Estimating the Spanish Energy Demand Using Variable Neighborhood Search

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Abstract. The increasing of the energy demand in every country has lead experts to find strategies for estimating the energy demand of a given country for the next year. The energy demand prediction in the last years has become a hard problem, since there are several factors (like economic crisis, industrial globalization, or population variation) that are not easy to control. For this reason, it is interesting to propose new strategies for efficiently perform this estimation. In this paper we propose a metaheuristic algorithm based on the Variable Neighborhood Search framework which is able to perform an accurate prediction of the energy demand for a given year. The algorithm is supported in a previously proposed exponential model for estimating the energy, and its input is conformed with a set of macroeconomic variables gathered during the last years. Experimental results show the excellent performance of the algorithm when compared with both previous approaches and the actual values.

Keywords: Energy demand · VNS · Metaheuristics · Estimation

1 Introduction

The estimation of the energy demand for a given country has become a relevant problem that needs to be tackled each year in every country [4]. Furthermore, the energy demand is constantly increasing, mainly due to the global industrialization experienced in the last decades. It is worth mentioning that approximately 50 % of the total energy demand of a given country is performed by the industry, which clearly shows the importance of this sector in the energy demand estimation. The variation in the population as well as the globalization are two additional key factors in the estimation of the energy demand of a country.

This problem has been previously addressed using different heuristic approaches. Most of the previous works have been devoted to predict the energy demand in developing countries like Turkey [1,4,7–9,14–16]. However, several algorithms have been proposed to perform a similar task in China [17–19], Iran [12], Korea [5], and Spain [13], among others. The algorithms proposed in these

works base their effectiveness on the use of socio-economic variables. This fact can be illustrated with the Genetic Algorithm (GA) proposed in [1], which introduces a model based on four macroeconomic variables: Gross Domestic Product (GDP), population, import and export size. These variables are used again in a Multilayer Perceptron Neural Network [5] proposed for estimating the energy demand in Korea.

More bio-inspired heuristic algorithms have been used for solving this task. For instance, Particle Swarm Optimization (PSO) has been used as a stand-alone algorithm [9,16] and hybridized with other bio-inspired algorithms, as Ant Colony Optimization (ACO) and GA, for estimating the energy demand in several countries [8,17–19]. Several prediction models based on logarithmic and exponential functions have been proposed [12], supported by a GA for energy demand estimation in Iran. Finally, the prediction of the energy demand in Spain has been recently tackled with a Harmony Search algorithm combined with Extreme Learning Machine [13].

This work is intended to solve the estimation of the Spanish energy demand one-year-ahead, selecting the most relevant set of socio-economic variables, among the ones used in previous works. The prediction is performed by using a previously proposed exponential model [13], where a Variable Neighborhood Search (VNS) algorithm is responsible of selecting the best parameters for the model.

The remainder of the paper is structured as follows: Sect. 2 presents the exponential model used for estimating the energy demand. The algorithmic proposal is introduced in Sect. 3, while the experiments performed to test the VNS method are described in Sect. 4. Finally, the conclusions derived from the experiments are discussed in Sect. 5.

2   Prediction Model

The estimation of the energy demand in a given country can be represented by different models that try to fit a function to the real energy demand. We can find in the literature several models, based on different mathematical functions, but most of works concludes that the exponential model fits better to the real energy demand of the country [12]. Furthermore, in this paper we focus on estimating the energy demand of Spain, where the best results have been found by using the exponential model [13]. For that reason, our algorithmic proposal is intended to optimize this model.

The exponential function to estimate the energy demand $\hat{E}(t)$ for a given year t is defined based on the values X_i of the considered macroeconomic variables in the previous year $t - 1$. In mathematical terms,

$$\hat{E}(t) = \epsilon + \sum_{i=1}^{|X|} \alpha_i X_i (t-1)^{\beta_i}$$

where ϵ, α_i and β_i are the parameters that need to be fitted in order to improve the energy demand prediction. Specifically, ϵ represents a bias in order to obtain a better fit, while α_i, β_i represent the weight of the macroeconomic variable X_i.

