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FORECASTING TRANSPORT ENERGY DEMAND IN IRAN USING META-HEURISTIC ALGORITHMS

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ABSTRACT

This paper presents application of an improved Harmony Search (HS) technique and Charged System Search algorithm (CSS) to estimate transport energy demand in Iran, based on socio-economic indicators. The models are developed in two forms (exponential and linear) and applied to forecast transport energy demand in Iran. These models are developed to estimate the future energy demands based on population, gross domestic product (GDP), and the data of numbers of vehicles (VEH). Transport energy consumption in Iran is considered from 1968 to 2009 as the case of this study. The available data is partly used for finding the optimal, or near optimal values of the weighting parameters (1968-2003) and partly for testing the models (2004-2009). Finally transport energy demand in Iran is forecasted up to the year 2020.

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KEY WORDS: transport energy; forecasting; optimization; charged system search; harmony search

1. INTRODUCTION

Growth in economic activity and population are the key factors for determining the

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transportation sector energy demand. With respect to energy planning, the transport sector is crucial because, in most regions, it is either the largest and/or most rapidly growing consumer of liquid fuels [1]. Energy demand in Iran has increased significantly during recent years due to rapid developments in different sectors such as industrial, agricultural, transportation, commercial, and residential. Among these sectors, the energy demand forecast of the transportation sector, referred to as the transport energy demand forecast, has been the focus of some papers. Fast growth on the GDP (Gross Domestic Product) per capital has led to an increase in the number of vehicle owners and hence increasing the energy demand in this sector [2].

Modeling energy consumption in the transport sector is dependent on many factors such as vehicular usage, type of car, income, housing size, vehicule type, and many other socio-economic parameters. Including all these parameters in a sectoral energy, makes the modeling a difficult task since it requires a great deal of detailed study and also much data, for which many of the data are unavailable. Therefore, it would be better to model transport energy consumption with simple forms of mathematical expressions using the available data [3]. Modeling energy demand was often performed through time series models, regression models, ARIMA models, econometric models, fuzzy logic models, ANN models, and optimization models [4].

Starting from the 1980s, a number of successful meta-heuristic optimization algorithms have been developed to solve the optimization problems. Among them the most well known are genetic algorithms (GAs), particle swarm optimization (PSO), ant colony optimization (ACO), harmony search (HS) algorithm, imperialist competitive algorithm (ICA) and charged system search (CSS). These algorithms impose fewer mathematical requirements and they do not require very precisely defined mathematical models. Meta-heuristic algorithms also provide efficacious solutions to the high-scale combinatorial and non-linear problems. Due to these advantages, application of meta-heuristics falls into a large number of areas; one of them is energy models for demand forecasting. Haldenbilen and Ceylan [5] have used GA to estimate the transport energy demand. In 2008 Ceylan and *et al*. [3] determined transport energy in Turkey using HS considering population, GDP and vehicle kilometers as input. Also the energy demand in Turkey is determined using ACO by Toksari [6] with independent variables such as GDP, population, and import and export amounts. PSO based energy demand forecasting (PSOEDF) is used to forecast the energy demand by El-Telbany and El-Karmi [7] in 2008. They have used PSO for short term forecasting of Jordon’s electricity demand.

The objective of this study is to develop a transport energy model which is able to predict Iran’s transport energy demand using the improved harmony search technique and charged system search algorithm. Various independent variables are selected. Then, future transport energy demand in Iran is forecasted based on the models.

The HS algorithm was originally proposed by Geem *et al*. [8] for solving combinatorial optimization problems. The method was conceptualized using the musical process of searching for a perfect state of harmony. Musical performances seek to find pleasing harmony as determined by an aesthetic standard, just as the optimization process seeks to find a global solution as determined by objective function [9]. On the other hand CSS is a new meta-heuristic optimization algorithm inspired by the governing laws of electrical physics and the Newtonian mechanics. In electrical physics, the electric charge can generate the electric field and exerts a force on other electrically charged objects. The electric field surrounding a point charge is specified by the laws of Coulomb and Gauss. Utilizing these principles, the CSS algorithm defines a number of solution candidates each of which is called charged particle (CP) and is treated as a charged sphere. Each CP can exert an electrical force on the other agents (CPs). These forces can change the position of other CPs according to the Newton's second law. Finally, considering the Newtonian mechanics, the new positions of CPs are determined [10, 11].

