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Tree-Seed Programming for Modelling of Turkey Electricity Energy Demand

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Abstract: Tree-Seed algorithm, TSA for short, is a population-based metaheuristic optimization algorithm proposed for solving continuous optimization problems inspired by the relation between trees and their seeds in nature. The artificial agents in TSA are trees and seeds which correspond to possible solutions to the optimization problem, and the optimization procedure is executed by the interaction between trees and seeds. In this study, a programming version of this algorithm by using a crossover solution generation mechanism has been proposed. The proposed algorithm is called TSp and its performance has been investigated on two problems, one of them is symbolic regression benchmark functions and the other is the long-term energy estimation model of Turkey. Firstly, the continuous parts of TSA, which are initialization and solution generation mechanisms, have been modified to solve automatic programming problems. The solution representation is also modified to solve the problem addressed by the study. As a result of these modifications, TSp has been obtained and applied to symbolic regression problems for performance judgment, energy estimation problems for real-world application. The experimental results of TSp have been compared with those of Genetic Programming, it is concluded that TSp is better than the GP in solving energy estimation problems.

Keywords: *Automatic programming, swarm intelligence, genetic programming, tree-seed algorithm, energy estimation and modelling*

1. Introduction

Energy is one of the most important factors for a sustainable life. This factor, whose importance can be easily understood and exemplified, has an important place in the social and economic development of a country. Due to the exponential increase in energy consumption, world population growth, and enhancing living standards, energy demand management emerges as a global problem. As for the development of energy models which has an important role in energy demand management reliable energy model helps efficient energy planning, energy estimation, and optimization of energy resources [1]. Recently, many studies have been done on energy modeling which is the focus of scientists, engineers, and researchers' interest. Generally, energy models are studied for a given country for total energy, different energy types, or different sectors, and various methods are applied to obtain these models. These methods can be divided into three groups: traditional methods, modified traditional methods, and methods based on artificial intelligence (AI) [2]. Energy is also an important factor for the social and economic development of Turkey, especially, in this country, the need for electricity is increasing rapidly. When it is considered that Turkey has limited oil and natural gas reserve, which are mainly energy resources, and the majority of the country's energy is imported, it makes the demand for a proper energy model inevitable. In this study, Turkey's electricity demand was modeled using an AI technique. As an AI technique, a new version of the tree-seed algorithm [3] which is a metaheuristic optimization algorithm introduced to solve continuous optimization problems, has been developed for programming and applied to the problem addressed by the study. The technique called tree-seed programming (Tree-seed programming- TSp) was introduced as an intersection product with SI and automatic programming. In this study, TSp was initially tested on symbolic regression problems to evaluate its efficiency and performance. Afterward, the control parameters showed good results in the symbolic regression problem were selected for electrical energy modeling. To get energy consumption model TSp was applied on 25 data (1992-2016) which shows the gross domestic product (GDP), population, import, and export indicators that affect electricity consumption. The electrical energy derived from the TSp implication has been used for the estimation problem, and estimated results have been produced up to 2025 for Turkey's electricity consumption. Although superficial studies were carried out by the State Planning Organization of Turkey in 1966, 1967, 1972, 1977, 1979, and the Ministry of Energy and Natural Resources (MENR) in 1973, 1975, 1977, and 1978, demand for energy obtained by statistical methods officially began to be used in 1984 first [4]. In Turkey's energy modeling there have been several studies that use artificial intelligence techniques such as swarm intelligence algorithms, genetic algorithms, neural networks. For example, Ceylan and Ozturk [5], Ersel Canyurt, Ceylan [6], Ozturk, Ceylan [7], Canyurt and Ozturk [8] have used a genetic algorithm to find coefficients of electrical energy model which has been determined in a quadratic or exponential form in advanced. An artificial neural network has been used for modeling different types of energy consumption in various sectors. Sözen,

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Arcaklioğlu [9], Hamzaçebi and Kutay [10], Hamzaçebi [11], Sözen and Arcaklioglu [12], Kavaklioglu, Ceylan [13], Yetis and Jamshidi [14], Murat and Ceylan [15], Kankal, Akpınar [16], Bilgili, Sahin [17], Uzlu, Akpınar [18] are example for the studies using neural network. As a swarm intelligence algorithm, Ünler [19] has used Particle Swarm Optimization (PSO), Toksarı [20] has used ant colony optimization (ACO), Kiran and Gunduz [21] have used a hybrid version of PSO and ACO, the authors of [22] have used PSO and Artificial Bee Colony (ABC) for Turkey's energy estimation modeling.