Unlike the original model [13], we do not fix the macroeconomic variables that are included in the model. Therefore, this model requires two different optimizations: (i) select the best subset of macroeconomic variables, and (ii) find the best values for the model parameters.

A solution $\mathcal{M}$ for the problem is given by both the subset of macroeconomic variables and the values for the parameters of the model. Let us define $X^\star$ as the set of all available macroeconomic variables. The solution is divided in two well-differenced sets: $X = \{X_1, X_m\} \in X^\star$ for the selected macroeconomic variables and $W = \{\epsilon, \alpha_1, \dots, \alpha_m, \beta_1, \dots, \beta_m\}$ for the bias and variable weights.

For the sake of clarity, we describe the evaluation of an example solution by using the proposed representation. We consider the solution $\mathcal{M} = (X, W)$, with $X = \{ME1, ME3, ME4\}$ and $W = \{4.1, 0.4, 0.1, 0.2, -0.05, 0.3, -0.1\}$. In this solution, we have selected the macroeconomic variables $X_1 = ME1, X_2 = ME3, X_3 = ME4$, where each one (*ME1, ME3, ME4*) represents a different value (i.e., GDP, import and export size, etc.). In order to estimate the energy demand for a given year t, we first need to obtain the variable values for the previous year $t - 1$. For this example, we set $X_1 = 0.1, X_2 = 0.4, X_3 = 0.2$. Notice that for each variable X_i (see for instance $\alpha_1 = 0.4, \beta_1 = 0.1$ for X_1) we provide a pair of coefficients α_i, β_i, plus the first bias coefficient ϵ (4.1 in the example).

The estimation of the energy demand for the current year is performed as follows:

$$\hat{E}(t) = \epsilon + \alpha_1 \cdot X_1(t-1)^{\beta_1} + \alpha_2 \cdot X_2(t-1)^{\beta_2} + \alpha_3 \cdot X_3(t-1)^{\beta_3}$$
$$= 4.1 + 0.4 \cdot 0.1^{0.1} + 0.2 \cdot 0.4^{-0.05} + 0.3 \cdot 0.2^{-0.1}$$
$$= 4.98$$

Each solution is evaluated using an objective function to analyze the similarity of the solution when compared with the real energy demand. In this work we minimize the mean squared error (MSE) between prediction and real value. The MSE is defined as follows:

$$f(\mathcal{M}) = \sum_{j=1}^{n} \left(E(j) - \hat{E}(j) \right)^2$$

where n is the number of samples used to test the quality of the solution. We use the same error measure previously considered in the related works [1,13] in order to ease the comparison among different proposals. Therefore, the objective is to find the solution $\mathcal{M}^\star$ with the minimum f-value. In mathematical terms,

$$\mathcal{M}^\star = \arg \min_{\mathcal{M} \in \mathbb{M}} f(\mathcal{M})$$

where $\mathbb{M}$ is the set of all possible solutions for the problem.

It is worth mentioning that all variable values and parameters are normalized in a traditional manner. Specifically, the value of each macroeconomic variable and each α, β parameter is normalized in the range $[-1, 1]$. However, the bias parameter considers a larger range $[-5, 5]$, as recommended in previous works [13], in order to obtain better results.

3   Variable Neighborhood Search

Variable Neighborhood Search (VNS) is a metaheuristic framework designed for solving hard optimization problems. VNS relies on systematic changes of neighborhood structures for finding high quality solutions, without guaranteeing their optimality. Several VNS strategies have been proposed during the study of this metaheuristic. Specifically, we can emphasize Variable Neighborhood Descent (VND), Reduced VNS (RVNS), Basic VNS (BVNS), Skewed VNS (SVNS), General VNS (GVNS), Variable Neighborhood Decomposition Search (VNDS), and Variable Formulation Search (VFS) among others (see [6] for a thoroughly review of the metaheuristic and its variants). This methodology has lead to several successfull research in recent years [3,10,11].

