Transport energy modeling with meta-heuristic harmony search algorithm, an application to Turkey

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ABSTRACT

This study proposes a new method for estimating transport energy demand using a harmony search (HS) approach. HAmony Search Transport Energy Demand Estimation (HASTEDE) models are developed taking population, gross domestic product and vehicle kilometers as an input. The HASTEDE models are in forms of linear, exponential and quadratic mathematical expressions and they are applied to Turkish Transportation sector energy consumption. Optimum or near-optimum values of the HS parameters are obtained with sensitivity analysis (SA). Performance of all models is compared with the Ministry of Energy and Natural Resources (MENR) projections. Results showed that HS algorithm may be used for energy modeling, but SA is required to obtain best values of the HS parameters. The quadratic form of HASTEDE will overestimate transport sector energy consumption by about 26% and linear and exponential forms underestimate by about 21% when they are compared with the MENR projections. This may happen due to the modeling procedure and selected parameters for models, but determining the upper and lower values of transportation sector energy consumption will provide a framework and flexibility for setting up energy policies.

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1. Introduction

The transport sector is one of the major consumers of primary energy production in the world. It consumes about one-fifth of the primary energy in the world (Asmann and Sieber, 2005) and is responsible for almost 60% of the oil consumption in Organization for Economic Co-operation and Development countries with an increasing consumption in the developing world according to the International Energy Agency (IEA, 2005). One of the main reasons for the increasing demand for energy use may be due to the rapid increase in population, mobility, businesses, globalization and transport 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. In many countries, the demand for transportation fuels tends to be rather unresponsive to changes in the price of crude oil because of the high level of consumer taxes (Wohlgemuth, 1997). When this high level of energy demand and price levels is considered, this sector takes one of the biggest shares in total energy consumption in many countries. Turkey may be a good example with 21% of the total energy consumption according to World Energy Council-Turkish National Committee (WEC-TNC, 2006).

Turkey expects a very large growth in energy demand in the future as its economy expands, especially for petrol in the transportation sector. Because of its limited energy resources, Turkey is greatly dependent on imported oil and gas, which is the most important diesel in Turkey, contributing 55% of Total Primary Energy Supply and importing 90% of its energy needs in 2004 (WEC-TNC, 2006). Passenger transport of Turkey increased by 2.5 times and goods transport increased by four times in the last two decades. The population increased by about 50% in the last two decades as well. Transportation demand increased more than gross domestic product (GDP) in Turkey when national economic parameters are compared to the transportation sector.

Modeling energy consumption in the transport sector is usually dependent on many factors such as vehicular usage, type of car, income, housing size, vehicular type and many other socio-economic parameters. Including all the parameters in sectoral energy modeling is a difficult task since it requires much 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 simplified forms of mathematical expressions using available data. In addition, it would be better to provide a framework for integrating knowledge of transportation sector energy use trends with analysis of sectoral energy growth in a developing country.
Much is known about energy modeling, but this is not so in transportation systems since it requires vehicular-related parameters. The transportation energy model would be capable of exploring alternative transportation systems in the developing worlds as a major priority for sustainable future. Any approach and method used to estimate the effects of policies and measures have to embody some assumptions regarding the way measures will affect sectoral trends on energy consumption and efficiency of the sector with technological development. Mathematical models are usually based on the assumption that methodology is chosen and formed according to the minimization of some objective values such as minimizing energy consumption values. Therefore, among the many meta-heuristic approaches, HArmony Search Transport Energy Demand Estimation (HASTEDE) models are proposed since it is considered as an effective and accurate mathematical approach in energy modeling studies. The HASTEDE models are in the form of linear, exponential and quadratic mathematical expressions that are solved with harmony notion. The HASTEDE models take population, GDP and vehicle ownerships as an input to estimate transport energy demand to forecast sectoral consumption until 2025 starting from 2006.