When the studies in the literature on the estimation of energy demand are analyzed, the swarm intelligence or evolutionary computation algorithms have been used for optimizing the coefficients of some models such as linear, quadratic, nonlinear, etc. In this study, the tree-seed algorithm is modified for solving the energy estimation problem. Briefly, it is aimed to model the estimation of energy demand instead of optimizing coefficients of the models. TSA is firstly proposed for solving continuous optimization problems in [3]. And TSA is modified to solve the constraint optimization problem – the pressure vessel design problem [23]. To handle the constraints in the problem, a penalty function is designed and the performance of the tree seed algorithm has been analyzed on the problem. In another constrained version of TSA [24], Deb's rules are integrated with TSA. Deb's rules in this version are used for comparing the candidate and actual solutions in the stand of TSA. Muneeswaran and Rajasekaran used TSA to optimize the values of clustering centers, width, and weights of the Radial Basis Function Neural Network applied to the numerical function approximation problem [25]. Since the proposed algorithm provides accurate mapping of numerical functions, it has better fitness values in all cases compared to the other considered algorithm built based on PSO. Zheng et al. sought a remedy to enhance the dynamic stability of hydroelectric generating units by devising a multi-mode intelligent model predictive control strategy (MPC) consisting of the excitation MPC mode and the integrated MPC mode which are designed by using TSA [26]. A terminal penalty cost and a terminal region designed offline enable the stability of the closed-loop system as well as feedback revision adjusts system parameters automatically. Results in the study reveal a significant improvement in voltage regulation and damping capabilities. Chen, Tan, and Cai utilized the Tree-Seed Algorithm to establish the parameters of equivalent circuit models for Li-ion batteries [27]. Thanks to its ability to handle bad initial values and gradient information and also multiple mode functions, TSA produces better results in comparison to others such as the Gauss-Newton method and genetic algorithm in terms of improving the accuracy and reducing time consumption for parameter identification problems. The RMSE of the proposed model based on TSA is reduced by 61.1% under the DST test and 75.9% under the FUDS test, which is a commonly used battery test profile. Suseela and Sivakumar deal with spectrum scarcity of wireless communication using cognitive multichannel networks optimized via PSO and TSA [28]. The higher probability of detection and lower probability of false alarm are criteria considered in the algorithm. TSA-based cognitive networks attained a lower probability of false alarm without reducing the transmission rate besides quicker convergence time than the PSO-based cognitive networks. A parallel version of TSA has been developed on the GPU-based platform and the performance of the parallel TSA has been compared with its serial version in terms of speed [29]. In the study of [30], a new parameter has been added to the basic algorithm to improve its performance on multimodal optimization problems. For each tree, an age limit is designed and if the number of produced seeds for this tree is not better than the current tree, it is assumed that the tree is on local optimum, and the tree is withered. In another study [31], the TSA has been applied to solve real-world optimization problems. While the TSA has been modified by using s-shaped and v-shaped logistics functions to solve binary optimization problems in [32], the logic operators and similarity-based modification of TSA for binary optimization have been proposed in [33]. The TSA has been discretized by using neighborhood operators for solving travelling salesman problems in [34]. In [35], the different search strategies have been integrated with TSA, and it is used for optimizing high dimensional functions. The TSA has been also applied to optimize weights in artificial neural networks in [36]. In another application of TSA [37], it has been applied to the selection and reduction of reference points on local GNSS/leveling geoid determination.

When the literature is detailed, it can be seen that some applications, modifications, and improvements can be found. However, in this study, the novel version of TSA is proposed for modeling. So, the novelty and originality of the algorithm and study have been come from the modification of TSA and its application to energy estimation modeling.