This paper is focused on the Basic VNS (BVNS) variant, which combines deterministic and stochastic changes of neighborhood during the search. Algorithm 1 shows the pseudocode of BVNS. The algorithm requires two parameters: an initial solution $\mathcal{M}$ and the maximum number of iterations. The procedure starts by exploring the neighborhoods from the first one (step 1). For each neighborhood, it randomly perturbs the current solution (step 4), with the shake procedure described in Sect. 3.1. Then, the perturbed solution is improved with the local search method presented in Sect. 3.2 (step 5). Finally, BVNS selects the next neighborhood to be explored (step 6). Specifically, if the search has found a new best solution, i.e., $f(\mathcal{M}'') < f(\mathcal{M})$, the method starts again from the first neighborhood ($k = 1$). Otherwise, it continues with the next neighborhood ($k = k+1$). These three steps are repeated until the maximum predefined neighborhood $k_{\max}$ is reached (steps 3–7). The VNS framework usually considers two different stopping criterion: time horizon or number of iterations. In this work the algorithm is executed a fixed number of iterations (steps 1–8).

Algorithm 1. Basic VNS($\mathcal{M}$, iterations)

1: **for** $i \in 1 \ldots$ iterations **do**
2:     $k \leftarrow 1$
3:     **while** $k \leq k_{\max}$ **do**
4:         $\mathcal{M}' \leftarrow \texttt{Shake}(\mathcal{M}, k)$
5:         $\mathcal{M}'' \leftarrow \texttt{LocalSearch}(\mathcal{M}')$
6:         $k \leftarrow \texttt{NeighborhoodChange}(\mathcal{M}, \mathcal{M}'', k)$
7:     **end while**
8: **end for**

The initial solution for the BVNS algorithm can be generated either with a specific constructive procedure or with a random method. We have decided to use a random procedure since we do not have *a priori* information about the problem that can be useful during the constructive phase. Therefore, for the initial solution we select a subset of macroeconomic variables (each one is selected with a probability of 0.5). Then, we select a random bias in the range $[-5, 5]$ and, for each variable, random values for its α and β parameters. The resulting solution (improved with the local search method) is used as the initial solution for the BVNS algorithm.

The representation of the solution selected splits it into two parts: the variables selected and the associated weights. Regarding the BVNS algorithm, each of the main procedures are devoted to modify a different part of the solution. In particular, the shake procedure focuses in the selected variables, while the local search method is intended to improve the values of their ϵ, α and β parameters.

3.1   Shake

In the context of VNS, the shake procedure consists of perturbing the incumbent solution in the corresponding neighborhood in order to diversify the search. Regarding the energy demand estimation problem, the shake procedure is intended to modify the macroeconomic variables selected in the solution. Given a solution $\mathcal{M}$, X represents the set of selected macroeconomic variables ($X \subseteq X^\star$). The current neighborhood k represents the perturbation size.

The shake procedure selects k variables from $X^\star$ at random. Then, for each selected macroeconomic variable X_i, the method includes it in the solution ($X \leftarrow X \cup \{X_i\}$) if it is not yet included ($X_i \notin X$). Otherwise ($X_i \in X$) the shake procedure removes that variable from the solution ($X \leftarrow X \setminus \{X_i\}$).

Fig. 1. Example of performing the shake procedure in a solution $\mathcal{M}$ with $k = 3$.

Figure 1 represents the shake procedure executed over a solution $\mathcal{M}$ where the macroeconomic variables selected are represented in with solid black color. Before executing the shake procedure, $\mathcal{M}$ includes the variables 2, 4, and 5. Since the neighborhood in the example is 3, the method selects three variables at random (1, 2 and 4, highlighted with an arrow). The first variable selected, is included in the new solution $\mathcal{M}'$, since it did not originally belong to $\mathcal{M}$. Variables 2 and 4 are removed from the new solution $\mathcal{M}'$ since they were already included in $\mathcal{M}$. Therefore, the resulting solution after executing the shake procedure only contains variables 1 and 5.

3.2   Local Search

Unlike the shake procedure, the local search procedure proposed in this paper is intended to improve a solution by modifying the value of the bias and the weights associated to each macroeconomic variable. Since these values belong to the real domain (i.e., $\{\epsilon, \alpha_i, \beta_i\} \in \mathbb{R}, \forall i \in 1 \ldots |X|$), the local search considers global optimization techniques. One of the most extended strategy for improving solutions in global optimization is the Line Search method, which has lead to several successful works in the recent years [2].