In this article the HS and CSS-based models are presented in the form of linear and exponential mathematical expressions. These models take population, GDP and vehicle ownerships as an input to estimate transport energy demand to forecast sectorial consumption. The results reveal the efficiency of CSS algorithm to estimate transport energy demand. The rest of this paper is organized as follows. Section 2 deals with the HS, CSS, and problem formulation. Section 3 is on solution methods for the proposed energy models and finally conclusions are drawn in Section 4.

2. DETERMINING TRANSPORT ENERGY DEMAND: AN OPTIMIZATION APPROACH

2.1. Constraint conditions for truss structures

When musicians improvise a harmony, they usually try various possible combinations of the music pitches stored in their memory. This kind of effective search for a perfect harmony is analogous to the procedure of finding an optimal solution in engineering problems. The HS method is inspired by the working principles of the harmony improvisation. Similar to the genetic algorithm and particle swarm algorithms, the HS method is a random search technique. It does not require any prior domain knowledge, such as gradient information of the objective function. However, different from those population-based approaches, it only utilizes a single search memory to evolve. Therefore, the HS method has the distinguished feature of algorithm simplicity [12]. There are four principal steps in this algorithm [9]:

Step 1. Initialize a harmony memory (HM). The initial HM consists of a certain number of randomly generated solutions for the optimization problem under consideration. For an n dimension problem, an HM with the size of HMS can be represented as follows

$$\mathrm{HM}=\begin{bmatrix} x_1^1 & x_2^1 & \dots & x_n^1 \\ x_1^2 & x_2^2 & \dots & x_n^2 \\ \dots & \dots & \dots & \dots \\ x_1^{HMS} & x_2^{HMS} & \dots & x_n^{HMS} \end{bmatrix} \tag{1}$$

where $(x^i_1,x^i_2,..,x^i_n)$, $(i=1,2,..,\mathrm{HMS})$ is a candidate solution. HMS is typically set to be between 10 and 100.

Step 2. Improvise a new solution ($x'_1, x'_2, .., x'_n$) from the HM. Each component of this solution, x'_j, is obtained based on the harmony memory considering rate (HMCR). The HMCR is defined as the probability of selecting a component from the *HM* members, and *1-HMCR* is, therefore, the probability of generating it randomly. If x'_j comes from the *HM*, it can be further mutated according to the pitching adjust rate (*PAR*). The *PAR* determines the probability of a candidate from the *HM* to be mutated.

Step 3. Update the *HM*. First, the new solution from Step 2 is evaluated. If it yields a better fitness than that of the worst member in the *HM*, it will replace that one. Otherwise, it is eliminated.

Step 4. Repeat Step 2 to Step 3 until a termination criterion (e.g., maximal number of iterations) is met.

The usage of harmony memory (*HM*) is important because it ensures that good harmonies are considered as elements of new solution vectors. In order to use this memory effectively, the HS algorithm adopts a parameter $HMCR \in [0,1]$, called harmony memory considering (or accepting) rate. If this rate is too low, only few elite harmonies are selected and it may converge too slowly. If this rate is extremely high, near 1, the pitches in the harmony memory are mostly used, and other ones are not explored well, leading not into good solutions. Therefore, typically, we use $HMCR$=0.7 ~ 0.95 [10]. Note that a low *PAR* with a narrow bandwidth (*bw*) can slow down the convergence of HS because of the limitation in the exploration of only a small subspace of the whole search space. On the other hand, a very high *PAR* with a wide bandwidth may cause the solution to scatter around some potential optima as in a random search. Furthermore large *PAR* values with small *bw* values usually cause the improvement of best solutions in final generations which algorithm converged to optimal solution vector. Some works have been performed in order to improve the convergence of the HS. Mahdavi *et al*. [13] proposed a new variant of the HS, called the improved harmony search. This algorithm dynamically updates *PAR* and *bw* according to Eqs. (2) and (3):

$$PAR(t) = PAR_{\min} - \frac{PAR_{\max} - PAR_{\min}}{Itr} \times t \tag{2}$$

$$bw(t) = bw_{\max} \exp\left(\frac{\ln\left(\dfrac{bw_{\min}}{bw_{\max}}\right)}{Itr} \times t \right) \tag{3}$$

where $PAR(t)$ is the pitch adjusting rate for iteration t, PAR_{min} is the minimum adjusting rate, PAR_{max} is the maximum adjusting rate, and *Itr* is the number of iteration. In addition, $bw(t)$ is the bandwidth for iteration t, bw_{min} is the minimum bandwidth and bw_{max} is the maximum bandwidth.