2. Tree-Seed Algorithm

Optimization problems are of great importance for both the industrial and scientific worlds. Many of the real-life problems appear as optimization problems. In general, an optimization problem can be defined as (S, Ω, f). Here, S refers to the search space and it is defined on a set of decision variables. Ω is a set of constraints to which variables are subjected. f is an objective function that assigns a value to each element of S. The objective in optimization problems is to minimize or maximize the objective function. In other words, the purpose is to find s∈S solution such that f(s)≤f(s^'), ∀s^'∈S (for minimization problems), f(s)≥f(s^'), ∀s^'∈S (for maximized problems) conditions are provided [38]. For optimization purposes, TSA was proposed as a population-based, heuristic optimization algorithm inspired by the relationship between trees and their seeds to settle continuous optimization problems in 2015 [3].

Traditional mathematical techniques ensure the optimal global solution for optimization problems. However, the implementation of these methods to real-world problems has many disadvantages. For example, the problem cannot be solved in polynomial time because of the increasing number of decision variables or the objective function is not differentiable. To overcome these deficiencies of mathematical techniques, heuristics optimization techniques have been proposed. These methods aim to find optimal or near-optimal solutions with a reasonable calculation cost [39].

Heuristic algorithms, which are inspired by nature, have been developed since the 1970s by imitating the physical or biological processes of natural phenomena or some living things. Intense interest in the development of such algorithms is continuing and [40], [41, 42], [43], [3] are new examples of heuristic algorithms being developed. As a natural phenomenon, the newly developed heuristic algorithm, the tree-seed algorithm, deals with the seed production of trees in nature, the spread of these seeds in various random directions, and the transformation of these seeds into new trees. In this algorithm, the positions of trees and seeds are possible solutions to the problem.

TSA is initiated by the creation of the initial population of trees, called a stand. Then, a certain number of seeds is produced for each tree in the stand. Once the specified number of seeds have been produced, their best is compared to the tree from which the seed is produced. If the best seed is better than the parent tree, the parent tree is removed from the stand and replaced with the best seed. Otherwise, no changes are made to the stand. The stand is obtained by using Equation 1.

$$T_{i,j} = L_{j,min} + r_{i,j}(H_{j,max} - L_{j,min}) \quad (1)$$

where $T_{i,j}$ represents j'th dimension of i'th tree. $H_{j,\max}$ is a higher bound of the search space, $L_{j,\min}$ is a lower bound of the search space and *r* is a randomly generated number in the range of [0,1]. Two equations (Equations 2 and 3) are presented to produce seeds for each tree. Furthermore, the number of seeds produced for each tree may be more than one, depending on the size of the population. In the analysis of the effect of control parameters' different values on the performance of TSA, 10% of the population size was accepted as the minimum value for this number and 25% as the maximum value for this number. Thus, the number of seeds is randomly selected from the range [10% population size, 25% population size]. When we consider the stand size as 20, the *k* index in Equations 2 and 3 should be the element of {1,2,3,4,5}.

$$S_{k,j} = T_{i,j} + \alpha_{i,j}(B_j - T_{r,j}) \quad (2)$$

$$S_{k,j} = T_{i,j} + \alpha_{i,j}(T_{i,j} - T_{r,j}) \quad (3)$$

Where $S_{k,j}$ j'th dimension of i'th seed which is produced from i'th tree. B_j j'th dimension of the best tree, $T_{r,j}$ is the j'th dimension of the r'th tree which is randomly selected from the stand. $\alpha_{k,j}$ is scaling factor randomly generated from a range of [-1,1]. Which of these equations will be used in seed production is controlled by a peculiar parameter of TSA whose name is search tendency (ST). ST is a predetermined number selected from [0,1]. If the random number selected from the range [0,1] is less than ST, then Equation 2 is used, otherwise, Equation 3 is used. The seed production process continues until the termination condition is met. As the termination condition, the maximum number of function evaluations (Max_Fes) is selected [3, 24].

3. Tree–Seed Programming -TSp

In this section, the new version of TSA for programming is introduced as a product of a combination of swarm intelligence and automatic programming. Automatic programming solves problems with automatically generated computer programs without a need to know a form of the solution in advance. One of the successful tools of automatic programming is Genetic Programming (GP) [44]. As an extended version of TSA, TSp is an automated programming approach. It means, solutions are computer programs that are represented by trees. Computer programs consist of variables, constants, functions. Variables and constants are called a terminal set, functions are called a function set [44]. As an example, the representation of $\sin^2 x + y^2$ the program in the tree structure is given as Fig. 1.