The Line Search method iterates over every parameter of the solution (including ϵ, α and β), trying to improve the quality of the solution by modifying one parameter at a time.

The improvement of a parameter $w \in \{\epsilon, \alpha_1 \ldots \alpha_{|X|}, \beta_1, \ldots, \beta_{|X|}\}$ whose available range is $[MIN, MAX]$ starts by performing a discretization of the search space in h different points. Then, the method iterates over each generated point, assigning its value to the current weight, and evaluating the resulting solution. If the new solution outperforms the previous best one, it is updated, and the search starts again.
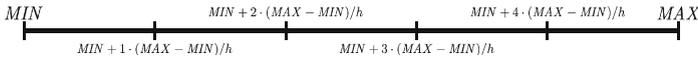

Fig. 2. Discretization of the search space with $h = 5$

Figure 2 shows the discretization of the search space for a parameter w in the range $[MIN, MAX]$. Since w belongs to the real domain, the search would need to explore infinite points in order to perform an exhaustive search for the best value. Let h be a parameter of the Line Search method. The algorithm generates h different values uniformly distributed through the variable domain. Therefore, in order to generate h discrete values, the gap between each pair of consecutive values is evaluated as $(MAX - MIN)/h$.

The search then traverses the set of values generated following a random order. If the method finds an improvement in a given value, then it is updated in the solution and the search starts again (first improvement strategy). Once all values generated have been evaluated without finding an improvement (local optimum), the search continues with the next parameters of the solution. It is worth mentioning that the next parameter to be explored is selected at random. The Line Search method ends when no improvement is found in any parameter, returning the best solution found during the search.

4   Computational Experiments

The problem addressed in this paper is completely focused in solving an actual problem. Therefore, the data used in the experiments needs to be real, in order

to analyze the applicability of the proposed algorithm to real-world data, which often include high level of noise. In particular, we have used the same data used in a previous work [13], related with the energy demand estimation in Spain. Specifically, the data contains information about several macroeconomic variables that were analyzed from 1980 to 2011.

For each year, the dataset contains information about 14 different macroeconomic variables, namely: Gross Domestic Product (GDP), population, export, import, energy production (kilotonne of oil equivalent, kTOE), electricity power transport (kW/h), electricity production (kW/h), GDP per unit of energy use, energy imports net (% of use), fossil fuel consumption (kW/h), electric power consumption (kW/h), CO_2 total emissions (Mtons), unemployment rate, and diesel consumption in road (kTOE).

The data have been split in two different sets in order to avoid overtraining. The training set contains data for 15 years, while the test set contains data for the remaining 16 years. Both sets have been generated at random, but considering the years related with the economic crisis (2010 and 2011) in the test set, with the aim of analyzing if the algorithm is able to predict these behaviors. It is worth mentioning that we have considered the same error measure, MSE, for the preliminary experimentation, in order to have comparable results.

Both, VNS (feature selection) and ELM (training) are executed only once. After that, a decision maker will only need to feed the trained algorithm in order to immediately obtain the energy demand prediction associated to the input data used, without requiring computing time. The computing time for training is 10 s per VNS iteration and 5 s for ELM.

The main objective of the first experiment is to select the best parameters for the BVNS algorithm proposed. In particular, it requires two different parameters: the number of iterations and the maximum neighborhood number to explore (k_{max}). Notice that the maximum neighborhood to be explored represents the maximum number of variations in the macroeconomic variables that will be performed. On the one hand, it is easy to see that both, quality and computing time, increase with the number of iterations, so we have selected 25 in order to maintain reasonable computing times. On the other hand, we have tested the following values for $k_{max} = \{2, 4, 6, 10\}$. Table 1 shows the results obtained for each variant in terms of the mean squared error obtained in the test set when considering the parameters selected by the algorithm in the training set. It is worth mentioning that the h parameter for the Line Search method has been experimentally set to 1000 during the whole experimentation.

