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A Systematic Socio-Techno-Economic Approach Toward Reducing Carbon Emissions: Decentralization of the Accounting and Financing for Electricity Use

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Abstract—This paper suggests a model for optimization of societal carbon footprints one person at a time through the decentralization of electricity use and accounting. Our model describes steps involved with developing a decentralized accounting system considering electricity as a "credit product". While describing the basic characteristics of both schemes, we also emphasize capabilities of the proposed model for reducing carbon footprints from other societal choices, for example, purchasing water (energy-water nexus), managing waste, or designing sustainable transportation systems. A simple yet complex model involved with familiar societal financial systems' rules and routines is proposed for achieving a resilient, sustainable, and prosperous future. The proposed model calls for creating a dynamic society (as a system) that can be efficiently adopted to take on challenges threatening the function, survival, and future developments of the societies.

Keywords—carbon emission, climate change, energy management, credit score, sustainability

I. Introduction

The relationship between carbon emission and electricity use is well established in the literature, showing that economic growth, financial development, and electricity consumption in both industrial and urban settings, as well as climate change itself, stimulate CO_2 emissions in both the short and long runs [7] [11]. More specifically, the rate of societal (households, businesses) electricity use has been shown to be a significant proportion of the gross national CO_2 emissions in countries such as China [5]. According to the estimate by the Environmental Protection Agency (EPA), on average we can expect emission levels of 7.07×10^{-4} MT CO_2 for every kWh use of electricity [4].

The relationship between the pattern of energy use and its impact on climate change has also been shown to depend on the value of contemporary and prospective electricity supply resources and how much and when they operate, and most importantly on the availability of large-scale storage. These parameters, particularly the quantity and timing of the demand for electricity, need to be adjusted in real time [9] since variations in the electricity supply and demand (quantity and timing of use) have clearly been shown to yield measurable impacts on CO_2 emissions. Statistics on varying sources of energy supply in the U.S., for example, indicate that energy-related CO_2 emissions declined by 861 million MT (14%) from 2005 to 2017, while short term projection suggests that CO_2 emissions would rise by 1.8%, from 5,143 million MT in 2017 to 5,237 million MT in 2018, then would remain virtually unchanged during 2019. The rate of electricity use in households, however, is shown to be a function of users' behaviors [3] [10]. Reference [6] suggests that energy use related emissions may decrease in households and companies by changing use patterns, as a consequence of managing the timing of electricity use more efficiently. For example, [6] projects decrease in emissions in the range of 3–8% as a result of optimizing the time of the use and demand loads.

The world is already experiencing severe impacts of CO_2 emission and its effects on climate change, evident from extreme heat waves and sea level rises to speeding up species die-off and crop failures. These changes have raised urgent needs for making deep structural and societal shifts to combat negative climate change consequences through a more proper management of CO_2 emissions. While the use of energy has long been identified to be the least efficient part of the global energy system, it has also been proven to have potential to be the largest deductible source for CO_2 emission [1]. Globally accepted strategies to reduce CO_2 emissions trace back to dealing with high demand for energy and excessive use of electricity related to managing residential and commercial buildings, which are contributing to 31% of carbon and greenhouse gas emissions in the last several decades [4].

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A. *Intellectual Merit of the Proposed Research Work and Research Tasks*

This paper proposes an innovative systemic socio-techno-economic model for reducing demand for electricity through the decentralization of accounting and financing energy use. Explicitly, the proposed model suggests the application of a financial tool, i.e., a reward system, for promoting reduction of individual carbon emissions (carbon footprints) associated with the use of electricity, which is by far the largest proven CO_2 reduction source [1]. The proposed financial reward system can over time create resilience against climate change through reducing societal carbon footprints one person at a time. The model demonstrates how combining SMART technologies and decentralizing electricity use and accounting could result in reducing carbon footprints associated with societal habits and patterns of use (demand) for electricity at the individual level, by advocating for the development of "a credit line" for energy use, with current focus on electricity users through a "decentralized accounting system" while considering electricity as a "credit product". The proposed models (Fig. 3 and Fig. 4) have the potential to be expanded and applied to other scenarios of reducing carbon footprints from societal choices, for example, purchasing water, generating waste (measured by the weight of waste disposal bags), or selecting transportation systems. Focusing on occupant behavior and the need for reducing energy consumption using a smart and innovative "Technological", "Financial", and "Societal" nexus, this research provides insights into the efficiency and distributional impacts of alternative policy design approaches for managing carbon emissions. The model envisions that by 2050 these new approaches will lower energy use and CO_2 emissions by demonstrating the immediate financial impact of energy conservation by individual users in both rural and urban settings, as well as in different economies. Fig. 1 suggests the working elements of the proposed model for reducing CO_2 emissions.