To improve TSp, linear coding and developing rules should be changed according to tree coding. Therefore, the first stand in TSp is formed by one of the methods used to create the first population in the GP. In addition, due to tree coding, the basic solution generation mechanism used for seed production in TSA cannot be applied directly to TSp. Consequently, in tree coding, seed production can be handled through the crossover operator. Equations (4) and (5) are considered in TSp using the crossover process as follows:

$$S_k = crossover(T_i, crossover(B, T_r)) \quad (4)$$

$$S_k = crossover(T_i, crossover(T_i, T_r)) \quad (5)$$

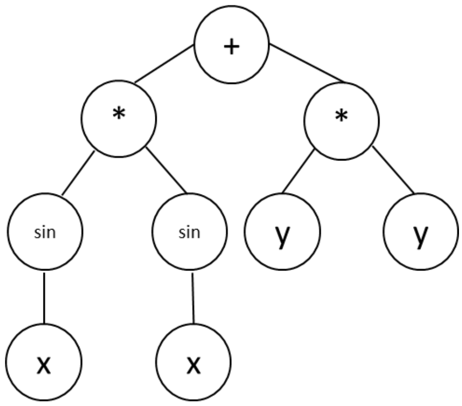

Figure 1. Representation of in tree form

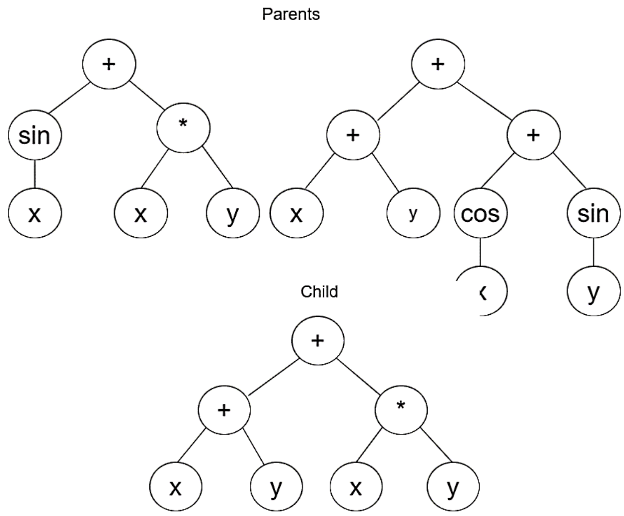

Figure 2. Crossover example

The most commonly used form, subtree crossover, was used for the crossover process aimed at creating a new offspring program from two parent programs. As regards the selection of parental programs, the most commonly used tournament method in Evolutionary Computation is used. Tournament selection is applied twice for crossover. In the two parent programs of different sizes and formats, the crossover node is selected randomly. Then, the offspring is obtained as shown in Fig. 2.

```
SET   the number of population size (NP)
SET   the lenghth of the tree form
SET   the depth of the tree form
SET   the number cycle (Counter)
WHILE counter<determined_constant
      FOR each tree in the population
          determine the number of seed (SN)
          increase Counter by the number of seeds produced
          FOR each seed in S
              IF rand <ST THEN
                  Produce seed using Eq 3.1
              ELSE
                  Produce seed using Eq 3.2
          END FOR
          Compare best seed with its tree
      END FOR
      IF termination condition THEN
          Problem solved
END WHILE
```

Figure 3. Pseudocode of the TSp algorithm

The sum of the absolute errors (SAE) is used to measure the performance of each computer program (Equation 6).

$$SAE_i = \sum_{j=1}^{N} \left\| (g_j - t_j) \right\| \tag{6}$$

where, N is the number of samples, is an actual output of j'th state, is targeted output of j'th state.