This paper has been organized in the following way. In the next section, some relevant literature review is given. Section 3 deals with the pHarmony search algorithm and problem formulation. Section 4 is on solution methods for the proposed energy modeling models. Sensitivity analyses (SAs) on harmony parameters are given in Section 5. Forecasting the future energy consumption in the transport sector is given in Section 6. Conclusions are drawn in Section 7.

2. Background and literature review

Energy studies were mainly carried out in the countries’ own Department for Energy. Studies on energy forecasting in Turkey are planned by Ministry of Energy and Natural Resources (MENR) and State Planning Organization within 5 years’ development planning periods. The MENR uses the Model for Analysis of Energy Demand model that requires very detailed and large number of data for the total and sectoral energy consumption (SEC) estimations. On the other hand, many models have been developed from many researches using various forms of mathematical formulations, which are directly or indirectly related to energy development models (Uri, 1980; Kavrakoglu, 1983; Yu and Been, 1984; Ebohan, 1996; Cheng and Lai, 1997; Ceylan and Ozturk, 2004; Canyurt and Ozturk, 2006; Say and Yucel, 2006).


Ulut and Hepbasli (2006) evaluated the energy and exergy utilization efficiencies in the Turkish transportation sector over the period from 2000 to 2020. In the study, energy and exergy analyses were performed for four transportation sub-modes and a comparison of Turkish transportation sector with the other countries was also presented. Similarly, Saidur et al. (2007) applied the useful energy and exergy analysis models for different modes of transport in Malaysia and compared the result with a few countries such as Turkey and their study. Results showed that the energy and exergy efficiencies of the Malaysian transportation sector are lower than that of Turkey.

Haldenbilen and Ceylan (2005) developed three forms of energy demand equations in order to forecast the transport energy consumption for future projections based on GA notion. They used population, GDP and Car Equivalent Approach as independent variables. Energy savings were also obtained under various scenarios. Similarly, Canyurt et al. (2006) developed GA approaches for the transport energy demand estimation using the socio-economic indicators, car, bus and track sales. Murat and Ceylan (2006) obtained that modeling the energy consumption may be carried out with ANNs with a lack of future estimation because ANN is good at solving current data, but is not good for forecasting.

It would be better to obtain vehicular ownership figures and their annual usage as a veh-km as well as socio-economic indicators since it shows the increase on vehicle ownerships on any country in order to estimate the transport energy demand. For example, Fig. 1 shows the rapid increase of motorization in Turkey between 1966 and 2004. Within this period, the fleet of cars, trucks and buses increased by about 40% according to General Directorate of Turkish Highways (GDTH, 2004). Energy consumption in the same period increased by about four times in this sector.

In 1970, energy consumption in the transport sector was 3208 Ton Oil Equivalent (TOE) and increased to a level of 13775 TOE in 2006. This shows the rapid increase of transport energy demand. For example, Fig. 1 shows the rapid increase of motorization in Turkey between 1966 and 2004. Within this period, the fleet of cars, trucks and buses increased by about 40% according to General Directorate of Turkish Highways (GDTH, 2004). Energy consumption in the same period increased by about four times in this sector.

At the same time, GDP, one of the main indicators for increasing vehicle ownership, can be seen in Fig. 2. It increased...
by about nine times and the demand for transport energy increased about four times for the period of 1970–2002.

During the last decades, several solution approaches have been proposed to obtain useful transport energy demand estimation models. Recently, meta-heuristic optimization algorithms have been used to solve these problems. Since the gradient-based optimization methods need derivative information of the mathematical equations and a good starting point for decision variables, their applications may be both difficult and unworkable. There are several studies in the literature that are based on the solution of these meta-heuristic algorithms. But, usually, these algorithms impose complex mathematical requirements, and their adaptation into real-world applications may require high computation times for most engineering optimization problems.

Recently, the meta-heuristic Harmony Search (HS) optimization algorithm, which is conceptualized using the musical process of searching for the perfect state of harmony, was developed by Geem et al. (2001). In the HS algorithm, musical performances seek a perfect state of harmony determined by aesthetic estimation, as the optimization algorithms seek a best state (i.e. global optimum) determined by objective function value. The HS algorithm has been recently applied to various engineering optimization problems including traveling salesman problem (Geem et al., 2001), optimization of the river flood model (Kim et al., 2001), optimum design of water distribution network (Geem, 2006), optimum design of truss structures (Lee and Geem, 2004), and the simultaneous determination of aquifer parameters and zone structures by an inverse solution algorithm (Ayvaz, 2007).