3.1. Charged system search algorithm

The CSS is a novel meta-heuristic based on the Coulomb and Gauss laws from electrical physics and the governing laws of motion from the Newtonian mechanics. This algorithm can be considered as a multi-agent approach, where each agent is a Charged Particle (CP). Each CP is considered as a charged sphere with radius a, having a uniform volume charge density and is equal to

$$f_{penalty}(x)=(1+\varepsilon_1.v)^{\varepsilon_2}\times w(\{x\}) \qquad v=\sum_{i=1}^{n}\max(0,g_{i,\max}) \tag{4}$$

$$q_i=\frac{fit(i)-fitworst}{fitbest-fitworst} \qquad i=1,2,...,N \tag{5}$$

where *fitbest* and *fitworst* are the best and the worst fitness of all the particles; *fit*(*i*) represents the fitness of the agent i, and N is the total number of CPs.

CPs can impose electric forces on the others, and its magnitude for the CP located in the inside of the sphere is proportional to the separation distance between the CPs, and for a CP located outside the sphere is inversely proportional to the square of the separation distance between the particles. The kind of the forces can be attractive or repelling and it is determined by using ar_{ij}, the kind of force parameter, defined as

$$ar_{ij}=\begin{cases}+1 & \text{w.p. } k_t\\ -1 & \text{w.p. } 1-k_t\end{cases} \tag{6}$$

where ar_{ij} determines the type of the force, where +1 represents the attractive force and −1 denotes the repelling force, and k_t is a parameter to control the effect of the kind of force. Therefore, the resultant force is redefined as

$$\mathbf{F}_j=q_j\sum_{i,i\neq j}\left(\frac{q_i}{a^3}r_{ij}\cdot i_1+\frac{q_i}{r_{ij}^2}\cdot i_2\right)ar_{ij}\,p_{ij}(\mathbf{X}_i-\mathbf{X}_j) \qquad \left\langle\begin{array}{l} j=1,2,...,N\\ i_1=1,i_2=0\Leftrightarrow r_{ij}<a\\ i_1=0,i_2=1\Leftrightarrow r_{ij}\geq a\end{array}\right. \tag{7}$$

where $\mathbf{F}_j$ is the resultant force acting on the jth CP; r_{ij} is the separation distance between two charged particles defined as

$$r_{ij}=\frac{\|\mathbf{X}_i-\mathbf{X}_j\|}{\|(\mathbf{X}_i+\mathbf{X}_j)/2-\mathbf{X}_{best}\|+\varepsilon} \tag{8}$$

where $\mathbf{X}_i$ and $\mathbf{X}_j$ are the positions of the *i*th and *j*th CPs, respectively; $\mathbf{X}_{best}$ is the position of the best current CP, and ε is a small positive number to avoid singularity. P_{ij} determines the probability of moving each CP toward the others as
Optimal design of frame structures is subjected to the following constrains according to LRFD-AISC [19] provisions:

$$\mathbf{X}_{j,new} = rand_{j1} \cdot k_a \cdot \frac{\mathbf{F}_j}{m_j} \cdot \Delta t^2 + rand_{j2} \cdot k_v \cdot \mathbf{V}_{j,old} \cdot \Delta t + \mathbf{X}_{j,old} \tag{9}$$

$$\mathbf{V}_{j,new} = \frac{\mathbf{X}_{j,new} - \mathbf{X}_{j,old}}{\Delta t} \tag{10}$$

where k_a is the acceleration coefficient; k_v is the velocity coefficient to control the influence of the previous velocity; and rand_{j1} and rand_{j2} are two random numbers uniformly distributed in the range (0,1). If each CP moves out of the search space, its position is corrected using the harmony search-based handling approach as described in [10]. In addition, to save the best design, a memory (Charged Memory) is utilized.