4. Benchmark Test of TSp

The effectiveness and performance of the proposed method were investigated in the commonly used symbolic regression problem to test the automated programming approach. Symbolic regression involves finding a mathematical expression in a symbolic form that provides a good or perfect fit between the values of independent variables and the associated values of dependent variables [45]. Test problems containing polynomial, trigonometric, logarithmic, square root, and two-variable functions are given in Table 1.
Terminals, and functions set must be selected by the user before applying the TSp to the problem. The function and terminal sets are selected in accordance with the 10 comparison functions:

Functions set ={+, -, ×, ÷, sin, cos, exp, rlog}x

Terminals set (for functions with one variable) = x

Terminals set (for functions with two variables) ={ x, y }
To evaluate the effect of stand size, Max_Fes and ST on the performance of the TSp, their different values were adjusted. Furthermore, another purpose of testing different values of control parameters is to select their best values for the problem of electrical energy modeling. Thus, each function was run 10 times for 3 different Max_Fes (10000, 50000, 100000), 4 different stands (50, 100, 250, 500) and 9 different ST values(0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9). In each study, the number of hits (SAE <0.01 is considered as the number of successes) is recorded. To sum up, we have 108 different tests and each of them is run with a random number of seeds 10 times. The results of the tests are given in Table 2-Table 10.

Table 1. Symbolic regression functions

Functions	**Description**
$f_1 = x^3 + x^2 + x$	20 random points ⊆ [−1,1]
$f_2 = x^4 + x^3 + x^2 + x$	20 random points ⊆ [−1,1]
$f_3 = x^5 + x^4 + x^3 + x^2 + x$	20 random points ⊆ [−1,1]
$f_4 = x^6 + x^5 + x^4 + x^3 + x^2 + x$	20 random points ⊆ [−1,1]
$f_5 = \sin(x^2)\cos(x) - 1$	20 random points ⊆ [−1,1]
$f_6 = \sin(x) + \sin(x + x^2)$	20 random points ⊆ [−1,1]
$f_7 = \log(x + 1) + \log(x^2 + 1)$	20 random points ⊆ [0,2]
$f_8 = \sqrt{x}$	20 random points ⊆ [0,4]
$f_9 = \sin(x) + \sin(y^2)$	100 random points ⊆ [−1,1] × [−1,1]
$f_{10} = 2\sin(x)\cos(y)$	100 random points ⊆ [−1,1] × [−1,1]

Table 2. Max_FES Evaluation for ST=0.1 ve pop=50, 100, 250, 500

	ST=0.1 pop=50			ST=0.1 pop=100			ST=0.1 pop=250			ST=0.1 pop=500		
	Fes=10000	Fes=50000	Fes=100000	Fes=10000	Fes=50000	Fes=100000	Fes=10000	Fes=50000	Fes=100000	Fes=10000	Fes=50000	Fes=100000
f1	5	7	7	8	10	10	0	9	10	0	10	10
f2	9	10	10	5	10	10	0	9	10	0	0	5
f3	9	9	10	3	10	10	0	9	10	0	0	5
f4	4	6	7	2	7	9	0	3	9	0	0	0
f5	0	1	0	0	0	2	0	0	0	0	0	0
f6	3	9	7	1	9	9	0	4	9	0	1	3
f7	0	0	0	0	0	1	0	0	1	0	0	0
f8	0	0	0	0	0	0	0	0	0	0	0	0
f9	5	6	8	2	8	9	0	5	10	0	0	3
f10	1	0	1	2	1	2	0	2	2	0	1	2
	36	**50**	**55**	**24**	**60**	**69**	**0**	**44**	**68**	**0**	**15**	**32**

Table 3. Max_FES Evaluation for ST=0.2 ve pop=50, 100, 250, 500

	ST=0.2 pop=50			ST=0.2 pop=100			ST=0.2 pop=250			ST=0.2 pop=500		
	Fes=10000	Fes=50000	Fes=100000	Fes=10000	Fes=50000	Fes=100000	Fes=10000	Fes=50000	Fes=100000	Fes=10000	Fes=50000	Fes=100000
f1	5	7	7	9	8	9	0	9	10	0	7	10
f2	7	10	10	6	10	10	0	10	9	0	1	5
f3	8	9	9	3	10	10	0	7	10	0	1	4
f4	1	6	7	1	5	6	0	0	6	0	0	0
f5	0	0	2	0	1	3	0	0	0	0	0	0
f6	6	5	8	4	8	9	0	9	10	0	1	4
f7	0	0	1	0	0	0	0	0	0	0	0	1
f8	0	0	0	0	0	**0**	0	0	0	0	0	0
f9	2	7	5	1	5	9	0	7	10	0	1	5
f10	10	0	0	0	0	1	0	1	4	0	1	0
	40	**47**	**49**	**24**	**51**	**57**	**0**	**46**	**59**	**0**	**13**	**29**