B. *Research Goals and Objectives*

The main objective of this study is to demonstrate how a simple yet novel systemic socio-techno-economic approach can be used to optimize the use of electricity through the decentralization of accounting and financing electricity use with a 2050 vision for CO_2 reduction. A rapid transformation of energy use patterns (and as such, emission reductions) are anticipated assuming that end-user technologies and user behaviors are less "locked-in" than capital-intensive and long-lived energy-supply technologies and infrastructures, opening up potential for more rapid changes. For example, one unit of useful energy conserved through demand management could translate into a reduction of 2.5 units of primary energy, and

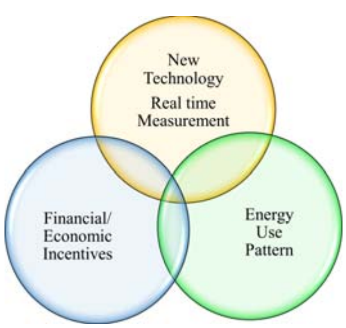

Fig. 1. Working elements of the proposed model

this would translate to emission reductions four times larger than efficiency improvement potentials in the energy supply upstream [1]. Data on electricity use are collected in real time by activating meters installed in every living environment to estimate quantity and pattern of electricity use and costs. The meter system is linked to the energy market in order to estimate the true cost of energy use during the period that system is activated. Use is recorded on a special credit card that the user must utilize to pay for electricity bills (we call it the ECard). Analysis of data involves application of the algorithm we developed for estimating the user's energy credit score based on the patterns of monthly energy use in kWh and US dollars. This score can be used to negotiate contracts or receive bonus coupons for energy bill payments or other economic incentives. The pattern of paying for energy bills using ECard is also recorded, e.g., paying the balance in full, or maxing out the ECard credit limit by skipping a few monthly bill payments. Like any other credit cards, the ECard will be issued and managed by credit organizations to estimate and monitor the user's credit score, and as such, economic incentives are assumed from practicing efficient and conscious use of electricity over time, as reflected in higher credit score. Data obtained from pilot studies can be used to also investigate conditions under which changes in patterns of energy use might occur. The proposed decentralized carbon footprint per capita reduction strategy/model is a novel approach with a new perspective compared to the previously practiced financial models to promote energy efficiency and conservation; it is decentralized, focuses on changing energy use habits one person at a time. It can present immediate financial incentives to those practicing sustainable use of energy, and it is built to gradually change societal behavior while employing new technical and financial tools. Finally, the ECard is designed to promote mandating measures for saving energy through the use of common social instrument "credit cards" and "credit scores" by incentivizing energy efficiency practices while changing energy use pattern and behavior.

II. METHODOLOGICAL APPROACH

Fig. 2 presents steps involved with developing the proposed innovative financial tool for building credit line for electricity users through a decentralized accounting system. There are two main steps involved: (I) The accounting system focuses on demonstrating how individuals can improve their

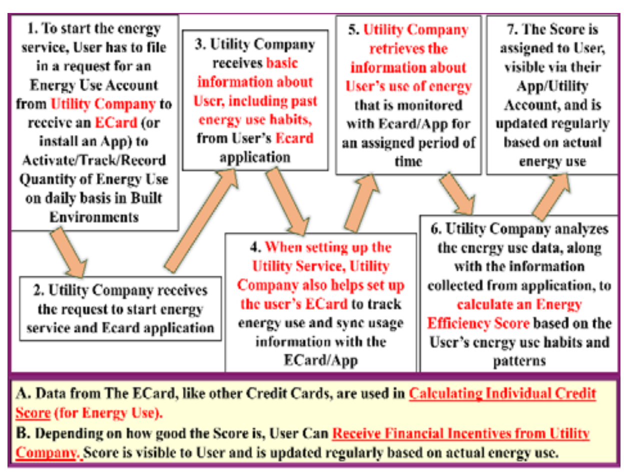

Fig. 2. Conceptual design: the reward system for managing demand and efficient use of electricity one person at a time

credit scores through conscientious use of electricity, in other words, through reducing their carbon footprint. To meet this goal, the model requires the creation of a green credit card for individuals via which they could purchase electricity as needed in either working or living environments. This credit card, like Visa or Mastercard, would be sponsored/managed by an energy/utility company and an affiliated bank, which would also monitor variations in the total amount of electricity use by individuals. (II) An Energy Credit Score is estimated incorporating green credit card data in the estimation of an individual's credit score, according to factors such as on-time payments or increase or decrease in total use, for example. Card users can easily observe impacts of their responsible behaviors in using electricity, for example, what would happen if they reduce their qualitative and quantitative demand for electricity on a daily basis, by observing their calculated Green Credit Score.