2.3. The proposed method

Predicting Iran's transport energy demand by using the structure of the Iran socio-economic conditions is the main objective of this paper. In order to fulfill this aim HS and CSS demand estimation models are developed to estimate the future transport energy demand values based on the figures of population, GDP, number of vehicles [14]. The objective function to be minimized is the sum of the squared residuals (F_{SSQ}) between the actual and predicted demand:

$$\min F_{SSQ} = \sum_{i=1}^{m} \left(TED_{act} - TED_{pre}\right)^2 \tag{11}$$

where TED_{act} and TED_{pre} are the actual and predicted energy demand; respectively, and m is the number of observations. Also the data related to the design parameters of Iran's population (POP), GDP, and numbers of vehicles (VEH) are shown in Table 1.

Forecasting of transport energy demand based on socio-economic indicators is modeled by using both linear and exponential forms of equations. The linear form of equations for the demand estimation is written as follows

$$Y_{\text{lin}} = w_1 X_1 + w_2 X_2 + w_3 X_3 + w_4 \tag{12}$$

The exponential form of equations for the demand estimation models is written as follows

$$Y_{\exp} = w_1 X_1^{w_2} + w_3 X_2^{w_4} + w_5 X_3^{w_6} + w_7 \tag{13}$$

Table 1. POP (×106), GDP (×109 Rials), VEH (×103), and TED (MBOE) for years 1968–2003

Years	POP	GDP	VEH	TED	Years	POP	GDP	VEH	TED
1968	27.04	99.00	20.278	13.9	1986	49.45	193.24	2584.726	78.7
1969	27.66	111.61	64.807	15.4	1987	50.93	191.31	2636.190	84.6
1970	28.31	122.59	118.757	17.7	1988	52.31	180.82	2672.395	83.4
1971	29.01	139.28	173.616	20.2	1989	53.60	191.50	2698.161	90.10
1972	29.76	162.56	245.107	22.3	1990	54.78	218.54	2760.234	96.20
1973	30.59	174.67	333.113	27.2	1991	55.85	245.04	2867.405	104.00
1974	31.51	196.58	476.198	31.3	1992	56.84	254.82	3010.511	110.70
1975	32.55	206.11	728.185	38.9	1993	57.77	258.60	3091.340	122.10
1976	33.71	242.33	996.238	47.0	1994	58.66	259.88	3162.697	144.60
1977	35.01	236.65	1306.176	57.2	1995	59.53	267.53	3253.854	141.90
1978	36.43	219.19	1529.441	57.5	1996	60.41	283.81	3379.396	147.90
1979	37.96	209.92	1631.406	58.5	1997	61.31	291.77	3555.776	153.20
1980	39.56	178.15	1732.485	54.0	1998	62.22	300.14	3760.960	161.20
1981	41.21	170.28	1858.478	53.6	1999	63.16	304.94	3975.413	170.30
1982	42.89	191.67	1979.818	58.6	2000	64.13	320.07	4341.927	183.40
1983	44.58	212.88	2197.524	72.5	2001	65.13	330.57	4741.493	194.20
1984	46.25	208.52	2411.405	78.0	2002	66.17	355.55	5300.463	208.90
1985	47.88	212.69	2526.353	82.8	2003	67.26	379.84	6084.973	220.80

where X_1, X_2 , and X_3 are the population, GDP, and number of vehicles; respectively. w_i (i=1,2,…) are the corresponding weighting factors. Here HS and CSS are applied in order to finding optimal values of weighting parameters based on actual data to estimate transport energy consumption in Iran. For aiming this purpose, following stages are done

Step 1: The proposed algorithms are applied in order to determine corresponding weighting factors (w_i) for each model according to the lowest objective functions. The related data from 1968 to 2003 are used in this stage.

Step 2: Best results (optimal values of weighting parameters) for each model are chosen according to step1. Model is validated using the available data partly for use in estimating the weighting factors and partly for the testing purposes.

Step 3: Demand estimation model are proposed using the optimal values of weighting parameters.

Step 4: In order to use optimization models for future projections, each input variable should be forecasted in future time. Following scenarios are defined for forecasting each socio-economic indicator in the future in Table 2.

Step 5: Finally, transport energy demand is forecasted up to year 2020.