Table 4. Max_FES Evaluation for ST=0.3 ve pop=50, 100, 250, 500

	ST=0.3 pop=50			ST=0.3 pop=100			ST=0.3 pop=250			ST=0.3 pop=500		
	Fes=10000	Fes=50000	Fes=100000	Fes=10000	Fes=50000	Fes=100000	Fes=10000	Fes=50000	Fes=100000	Fes=10000	Fes=50000	Fes=100000
f1	7	8	4	5	9	7	0	10	10	0	8	10
f2	7	9	9	5	10	8	0	7	10	0	0	2
f3	6	7	9	5	9	10	0	6	8	0	1	4
f4	3	6	6	2	5	5	0	3	6	0	0	1
f5	0	1	1	0	1	1	0	0	0	0	0	0
f6	2	5	7	5	7	9	0	8	10	0	3	5
f7	0	0	0	0	0	0	0	0	0	0	0	0
f8	0	0	0	0	0	0	0	0	0	0	0	0
f9	3	4	5	1	7	8	0	7	7	0	1	3
f10	0	0	0	0	2	0	0	1	3	0	0	1
	28	**43**	**41**	**23**	**53**	**48**	**0**	**45**	**54**	**0**	**17**	**26**

Table 5. Max_FES Evaluation for ST=0.4 ve pop=50, 100, 250, 500

	ST=0.4 pop=50			ST=0.4 pop=100			ST=0.4 pop=250			ST=0.4 pop=500		
	Fes=10000	Fes=50000	Fes=100000	Fes=10000	Fes=50000	Fes=100000	Fes=10000	Fes=50000	Fes=100000	Fes=10000	Fes=50000	Fes=100000
f1	6	7	8	5	6	8	0	9	10	0	10	10
f2	7	8	10	5	10	8	0	6	10	0	0	7
f3	4	8	10	6	9	8	0	6	8	0	3	5
f4	6	5	8	1	4	5	0	2	5	0	1	0
f5	0	0	0	0	0	2	0	0	0	0	0	0
f6	6	7	7	3	10	7	0	7	9	0	10	8
f7	0	0	3	0	0	0	0	0	1	0	0	0
f8	0	0	0	0	0	0	0	0	0	0	0	0
f9	2	5	7	1	7	6	0	5	10	0	4	10
f10	1	1	0	0	3	2	0	0	2	0	1	2
	27	**42**	**53**	**21**	**53**	**51**	**0**	**35**	**55**	**0**	**31**	**42**

Table 6. Max_FES Evaluation for ST=0.5 ve pop=50, 100, 250, 500

	ST=0.5 pop=50			ST=0.5 pop=100			ST=0.5 pop=250			ST=0.5 pop=500		
	Fes=10000	Fes=50000	Fes=100000	Fes=10000	Fes=50000	Fes=100000	Fes=10000	Fes=50000	Fes=100000	Fes=10000	Fes=50000	Fes=100000
f1	6	4	7	7	9	7	0	10	9	0	10	10
f2	9	8	7	5	9	10	0	8	9	0	3	6
f3	7	9	9	4	8	8	0	4	9	0	3	4
f4	2	4	3	1	4	7	0	1	2	0	0	0
f5	0	0	0	0	0	1	0	0	0	0	0	0
f6	3	5	9	7	8	6	0	6	8	0	4	6
f7	0	0	0	0	0	1	0	0	0	0	0	0
f8	0	0	0	0	0	0	0	0	0	0	0	0
f9	6	3	4	4	6	10	0	8	8	0	8	6
f10	1	0	1	0	1	2	0	1	1	0	1	2
	34	**36**	**40**	**29**	**50**	**52**	**0**	**42**	**46**	**0**	**32**	**34**