The proposed model assumes utilization of smart electricity metering technologies, specifically those already tested in working and living environments, and the development of innovative financial tools capable of rewarding cognizant use of electricity. We are hypothesizing that over time such practices could result in engineering societal habits and behaviors toward different aspects of energy use. The next section describes the proposed financial model, the context of the proposed credit scoring and rating system, model development processes, and model capabilities for simulating credit scores under different scenarios. Results of theoretical analysis are further discussed while validating the importance of financially rewarding individuals for their conscientious use of electricity through building a credit line for electricity users in a decentralized accounting system.

III. MODELING AND SIMULATION

Our credit scoring model employs the same methods commonly used by credit companies for individual credit ratings [8]. Starting with the existing customers' credit data, we first characterized credit-user variables according to the Age, Income, Credit Use and Credit Payment Patterns, etc. These variables then were further classified according to Individual Background, Financial Status, and Credit Behaviors as shown in Fig. 3. These variables were selected since they could describe a complete picture of each credit user's profile and Credit Behaviors. Each variable is then classified into different ranges in order to estimate percentage of customers being a good borrower vs. those being a bad borrower.

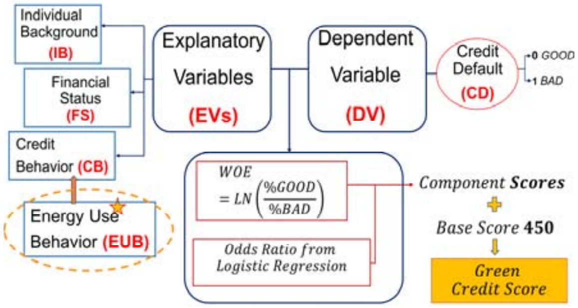

Fig. 3. Proposed Green Credit Score model

The Weight of Evidence (WOE) was then estimated as follows:

$$WOE_i = LN\left(\frac{\%GOOD}{\%BAD}\right) \tag{1}$$

We defined good and bad borrowers from tracking their monthly payments of outstanding credit balances over a given trial period, e.g., 12 consecutive months. If the credit user makes late payments or misses payments during the trial period, she/he is noted as a bad borrower with a possibility of credit default. This credit default probability is shown by the binary variable Credit Default, which takes the value of 0 for not having a significant chance of defaulting on credit borrowing and 1 for having shown a high enough probability for defaulting.

Next, we fit a logit regression using Credit Default as the dependent variable, and the characteristic variables as explanatory variables. Beforehand, we calculated the Information Value (IV) of the explanatory variables to determine how relatively important each one is in explaining Credit Default:

$$IV = \sum (\%GOOD\text{-}\%BAD) \times WOE \tag{2}$$

Following [2] and [8], we chose a cut-off IV level of 0.02 to determine whether the explanatory variable is useful, and thus should be included in modelling. Variables with IVs of 0.02 or higher are considered significant and used as independent variables in the logistic regression. The WOE of a range is then scaled with the odd ratio from the logit regression to come up with the component credit score of that range:

$$Score_{ij} = WOE_i \times Odd\ Ratio_j \tag{3}$$

Overall, as shown in part for this example in Table 1, we have a scorecard that contains characteristic variables significantly related to the credit profile of an individual; each of those characteristics is divided into various ranges, each range with a component credit score calculated from the existing database. Individuals being scored will be assigned component scores for their characteristics based on the scorecard. Combining the component scores with a base score

TABLE I. EXAMPLE OF CREDIT SCORECARD

Variable	Description	Range	Score
AGE	Current age of the credit user	18-25	20
		25-35	13
		35-45	20
		45-55	13
		55-75	20
		Over 75	-20
INCOME	Current annual income of the credit user	Up to $45,000	0
		$45,000-$70,000	8
		$70,000-$90,000	13
		$90,000-$130,000	13
		Over $130,000	18

given to all borrowers, for example, a base score of 450, which is commonly used in the individual credit rating market [2] [8], we come up with the final credit score for an individual.