Table 2. Scenarios for forecasting each socio-economic indicator

Scenario	*Population**	*GDP**	*Number of vehicles**
(a)	1.6%	4.5%	6.0%
(b)	1.4%	4.5%	6.5%
(c)	1.5%	5.0%	7.5%

* The annual average growth rates during 2009-2020.

3. RESULTS AND DISSCUTION

In order to test the performance of the proposed methods, a numerical example is given in this section. For the optimization process, solution parameters of the HS are set as HMS = 100, HMCR = 0.98 and PAR_{max} = 0.95, PAR_{min} = 0.35, bw_{min} = 10^{-5}, bw_{max} = 0.06 and number of maximum iterations = 80,000. For the CSS algorithm, a population of 600 CPs is used also CMS is set as 100. 2000 iterations are selected as the termination criterion in order to stop the searching process. All computations are performed by developing a MATLAB code.

Solutions of the HS and CSS models are

$$\begin{aligned} Y_{\text{lin-HS}} &= 0.4705X_1 + 0.5411X_2 + 0.3075X_3 + 0.2834 \\ Y_{\text{lin-CSS}} &= 0.4708X_1 + 0.5126X_2 + 0.3062X_3 + 0.2995 \end{aligned} \tag{14}$$

$$\begin{aligned} Y_{\text{exp-HS}} &= 0.7840X_1^{0.7558} + 0.7296X_2^{0.8588} + 0.0254X_3^{1.3717} + 0.4660 \\ Y_{\text{exp-CSS}} &= 0.7651X_1^{0.7220} + 0.4702X_2^{1.1374} + 0.1878X_3^{1.0283} + 0.4047 \end{aligned} \tag{15}$$

The comparison of HS and CSS outputs and their relative errors in the testing period are provided in Tables 3 and 4 for the period of 2004–2009. The relative errors are based on the observed values and the values obtained from HS and CSS techniques. For the best results of HS, the average relative errors on testing data are 3.325% and 3.405% for the HS linear and HS exponential while it is 3.312% and 3.408% for the CSS linear and CSS exponential, respectively. The linear form of the CSS resulted in lower relative errors when it is compared to other forms of the CSS and HS. Considering 10^6 evaluations, the CSS-based model found the best solution, while the HS-based method obtained the best result after 8×10^6 function evaluations. It means that, the CSS algorithm performed really fast, since the required number of analyses is the lowest. The validated TED together with the observed

TED are shown in Figures 1 and 2. The plot depict that the resulting TED, using the parameters estimated from CSS, closely follow the observed data. Also Comparison between presented models in the literature and presented models in this study is shown in Table 5. Compared to other standard meta-heuristic algorithms, numerical results indicate the efficiency of the CSS method.

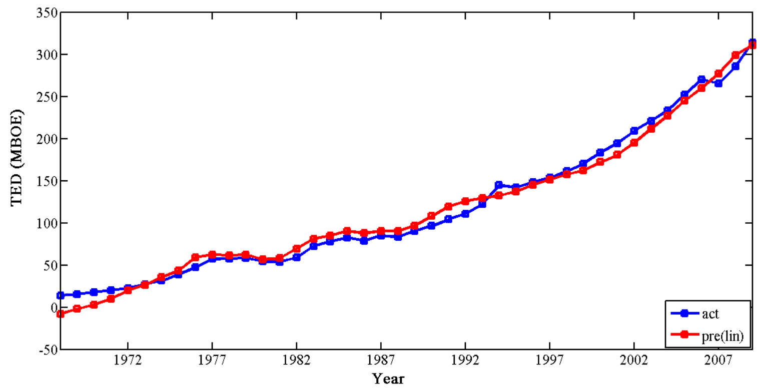

Fig. 1. Comparison of the actual and linear validated TED using the CSS during 1968-2009