Notice that those macroeconomic variables selected in all variants are highlighted in bold, since they seem to be relevant features. In particular, the common macroeconomic variables are import, energy imports net, and CO_2 total emissions. From these results we can extract that $k_{max} = 4$ presents the best results in terms of MSE, emerging as the best BVNS variant. It can be seen that the MSE increases with the size of the maximum neighborhood. However, the worst results are obtained when considering $k_{max} = 2$, which may reveal that it is a

small maximum neighborhood to be used in this kind of problems. Therefore, BVNS with $k_{\max} = 4$ is selected for the remaining experiments.

The next experiment is intended to compare the results obtained by our proposal when compared with the best previous works. Table 2 shows the results obtained by our BVNS compared with a Harmony Search algorithm isolated (HS) and combined (HS+ELM) with a neural network [13], and, finally, a Genetic Algorithm (GA) [1]. The bad performance of Genetic Algorithm can be partially motivated by its design, in which the algorithm is only able to consider 4 joint macroeconomic variables. The remaining algorithms are more versatile, since they consider a variable number of macroeconomic variables, increasing the explored region of the search space. We can also see an improvement of 0.20 % in HS+ELM with respect to HLM isolated, which reveals the relevance of the neural network in the algorithm. Finally, our BVNS emerges as the best algorithm, improving the combination of HS with ELM.

The final experiment is intended to test how the best results obtained by BVNS fit with the real energy demand values for each year available in the dataset. Figure 3 presents these results in a line graph where the x-axis represents the year evaluated and the y-axis indicates the total energy demand, measured in kilotonne of oil equivalent (kTOE). The line with triangle markers for each year represents the real measure, while the one with rectangle markers represents the estimation given by BVNS.

Table 1. Performance of BVNS with the proposed values of $k_{\max}$. Common features selected in all cases are highlighted in bold font.

$k_{\max}$	MSE (%)	Selected variables
2	3.40	{**4**, 7, **9**, **11**, 13, 14}
4	2.10	{3, **4**, 8, **9**, **11**, 13}
6	2.59	{1, 3, **4**, 5, 8, **9**, **11**}
10	2.86	{2, 3, **4**, 6, 7, **9**, **11**, 12}

Table 2. Results obtained by BVNS when compared with the best previous algorithms: Harmony Search (HS), Harmony Search with neural network (HS+ELM), and Genetic Algorithm (GA).

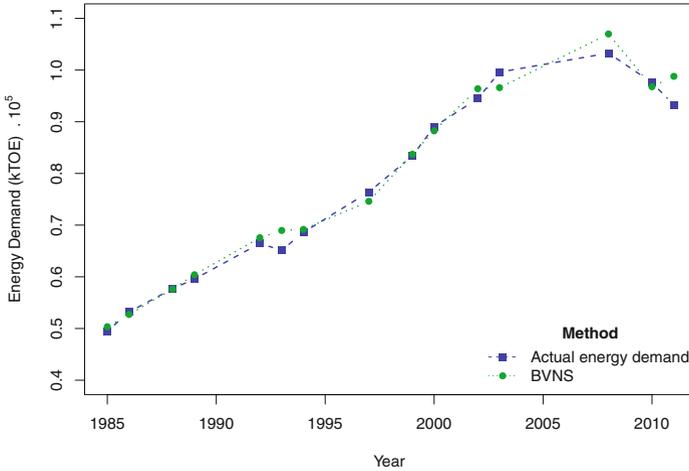| Algorithm	MSE (%)	Selected variables
BVNS	2.10	{3, 4, 8, 9, 11, 13}
HS+ELM	2.16	{1, 2, 3, 7, 8, 9, 12}
HS	2.36	{1, 2, 3, 7, 8, 9, 12}
GA	2.89	{1, 2, 3, 4}

Fig. 3. Comparison of the BVNS prediction when compared with the real values

5 Conclusions

This paper has introduced a new metaheuristic algorithm, based on the Variable Neighborhood Search framework, for estimating the energy demand of a country. The experiments has been performed using a dataset which contains macroeconomic information about Spain for the last years. The thoroughly experimentation presented has been used for selecting the best parameters for the algorithms, as well as for comparing the best results obtained with respect to the actual energy demand of the years in which the data is available. The obtained results have shown the superiority of our proposal, reducing the error obtained when compared to the best previous approach, based on a Harmony Search method. We do believe that this algorithm can become a precise tool for helping decision makers.

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