$$Credit\ Score = Base\ Score + \sum_{j=1}^{n}\sum_{i=1}^{m} Score_{ij} \qquad (4)$$

From our sample of borrowers, credit scores span from a low of just over 360 to a high of around 840. Fig. 6 shows the histogram of score distribution of our sample. We then divided the scores into ranges from Bad to Exceptional Credit Quality so that the Average range has the highest frequency. As a result, about 21% of our sampled borrowers have an average credit score between 524 to 603, around 10% have a bad score of 523 or lower, while only about 3% of borrowers have an exceptional credit score of at least 764.

Building upon the Standard Credit Scoring model, we propose two models to evaluate the individual energy using Behaviors, the Green Credit Score model (Fig. 3) and the Energy Efficiency Score model (Fig. 4). For both models, our assumed perspective is that, when individuals consume an amount of energy such as electricity or gas, which has a monetary value during the month, it is viewed as they are borrowing that amount of money from the utility company for personal use. When they pay off the utility bill at the end of the month, they are paying off that borrowing. The energy consumption activity can thus be considered a credit activity, and energy-using behaviors, including how the borrowers use the credit, in this case energy, and also their credit payment, in this case how they pay off their utility bills, can be viewed as credit behaviors. Energy users can therefore be classified as good and bad borrowers (of energy) based on their energy behaviors. In our models, we defined good and bad energy borrowers according to their payment patterns of monthly utility bills over a period. Those who pay off their utility bills in time and in full are considered good borrowers, while those who make late or partial payments are bad borrowers of energy.

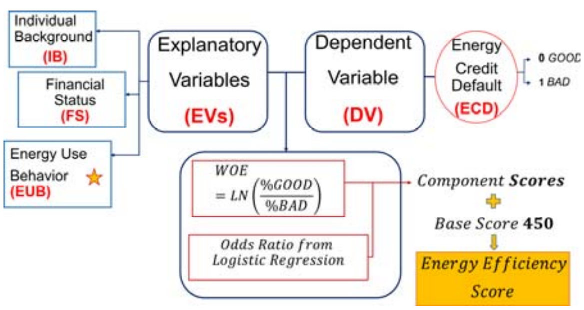

Fig. 4. Energy Efficiency Score model

The main purpose of our models is to promote more efficient behaviors of energy use by individuals, therefore we need certain variables to track and evaluate how efficiently the person is using energy on a daily basis. We conducted a preliminary analysis focusing on electricity use upon a sample of university faculty and students and professionals of a multinational audit company based in Chicago; from that we introduced three variables to measure daily energy use patterns, in this case electricity. These include ACOVERUSE which demonstrates the time of overusing the AC system at home compared to the time of actual demand, LGTOFF as a binary variable to show the habit of leaving the light on when leaving the workplace or home which is also a strong signal of electricity use inefficiency, and OVERCHRG which shows the pattern of overcharging personal electrical devices, such as keeping charging after the battery is full, or the habit of charging electrical devices overnight. We also introduced variables to track the utility bill payment pattern, for example PMTMTD, which refers to the payment methods, such as cash, check, or bank account, and PMTLAG, which shows how soon an individual pays off the monthly electricity bills.