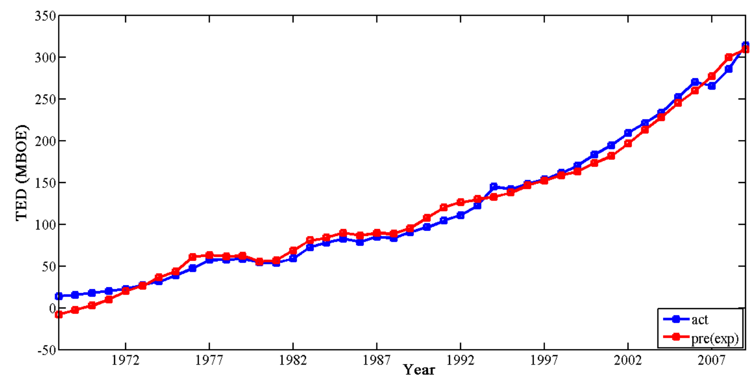

Fig. 2. Comparison of the actual and exponential validated TED using the CSS during 1968-2009

Table 3. Comparisons of the HS outputs and their relative errors for the period of 1996–2005

Years	Transport energy demand	TED $_{pre}$ (lin-HS)	Relative error (%)	TED $_{pre}$ (exp-HS)	Relative error (%)
2004	233.400	227.386	2.58	226.049	3.15
2005	252.300	244.560	3.07	243.661	3.42
2006	270.040	259.594	3.87	259.353	3.96
2007	265.170	276.925	-4.43	277.447	-4.63
2008	285.210	298.665	-4.72	300.082	-5.21
2009	313.900	309.922	1.28	313.715	0.06
Mean absolute error	-	-	3.325	-	3.405

Table 4. Comparisons of CSS outputs and their relative errors for period of 1996–2005

Years	Transport energy demand	TED $_{pre}$ (lin-HS)	Relative error (%)	TED $_{pre}$ (exp-HS)	Relative error (%)
2004	233.400	227.132	2.68	227.749	2.42
2005	252.300	244.528	3.08	244.589	3.06
2006	270.040	259.748	3.81	259.402	3.94
2007	265.170	277.158	−4.52	276.993	−4.46
2008	285.210	298.852	−4.78	299.712	−5.08
2009	313.900	310.751	1.00	309.212	1.49
Mean absolute error	-	-	3.312	-	3.408

Table 5. Comparison of different models presented in the literature and present study

Reference	Method	Target/Country	Average relative errors (%)
Canyurt and Ozturk [15]	Genetic Algorithm	Coal/Turkey	3.22
Amjadi *et al*. [16]	Particle Swarm Optimization	Electricity/Iran	3.92
Ceylan *et al*. [3]	Harmony Search	Transport energy/Turkey	13.41
Present study	Improved Harmony Search	Transport energy/Iran	3.32
Present study	Charged system search	Transport energy/Iran	3.31

The annual average of growth rate for oil consumption based on best model (CSS linear) between 2010 and 2020 for scenario (a), scenario (b) and scenario (c) were 4.73%, 5.01%, and 5.63%, respectively. The annual average of growth rate for transport energy consumption from 1968 to 2009 was 7.99%.

4. CONCLUSION

The improved HS algorithm and CSS method have been applied to various engineering fields. However, their application to transport energy demand modeling is quite new, proposed in this study. Here, the HS and CSS models are used as an alternative solution and estimation technique. The HS algorithm, similar to CSS, includes a memory storing the feasible vectors. A new harmony vector is generated from the harmony memory, the memory considerations, pitch adjustments, and randomization. In each iteration of HS only one solution vector is generated, while in CSS a number of CPs are created. The HS utilizes the stored vectors in HM to create new vectors directly, while CSS uses the stored vectors in determining the electrical forces. Only when a CP swerves from the search space, the charged memory is utilized directly. In special conditions, the CSS works as a HS method and uses some of operators of the HS algorithm as an auxiliary tool.

Here, the data for 37 years (1968-2003) is utilized for developing two forms (linear and exponential) of HS and CSS demand estimation models, and the results reveal that the linear forms of the CSS-based model is a better choice for energy modeling. Three scenarios are designed in order to estimate Iran's transport energy demand during 2010-2020. Validations of models show that CSS demand estimation models are in good agreement with the observed data. For the best results of CSS the average relative errors on testing data were 3.31%. The corresponding values in forecasting for scenarios (a), (b), and (c) were 4.73%, 5.01%, and 5.63%, respectively. Also it can be concluded that the proposed models are satisfactory tools for successful transport energy demand prediction. The presented results are instrumental to researchers, policy makers, and traffic engineers as a potential tool for developing energy plans.

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