. With renewable energy such as solar where the running costs are essentially zero, η'_c can be substantially lower than η_c, perhaps even zero. In this case, the customer may perceive as gaining even without selling anything back to the utility. This aspect is crucial for the rebound effect discussed below.

Let us now estimate the γ_t factors for our simplified situation. We shall assume that the feedback can modestly lower the energy consumption as reported in [13]. Since we are considering an idealized situation where all N customers have equal energy consumption, social influence has little role to play here, and $\gamma_{si} = 1$.

In order to estimate γ_{bs}, we assume a limited rebound effect where the customer increases its energy consumption to match the cost associated with the case of centralized generation only (that is, any energy reduction effects due to γ_{pf} and γ_{si} factors still hold). Thus, by equating the costs from eqns 4 and 5 and setting $\gamma_{bs} = \frac{R'_c}{R_c}$, we have:

$$\gamma_{bs} == 1 + [\alpha(1 - f_L)\frac{\eta_{cu}}{\eta_{uc}} - \frac{\eta_c}{\eta_{uc}} + (1 - \alpha f_L)]\frac{G_c}{R_c} \tag{6}$$

In reality, there is a limit to how much energy a customer can consume. We assume that a customer cannot increase his consumption by more than by a factor denoted as “Limit”. And finally, $\gamma_t = \gamma_{pf}\gamma_{bs}$.

Let us now consider the estimation of Γ_t factors. We denote the carbon footprint of resource R as $\zeta(R)$. As discussed before, we assume that $\zeta(R) = C\,R$ where C is an appropriate constant. In particular, we use two constants, C_r for renewable energy, and C_f for fossil fuel based energy. Both of these constants would generally depend on the size of the installation, with larger installations having a lower carbon footprint per watt. In all cases, the carbon footprint needs to consider the average energy generation per customer, not just the consumption. The difference – T&D losses – do contribute to carbon footprint. With this, and eqn (2), we have:

$$\zeta(R_c) = C_f\,G_u/N = C_f R_c/(1 - f_L) \tag{7}$$

In case of smart grid where a customer produces G_c KW of energy locally and requires generation of G'_u/N units centrally. Therefore, from eqn (3), we have

$$\begin{aligned} \zeta(R'_c) &= C_r\,G_c + C_f\,G'_u/N \\ &= C_r\,G_c + C_f\,[\gamma_{bs}R_c - G_c(1-\alpha f_L)]/(1-f_L) \end{aligned} \tag{8}$$

Since $\Gamma_{bs} = \zeta(R'_c)/\zeta(R_c)$, it follows that

$$\begin{aligned} \Gamma_{bs} &= \frac{[C_r\,G_c(1 - f_L) + C_f\,[\gamma_{bs}R_c - G_c(1 - \alpha f_L)]]}{C_f R_c} \\ &= \gamma_{bs} - G_c/R_c[1 - \alpha f_L - C_r/C_f(1 - f_L)] \end{aligned} \tag{9}$$

Also, $\Gamma_t = \Gamma_{pf}\Gamma_{bs}$.

We now show the behavior of γ_t and Γ_t as a function of various parameters. For this, let us first describe the situation considered in our rather simple model. We assume that the customer receives power from the utility (η_{uc}) at the rate of 12 cents/KWHr, and the utility is willing to purchase power from the customer (η_{cu}) at 9 cents/KWHr. We assume that the real cost of locally generated power is 15 cents/KWHr, but as indicated earlier, the customer may perceive a lower cost. Since our simple analysis does not use the underlying costs, the results are the same irrespective of whether the assumed costs are real or perceived. Therefore, we will show results for (real or perceived) rates of 0, 5, 10, and 15 cents/KWHr. We assume that the T&D losses are 20%, which are somewhat on the optimistic side but perhaps achievable with smart grid. Finally, we assume that the smart grid can maintain a 5% gain in efficiency of the regular grid due to continuous customer feedback. We also assume that the rebound effect is limited to at most 60% increase in energy consumption over the baseline; i.e., the “Limit” parameter is set to 1.6.