3. Harmony search algorithm and model development

The HS algorithm proposed by Geem et al. (2001) is a meta-heuristic optimization algorithm and is based on the musical process of searching for a perfect state of harmony, such as jazz improvisation. In this improvisation process, members of the musical group try to find the best harmony as determined by an aesthetic standard, just as the optimization algorithm tries to find the global optimum as determined by the objective function. The notes and the pitches getting played by the individual instruments determine the aesthetic quality, just as the objective function value is determined by the values assigned to design variables. The harmony quality is enhanced with practice, just as the solution quality is enhanced with iteration (Geem, 2006).

The procedure of HS is composed of five parts as follows:

Step 1: Initialization of the problem and algorithm parameters

The optimization problem is

$$\min Z = f(x) \quad \text{subject to} \quad x_i \in X_i, \ i = 1, 2, \ldots, N$$

where \(f(x)\) is the objective function to be minimized, \(x\) is the set (so called orchestra) of decision variables \(x_i\); \(N\) is the number of decision variables (music instruments); and \(X_i\) is the set of the possible range of values for each decision variable (the pitch range of each instrument).

Four algorithm parameters are used to control the solution procedure of the HS; Harmony Memory Size (HMS) that represents the number of solution vectors in the harmony memory (HM); Harmony Memory Considering Rate (HMCR) that is the probability of assigning the values to the variables from HM; Pitch Adjusting Rate (PAR); and the number of improvizations (NI) that represents the number of iterations to be used during the solution process. NI also can be assumed as the termination criterion.

Step 2: Initialization of the harmony memory

The HM is a memory location where all the solution vectors and corresponding objective function values are stored. The function values are used to evaluate the quality of solution vectors. The HS algorithm also considers several solution vectors simultaneously, in a manner similar to the GAs. However, the major difference between the GA and the HS algorithm is that the latter generates a new vector from all the existing vectors, whereas the former generates a new vector from only two of the existing vectors. In addition, iterations in the HS algorithm are faster than that in GA (Lee et al., 2005).

In this step, the HM matrix is filled with as many randomly generated solution vectors as the HMS and their corresponding fitness function values are shown below

$$HM = \begin{bmatrix}
    x_1^1 & x_2^1 & \ldots & x_{HMS-1}^1 & x_N^1 \\
    x_2^1 & x_2^2 & \ldots & x_{HMS-1}^2 & x_N^2 \\
    \vdots & \vdots & \ddots & \vdots & \vdots \\
    x_1^{HMS-1} & x_2^{HMS-1} & \ldots & x_{HMS-1}^{HMS-1} & x_N^{HMS-1}
\end{bmatrix}$$

$$\Rightarrow \begin{bmatrix}
    f(x^1) \\
    f(x^2) \\
    \vdots \\
    f(x^{HMS-1})
\end{bmatrix}$$

Step 3: Improvisation of a new harmony

In the improvisation step, a New Harmony vector \(x' = (x_1', x_2', \ldots, x_N')\) is generated based on three rules. These rules are memory consideration, pitch adjustment and random selection, respectively. In memory consideration, the value of the first decision variable \(x_1'\) for the new vector is selected from any value in the specified HM range \([x_1^1, x_1^N]\). Values of the other decision variables \((x_2', \ldots, x_N')\) are selected in the same manner. The HMCR parameter varies between 0 and 1 and represents the rate of choosing one value from HM whereas \((1-HMCR)\) is the rate of randomly selecting a value from the possible range. Each decision variable is selected with the procedure that is given in (3).

$$x_i' \leftarrow \begin{cases} 
    x_i' \in [x_i^1, x_i^2, \ldots, x_i^{HMS}] & \text{with probability HMCR} \\
    x_i' \in X_i & \text{with probability } (1 - \text{HMCR})
\end{cases} \quad (3)$$