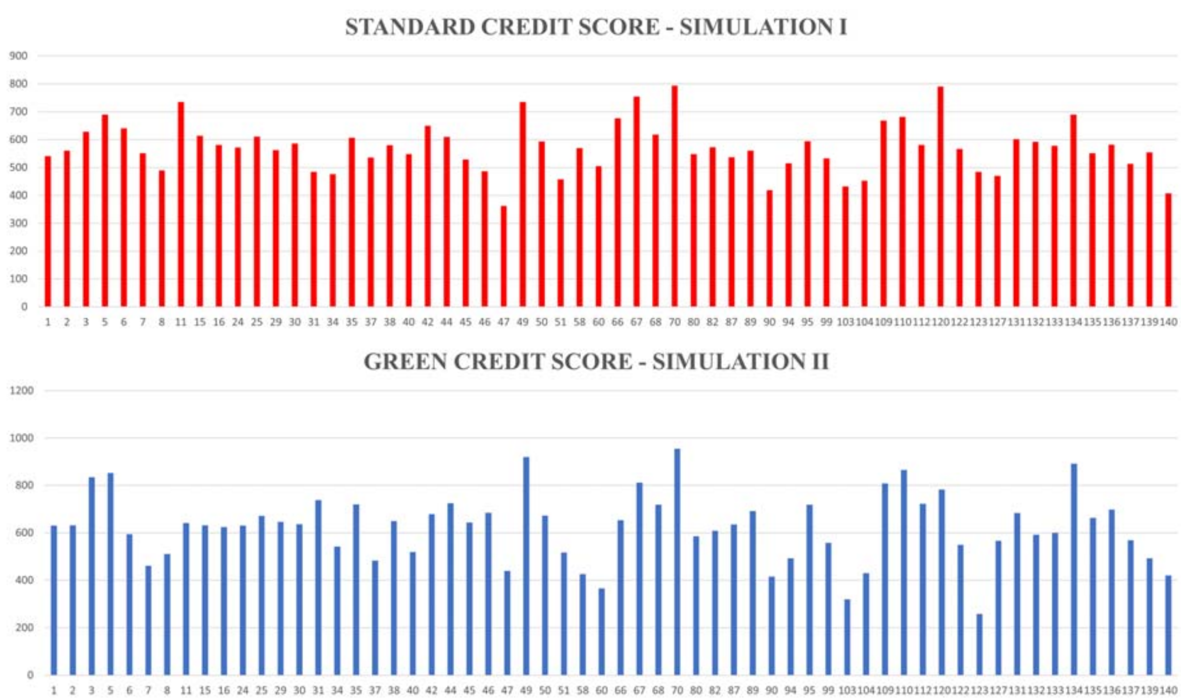

Fig. 5. Simulated Standard Credit Score and proposed Green Credit Score

Fig. 6. Score range distribution of Standard Credit Score and proposed Green Credit Score

We classified these variables as Energy Use Behavior variables and they are used in both of our proposed models, though in different ways.

In the Green Credit Score model, we update the Credit Behavior variable group by adding in the Energy Use Behavior variables. Due to our perspective that the activity of consuming and financing electricity can be considered a credit activity with electricity being a credit product, the quality of electricity use behaviors might also help predict how well in general an individual manages his/her credit situation. For example, if a person frequently makes late payments on monthly utility bills, it could be an indicator that the person might also make late payments on credit card bills. Or, if a person has a habit of constantly overusing electricity at home, it would very likely put more burden on his/her financial budget and might impact the capability of paying off credit debts. As shown in Fig. 3, the new focus of analysis is now on the updated Credit Behavior variable group, which contains variables showing individual's energy use behaviors.

We employed the same method of the Standard Credit Scoring model [8] to calculate the new Green Credit Score on the same sample of borrowers. Our characteristic variables include those of general demographic and financial backgrounds, and those containing information about credit behaviors, including the behaviors of using and paying for electricity, as in Fig. 3. We calculated WOE for each range of each characteristic variable using (1) and used IV of the variables from (2) for screening and kept only those with IV of at least 0.02 to include into a logit regression upon the Credit Default dependent variable [2] [8]. The final result is the new Green Credit Score, which according to our model is an updated version of the Standard Credit Score that also shows the quality of electricity use behaviors and how those behaviors can financially impact an individual's credit situation. The score distribution is from about 250 to just over 1000 and is also categorized into ranges of credit quality from Bad to Exceptional, as in Fig. 5 and Fig. 6. The influences of energy use behaviors on credit rating, i.e., the difference between Standard Credit Score and Green Credit Score is demonstrated in Fig. 7. For some individuals, their Green Credit Score is lower than their normal Credit Score due to their inefficient use of electricity, while in other cases, some borrowers are rewarded with a higher Green Credit Score than their Standard Credit Score as a result of having good electricity use habits.

In the Energy Efficiency Score model, we focus more heavily on the use of energy, in this case electricity, as a "credit product", without considering other conventional credit activities. We therefore eliminated from the model all variables of credit behaviors that are not directly related to electricity use, such as variables tracking the use and payment of conventional credit cards to purchase other products and