Table 7. Max_FES Evaluation for ST=0.6 ve pop=50, 100, 250, 500

	ST=0.6 pop=50			ST=0.6 pop=100			ST=0.6 pop=250			ST=0.6 pop=500		
	Fes=10000	Fes=50000	Fes=100000	Fes=10000	Fes=50000	Fes=100000	Fes=10000	Fes=50000	Fes=100000	Fes=10000	Fes=50000	Fes=100000
f1	6	7	5	6	8	7	3	10	10	9	10	9
f2	7	9	8	4	7	5	0	6	10	1	3	3
f3	7	6	8	5	6	9	0	3	5	0	3	6
f4	2	2	1	1	5	2	0	2	2	0	0	0
f5	0	1	0	0	2	3	0	0	0	0	0	0
f6	3	2	7	4	8	5	0	9	8	0	8	7
f7	0	0	1	0	0	1	0	0	0	0	0	0
f8	0	0	0	0	0	0	0	0	0	0	0	0
f9	1	3	3	3	8	8	0	7	10	0	6	9
f10	0	1	0	0	1	1	0	3	4	0	4	1
	26	**33**	**33**	**24**	**45**	**41**	**3**	**42**	**49**	**10**	**40**	**35**

Table 8. Max_FES Evaluation for ST=0.7 ve pop=50, 100, 250, 500

	ST=0.7 pop=50			ST=0.7 pop=100			ST=0.7 pop=250			ST=0.7 pop=500		
	Fes=10000	Fes=50000	Fes=100000	Fes=10000	Fes=50000	Fes=100000	Fes=10000	Fes=50000	Fes=100000	Fes=10000	Fes=50000	Fes=100000
f1	4	3	8	6	6	7	2	9	9	4	10	9
f2	6	7	7	4	6	8	1	7	7	1	0	4
f3	8	7	7	5	6	7	0	4	5	0	2	2
f4	1	1	2	2	1	2	0	2	2	0	2	0
f5	0	0	1	0	0	2	0	0	2	0	1	0
f6	5	5	6	2	9	6	0	8	9	0	7	10
f7	0	0	0	0	0	0	0	0	0	0	0	0
f8	0	0	0	0	0	0	0	0	0	0	0	0
f9	1	2	5	2	5	8	0	10	10	0	2	6
f10	0	2	0	0	3	2	0	4	2	0	1	2
	25	**29**	**36**	**22**	**37**	**42**	**4**	**51**	**46**	**7**	**28**	**33**

Table 9. Max_FES Evaluation for ST=0.8 ve pop=50, 100, 250, 500

	ST=0.8 pop=50			ST=0.8 pop=100			ST=0.8 pop=250			ST=0.8 pop=500		
	Fes=10000	Fes=50000	Fes=100000	Fes=10000	Fes=50000	Fes=100000	Fes=10000	Fes=50000	Fes=100000	Fes=10000	Fes=50000	Fes=100000
f1	3	4	5	5	6	6	3	7	10	3	10	9
f2	2	6	7	0	8	7	0	6	8	0	1	4
f3	9	8	5	1	3	5	0	2	6	0	1	4
f4	0	1	2	0	5	4	0	2	2	0	0	0
f5	0	0	2	0	1	1	0	1	0	0	5	0
f6	3	1	5	9	8	7	0	5	10	0	7	5
f7	0	0	0	0	0	2	0	0	0	0	0	0
f8	0	0	0	0	0	0	0	0	0	0	0	0
f9	1	4	2	1	6	7	0	9	10	0	5	7
f10	0	0	0	3	3	1	0	3	2	0	4	0
	18	**28**	**28**	**19**	**41**	**40**	**0**	**39**	**48**	**3**	**37**	**29**

Table 10. Max_FES Evaluation for ST=0.9 ve pop=50, 100, 250, 500

	ST=0.9 pop=50			ST=0.9 pop=100			ST=0.9 pop=250			ST=0.9 pop=500		
	Fes=10000	Fes=50000	Fes=100000	Fes=10000	Fes=50000	Fes=100000	Fes=10000	Fes=50000	Fes=100000	Fes=10000	Fes=50000	Fes=100000
f1	5	7	4	5	6	9	3	9	10	2	9	9
f2	4	6	2	3	6	3	1	2	7	2	1	3
f3	4	7	4	4	4	4	0	0	5	0	2	4
f4	3	3	5	2	4	2	0	0	1	0	0	2
f5	1	5	0	0	1	4	0	0	1	0	0	0
f6	5	2	3	4	8	3	0	7	8	2	6	10
f7	0	0	0	0	0	0	0	0	0	0	0	0
f8	0	0	0	0	0	0	0	0	0	0	0	0
f9	6	4	5	3	10	4	0	8	10	0	9	9
f10	0	0	0	0	1	0	0	3	2	0	1	4
	29	**34**	**23**	**21**	**42**	**29**	**4**	**31**	**44**	**7**	**32**	**41**