The next step under the improvisation process is to check whether the pitch adjustment is necessary or not. After the memory consideration, pitch adjustment probability is evaluated with parameter of PAR, which represents the pitch adjusting and...
varies between 0 and 1 as follows:

\[ x'_i = \begin{cases} 
  x'_i + \text{Rnd}(0; 1) \times \text{bw} & \text{with probability } \text{PAR} \\
  x'_i & \text{with probability } (1 - \text{PAR}) 
\end{cases} \]  

where bw is an arbitrary bandwidth and Rnd(0;1) is a random number between a value range of 0–1. The pitch adjusting process is performed only after a value has been chosen from the HM. The value \((1 - \text{PAR})\) sets the rate of doing nothing. Note that the HMCR and PAR parameters introduced in the HS help the algorithm to find globally and locally improved solutions, respectively (Lee and Geem, 2005). Lee et al. (2005) has recommended that parameter values ranged between 0.7 and 0.95 for HMCR, 0.2 and 0.5 for PAR, and 10 and 50 for HMS to produce good performance of the HS algorithm.

A flowchart for the harmony improvization strategy is given in Fig. 3.

**Step 4: Update the HM**

All of the objective function values in HM are set in order from the best to the worst and a New Harmony vector is compared with the vector giving the worst objective function value in this step. If the New Harmony vector gives a better function value than the worst one, the New Harmony vector is included to the HM and the worst harmony is excluded from the HM.

**Step 5: Check the termination criterion**

Steps 3 and 4 are repeated until the termination criterion (NI) is satisfied.

4. The HASTEDE Models

Forms of HASTEDE models are as follows:

\[ f(x)_{\text{linear}} = w_1x_1 + w_2x_2 + w_3x_3 + w_4 \]  
\[ f(x)_{\text{exp}} = w_1x_1^{w_2} + w_3x_2^{w_4} + w_5x_3^{w_6} + w_7 \]  
\[ f(x)_{\text{quad}} = w_1x_1 + w_2x_2 + w_3x_3 + w_4x_1x_2 + w_5x_1x_3 + w_6x_2x_3 + w_7 \]  

where \( f(x)_{\text{linear}}, f(x)_{\text{exp}} \) and \( f(x)_{\text{quad}} \) are, respectively, linear, exponential and quadratic forms of the HASTEDE models, and \( x_1, x_2 \) and \( x_3 \) are the GDP (10^9$), population (10^6) and total annual veh-km (10^9), respectively, \( w_i \) are the corresponding weighting factors and \( N \) is the number of decision variables that changes from one model to another. The optimization function, \( Z \), to be minimized is

\[ \text{Min} Z = \sum_{i=1}^{m} (TED_{\text{actual}} - TED_{\text{predicted}})^2 \]  

---

**Fig. 3.** A harmony improvization flowchart for continuous variables (Lee and Geem, 2005).
where TED\textsubscript{actual} and TED\textsubscript{predicted} are the actual and predicted transport energy demand, \( m \) is the number of observations.

### 4.1. Data for HASTEDE

The GDP and the SEC are collected from the Central Bank of Turkey (2007) and the WEC-TNC (2006). Observed veh-km is taken from the GDTH (2005). The observed general trend of energy demand, GDP, population and veh-km between 1970 and 2005 can be seen in Fig. 4. During the HASTEDE modeling process, each form of the model is validated using the available data partly for use in estimating the weighting factors and partly for the testing purposes. The first 26 years observed data from 1970 to 1995 are used for estimating the weighting factors and the 10 years data from 1996 to 2005 are used for testing. The testing procedure is carried out to obtain the minimum relative errors between the observed and estimated values in the period of 1996–2005.

### 4.2. Numerical example

In order to test the performance of the proposed solution algorithm, a numerical example is given in this section. For the optimization process, solution parameters of the HS algorithm are set as: HMS = 20, HMCR = 0.90 and PAR = 0.40. NI = 100.000 is set as the termination criterion in order to stop the searching process. All computations are performed by developing a Visual Basic code scheme PC.