We assume that a customer generates some percentage of its requirements G_c/R_c, locally and receives rest from the grid. If the local generation is small (up to $\theta_0 = 20\%$ in our example), all power can be used locally and none is sold to the utility. At higher local generation capacity, we assume that the customer is able to absorb $\theta_1 = 25\%$ of the excess, and sells the rest. That is,

$$\alpha = \begin{cases} 0 & \text{if } G_c/R_c \le \theta_0 \\ \theta_1(G_c/R_c - \theta_0) & \text{otherwise} \end{cases} \tag{10}$$

The parameter θ_0 depends on customer’s decision regarding the sizing of its local generation capability and θ_1 indicates variability of his demand. If the demand is constant, we can set $\theta_1 = 1$; that is, the customer will use all of the local power up to the limit θ_0 and then export all the rest. A local power storage would allow the customer to reduce θ_1 so that it can keep the local power to handle its short term demand variations.

For the carbon footprint, we assume that the C_f is relatively independent of the capacity, but C_r decreases modestly with the size of the installation. In particular, we assume that as a function of G_c/R_c, C_r/C_f varies from 0.25 for a small installation to 0.15 for the case of $G_c/R_c = 1$. That is, we are assuming that a large renewable plant has only about 15% carbon footprint as compared to a conventional plant.

Figs. 1 and 2 show the energy and carbon footprint efficiencies of smart grid (γ_t and Γ_t) as a function of G_c/R_c

and for different costs η_c. Let us first compare the different curves. As expected, if the perceived or real cost is lower, the rebound effect prompts the user to consume more energy (up to 60%), which explains the systematic ordering of the 4 curves. In particular, if the customer thinks that its local energy costs significantly less than the utility power, the energy consumption goes higher than that for the centralized generation case (i.e., more than 1.0). The carbon footprint shows a similar but somewhat better behavior, as we shall discuss shortly.

Let us now consider the behavior with respect to G_c/R_c. When the perceived or real cost of local generation is small, an increasing G_c implies that the user is able to reduce its cost which in turn prompts him to consume more energy. Therefore, the consumption also increases monotonically with G_c (up to the assumed limit). Note that if the perceive or real cost of consumer generated power is higher than the cost of utility power, the net effect is the price based reduction in consumption as shown by the $\eta_c = 0.15$ curve. Not surprisingly, when the local generation fraction $G_c = 0$, all curves merge at the same point. This point is really at 0.95, rather than 1.0, and reflects the 5% feedback based advantage of the smart grid.

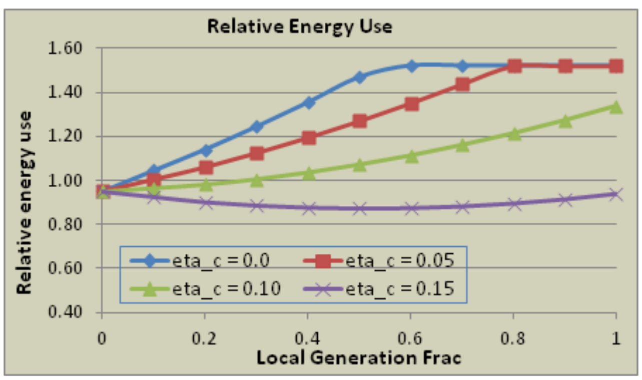

Fig. 1. Relative Energy Use vs. locally generated power fraction

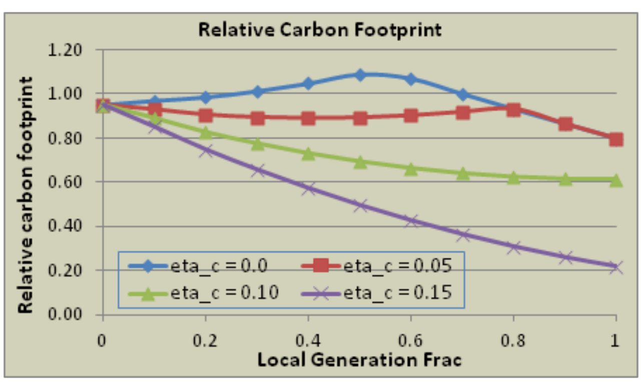

Fig. 2. Relative Carbon Footprint vs. locally generated power fraction

The primary difference between carbon footprint and energy use curves is our assumption that the local generation by the customer uses renewable source which has a much lower carbon footprint than the utility generated power. This aspect works against the increase in carbon footprint due to increase in energy consumption, hence the rather peculiar shape of the curves. In particular, when η_c is closer to the actual cost, the carbon footprint actually shows a monotonic decline with G_c/R_c.