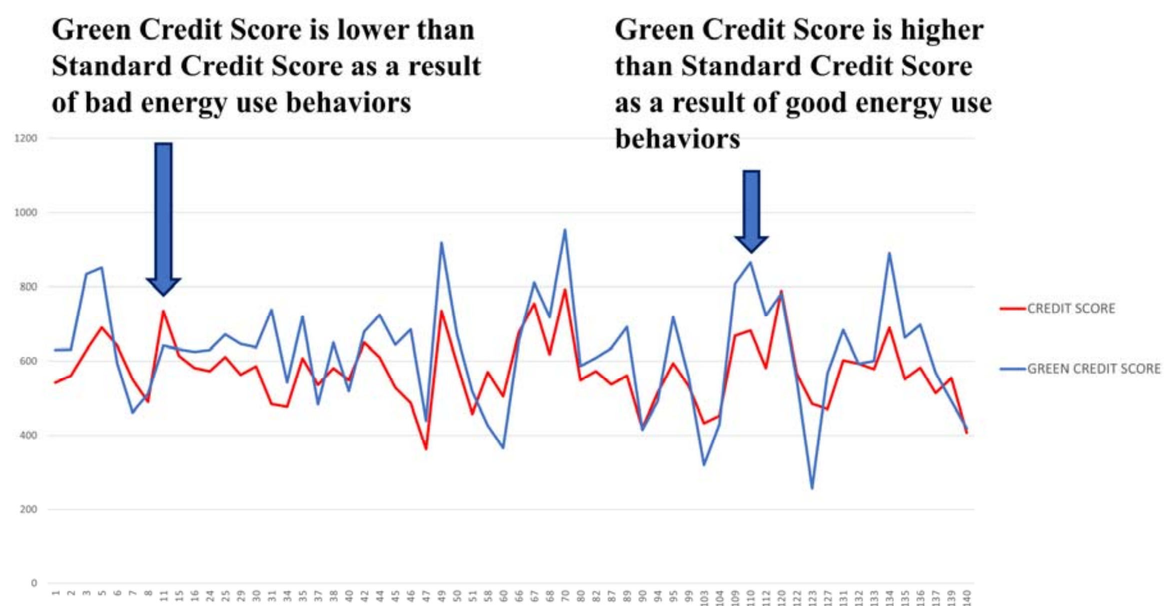

Fig. 7. Difference between Standard Credit Score and proposed Green Credit Score due to energy use behaviors

services. We replaced them with variables of the group Energy Use Behavior that we introduced before, along with variables of Individual Background and Financial Status that we kept from the standard model, as in Fig. 4. Since we no longer dealt with conventional credit activities, we also had to replace the dependent variable Credit Default in the logit regression with another. We used Energy Credit Default, which is also a binary variable, to demonstrate the event that a user of electricity, as a credit product, does not meet the payment obligation. In that case the variable takes on a value of 1. Employing the same method for calculating Standard Credit Score and Green Credit Score following [2] [8], we got a scorecard that can be used to specifically score an individual's energy credit worthiness, as partially shown as an example in Table II. Combining all the component scores received from the scorecard, the individual will get an Energy Efficiency Score, which is a credit score to specifically evaluate his/her behaviors of using electricity as a credit product.

TABLE II. EXAMPLE OF ENERGY EFFICIENCY SCORECARD

Variable	Description	Range	Score
ACOVERUSE	The percentage of time turning on AC at home over time of actual demand, i.e., staying at home	0%-50%	62
		50%-70%	20
		70%-90%	20
		90%-100%	41
		100%-120%	-20
		Over 120%	-20
LGTOFFTM	The average amount of time leaving before turning off light at the venue (minutes)	0	44
		0-5	23
		5-10	22
		10-20	-8
		Over 20	-32

IV. SUMMARY AND CONCLUSION

The proposed systemic socio-techno-economic model was designed on the basis of a charge and reward mechanism aimed at lowering the societal carbon footprint while providing ecological, social, and economic benefits. The proposed model is expected to promote significant CO_2 reduction, for example, 17,350,055.42 MT of CO_2 can be reduced per month for a scenario in which 189 million adults who have at least one credit card will also use their ECard to pay for the cost of electricity. Traditionally, energy saving programs promote the benefit of efficient energy use to households as reduced utility bills, which is vague and not attractive enough. Creating a credit line for energy use as a reward system, however, could reduce users' carbon footprints while building financial incentives for both the end users and utility companies, making it much more effective to promote the optimization of energy use by individuals. The reward system operates similarly to that of a banking credit card system, in which users are rewarded for maintaining and developing good behaviors. Implementation may require development of energy policies and social awareness campaigns. The barriers could be associated with government/political systems' commitment to climate change programs, social attentiveness, financial regulatory system rules/guidelines, energy (utility) industry willingness to participate, privacy issues, meeting credit bureau (TransUnion, Equifax, Experian) guidelines, and techno-economic factors.

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