![General trend of SEC and related parameters](image)

**Fig. 4.** General trend of SEC and related parameters.

### 5. Sensitivity analysis

Choosing the solution parameters for the HS algorithm (i.e. HM, HMCR and PAR) is a very important step for the algorithm to find global or near-global optimum results. Therefore, an SA is performed for different values of the HS parameters in order to see how the accuracy changes during the solution process. The six different cases chosen for the SA for different solution parameter sets are shown in Table 2. During the SA stage, the maximum number of iterations (NI) is set as 100,000. The convergence graphs for six cases are given in Figs. 5–7 for the \( f(x)_{\text{linear}} \), \( f(x)_{\text{exp}} \) and \( f(x)_{\text{quad}} \) models, respectively. Results and best fit values for each case are given in Table 3.

<table>
<thead>
<tr>
<th>Years</th>
<th>Transport energy demand (observed) (MTOE)</th>
<th>( f(x)_{\text{linear}} ) (MTOE)</th>
<th>Relative error (%)</th>
<th>( f(x)_{\text{exp}} ) (MTOE)</th>
<th>Relative error (%)</th>
<th>( f(x)_{\text{quad}} ) (MTOE)</th>
<th>Relative error (%)</th>
<th>MENR (MTOE)</th>
<th>Relative error (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1996</td>
<td>11.78</td>
<td>11.47</td>
<td>2.58</td>
<td>11.59</td>
<td>1.58</td>
<td>11.76</td>
<td>0.17</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>2000</td>
<td>12.12</td>
<td>14.50</td>
<td>–19.65</td>
<td>15.07</td>
<td>–24.38</td>
<td>17.00</td>
<td>–40.33</td>
<td>17.61</td>
<td>–32.15</td>
</tr>
</tbody>
</table>

Mean absolute error = 12.13

\[
\text{Relative error} = \frac{\text{absolute error}}{\text{observed value}}
\]

\[
f(x)_{\text{linear}} = 0.0077X_1 - 0.0351X_2 + 0.2473X_3 + 2.999
\]

\[
Z = 6.46, \quad R^2 = 0.94
\]
As can be seen from Table 3, the best values among the cases are Case 1 after 100,000 function evaluations. Note that the worst $Z$ values are obtained in Case 5. Thus, values of case 1 are considered to be the optimum or near-optimum solutions for the HASTEDE models and selected for future transport energy consumption estimation.

6. Forecasting transport energy demand

6.1. Estimation of HASTEDE parameters

In order to make the future projections for the transport energy consumption by way of the three forms of the GATEDE model, the GDP, population and the total annual average veh-km needs to be estimated first for each year. Then the future demand can be obtained with respect to these three parameters. The estimation of the GDP, the population and total annual veh-km is obtained in the following way.

<table>
<thead>
<tr>
<th>Cases</th>
<th>HM</th>
<th>HMCR</th>
<th>PAR</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>10</td>
<td>0.80</td>
<td>0.40</td>
</tr>
<tr>
<td>2</td>
<td>10</td>
<td>0.90</td>
<td>0.45</td>
</tr>
<tr>
<td>3</td>
<td>20</td>
<td>0.80</td>
<td>0.45</td>
</tr>
<tr>
<td>4</td>
<td>20</td>
<td>0.90</td>
<td>0.40</td>
</tr>
<tr>
<td>5</td>
<td>30</td>
<td>0.80</td>
<td>0.40</td>
</tr>
<tr>
<td>6</td>
<td>30</td>
<td>0.90</td>
<td>0.45</td>
</tr>
</tbody>
</table>

Table 2
Six cases and their related parameters used in the sensitivity analysis

Fig. 5. Convergence history of the HS solution for the $f(x)_{\text{linear}}$ model.