It can be seen that in spite of its simplicity, the model can be used to address a number of scenarios. The model can also be tweaked to study a time-series of dynamically varying demands, though we do not pursue this due to lack of space.

VI. Conclusions

In this paper, we highlighted the need for metrics that capture the human behavior in characterizing the resource use and environmental impact of the smart infrastructure. We also developed a simple metric for the smart grid and showed its usefulness in evaluating the sustainability impact of the smart-grid. Similar analysis can be carried out for other smart infrastructures as well.

Admittedly, our model and analysis are rather simple, and the calibration parameters are somewhat arbitrarily chosen. The future work involves a more comprehensive modeling that accounts for heterogeneous customer base, a deeper modeling of the human behavior aspects, and the consideration of temporal aspect (i.e., the fact that energy demand and even the customer behavior varies with time). The ultimate worth of this exercise is to find ways of influencing human behavior in ways that can lead to more efficient resource usage and reducing its carbon impact without sacrificing comfort or safety. It is hoped that a more detailed modeling will provide insights into how to do this.

References

[1] S. J. Bossart and J. E. Bean, “Metrics and Benefits Analysis and Challenges for Smart Grid Field Projects”, U.S. Department of Energy, Proc. of EnergyTech, May 2011.
[2] Electric Power Research Institute, “Methodological Approach for Estimating the Benefits and Costs of Smart Grid Demonstration Projects”, Palo Alto, CA: 2010. 1020342.
[3] C. Fischer, “Feedback on household electricity consumption: a tool for saving energy”, Energy Efficiency, 2008, pp 79-104.
[4] A. Faruqui, R. Hledik, C. Davis, “Sizing up the Smart Grid,” presented at Elster EnergyAxis User Conference, Feb. 24, 2009
[5] J. Froehlich, E. Larson, S. Gupta, et al., “Disaggregated End-Use Energy Sensing for the Smart Grid”, IEEE Pervasive Computing, Vol.10, No.1, pp 28-39, Jan.-March 2011
[6] J.M. Polimeni, K. Mayumi, and M. Giampietro, *The Jevons Paradox and the Myth of Resource Efficiency Improvements*, Earthscan. pp 79140.
[7] T. Godfrey and C. Rodine, “Unified Metrics for Management of Smart Grid Home Area Networks”,
[8] E.D. Kuligowski and S.M. V. Gwynne, “The Need for Behavioral Theory in Evacuation Modeling”, Pedestrian and Evacuation Dynamics 2008, 2010, Part 3, 721-732.
[9] S.A. Levine and W.C. Clark, “Towards a science of sustainability”, Report from workshop, Nov 2009, available at http://www.nsf.gov/mps/dms/documents/SustainabilityWorkshopReport.pdf
[10] J. Miller, “Smart Grid Metrics: Monitoring Our Progress,” presented at the Smart Grid Implementation Workshop, June 19, 2008
[11] J. Thgersen and A. Grnhj, “Electricity saving in householdsA social cognitive approach”, Energy Policy, Vol. 38, No. 12, Dec 2010, pp7732-7743
[12] C. Triki and A. Violi, Dynamic pricing of electricty in retail markets, Q. J. Oper. Res., vol. 7, no. 1, pp 2136, Mar. 2009.
[13] J.H. Wang, “Behavioral Policy Modeling: Consumer Behavior Impacts on Residential Energy Consumption”, available at www.spp.gatech.edu/faculty/WOPRpapers/Wang.WOPR11.pdf
[14] L. Zhaoa, G. Yanga, W. Wanga, et al., “Herd behavior in a complex adaptive system”, Proc. of National Academy of Sciences, Vol 108, No 37, pp 15058-15063, Sept 2011.