Fig. 6. Convergence history of the HS solution for the $f(x)_{\text{exp}}$ model.
For the annual GDP, 
\[ y = 0.1418x^2 + 1.6654x + 25.045 \quad R^2 = 0.817 \]  \hspace{1cm} (12)
where \( y \) is the GDP in \( 10^9 \)$/year, and \( x \) is the time series (1970 = 1, 1981 = 2...2005 = 36).

For the population, 
\[ y = 1.0975x + 33.18 \quad R^2 = 0.9983 \]  \hspace{1cm} (13)
where \( y \) is the population in \( 10^6 \)/year, and \( x \) is the time series (1970 = 1, 1981 = 2...2005 = 36).

For the total annual veh-km, 
\[ y = 0.0219x^2 + 0.5239x + 6.5904 \quad R^2 = 0.9811 \]  \hspace{1cm} (14)
where \( y \) is the total annual veh-km in \( 10^9 \)/year, and \( x \) is the time series (1970 = 1, 1981 = 2...2005 = 36).

The annual changes of HASTEDE model parameters and their expected corresponding values can be seen in Figs. 8–10, respectively.

### 6.2. Forecasting with the HASTEDE models

Future estimation of the three forms of the HASTEDE and the MENR (WECTNC, 1996) projections are shown in Fig. 11. The quadratic form of the HASTEDE model overestimates the energy demand to a value of about 45 MTOE when it is compared with the MENR projections as seen in Fig. 11. The MENR estimates transport sector energy consumption is about 38 MTOE. The linear and the exponential forms reach a value of 30 MTOE, which gives values very close to each other, and underestimates the energy demand when they are compared with the MENR projections. It can be seen that the MENR projections overestimate (about 18%) the transport energy demand when the MENR (WECTNC, 1996) projections are compared with the observed transport energy demand between 2000 and 2005. Therefore, exponential forms of
steady convergence toward an optimum. Although each of the SAs
will provide an alternative way of energy planning during
transport energy demand, but the linear form underestimates the
other forms of the HASTEDE model. The HASTEDE model can be used as an alternative solution and
demand modeling is quite new, proposed in this study. The
factors that directly affect the energy consumption are analyzed. The HS algorithm is
proposed and model applications are correspondingly given. The SA on HS algorithm parameters is carried out and best fit values of
the HS parameters are obtained. The HASTEDE models are compared with the MENR projections. The following results may
be drawn from this study.

The HS algorithm approach has been applied into the various engineering fields. However, its application to transport energy
demand modeling is quite new, proposed in this study. The HASTEDE model can be used as an alternative solution and
the estimation technique to available estimation techniques.

Three forms of the HASTEDE model may be used for estimating transport energy demand, but the linear form underestimates the
energy demand and the quadratic form overestimates the demand although they usually provide minimum objective function
values. Thus, exponential forms of the models would be better to choose for energy modeling. Other forms of the HASTEDE models will provide an alternative way of energy planning during
the decision-making process and they also provide useful information for scientists.

The solution of the HASTEDE models for each form showed a
steady convergence toward an optimum. Although each of the SAs
cases may be used for model solution, the values of case 1 are selected as a best-fit HASTEDE and then selected for future forecasting.

The quadratic form of HASTEDE will overestimate transport sector energy consumption by about 26% and linear and
exponential forms will underestimate by about 21% when they are compared with the MENR projections. This is usually
unavoidable due to the modeling procedure and selected socio-economic parameters, but determination of the upper and lower values for sectoral consumption would provide a framework and flexibility for energy policy developers.

Further studies will be on the SA of selected socio-economic and transportation-related indicators with respect to an S-shaped
fuel type for vehicles to save energy consumption.

7. Conclusions

The importance of energy demand and transportation sector energy analysis is dealt with in this study. The factors that directly
affect the energy consumption are analyzed. The HS algorithm is
proposed and model applications are correspondingly given. The SA on HS algorithm parameters is carried out and best fit values of
the HS parameters are obtained. The HASTEDE models are compared with the MENR projections. The following results may
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Fig. 10. The general trend of veh-km between 1970 and 2005.

Fig. 11. Future estimations of transport energy demand using HASTEDE and MENR.