When we analyze the results tables, the better results are obtained under Max_FES = 100000, ST = 0.1 and population size = 250 conditions. So, we select these parameters for the parameters of energy estimation modeling.

5. Electrical Energy Estimation Modeling for Turkey

The problem of electricity prediction can generally be divided into three categories: short-term prediction, medium-term prediction, long-term prediction. Short- and medium-term forecasts are used by power generation facilities. Long-term forecasting is the basis for energy system expansion planning for both developing and developed economies. Long-term forecasting requires historical data of selected indicators that will impact electricity consumption for all approaches used. The quality of forecasting models is based on current historical data and information on factors affecting energy demand [46].

This study aims to obtain Turkey's electricity consumption modeling and make long-term forecasts planning until 2025. For this purpose, the observed historical data given in Table 5.1 has been used. As it can be seen from Table 5.1, 4 indicators have been selected to model electrical energy: GDP, population, import, and export factors so this indicator selection is proper to the research in the literature. Because, these indicators are directly related to energy, especially electrical energy consumption. Obviously, as the population increases, more electricity will be consumed. Since import and export is a factor related to the manufacturing procedure in Turkey, it has a profound effect on electricity consumption. GDP, on the other hand, is a measure of all economic activities, and its increase means the development of livelihood standards and it has a huge effect on the increase in electricity consumption.

Here, data for GDP, population, imports, and exports are obtained from WORLD BANK, and electricity consumption is obtained from the Ministry of Energy and Natural Resources. In other words, the terminal set of TSp consists of GDP, population, import, and export indicators. As to the selection of the function set of TSp, 3 cases were evaluated. Since we aim to find the mathematical model for electrical energy, +, -, /, *, cos, sin, log, exp operations are considered for the function set. To the selection of the best function set, the conditions in Table 12 were evaluated. Then, the obtained results on these sets are given in Table 13.

Table 11. Turkey's data from 1992 to 2016

Years	GDP ($ 10^9)	Population (10^9)	Import ($ 10^9)	Export ($ 10^9)	Electricity consumption (10^9 kWh)
1992	158	55,748	27,485	22,806	67,217
1993	180	56,653	34,851	24,636	73,432
1994	131	57,564	26,64	27,918	77,783
1995	169	58,486	41,272	33,713	85,552
1996	181	59,423	50,499	39,095	94,789
1997	190	60,372	57,688	46,665	105,517
1998	276	61,329	54,343	56,721	114,023
1999	256	62,287	48,167	47,538	118,485
2000	273	63,24	61,562	53,091	128,276
2001	200	64,191	45,699	53,223	126,871
2002	238	65,143	54,838	58,321	132,553
2003	312	66,085	72,837	69,359	141,151
2004	405	67,007	102,691	92,091	150,018
2005	501	67,903	122,443	105,387	160,794
2006	552	68,763	146,413	119,616	174,637
2007	676	69,597	176,169	143,4	190
2008	764	70,44	206,983	174,469	198,085
2009	645	71,339	150,58	145,519	194,079
2010	772	72,326	196,452	157,845	210,434
2011	833	73,409	253,092	185,34	230,306
2012	874	74,569	249,766	206,849	242,37
2013	951	75,787	266,904	211,715	246,357
2014	934	77,03	258,3	222,003	257,22
2015	860	78,271	223,151	200,728	265,724
2016	864	79,512	214,64	189,717	278,345

Table 12. Different states of the set of functions

Symbols	F1	F2	F3
T	State1	State2	State3

F1={+, -, /, *}
F2={+, -, /, *, cos, sin}
F3={+, -, /, *, cos, sin, log, exp}
T={GDP, population, import, export}

Table 13. State evaluation for function set

Years	Actual value	Result(state1)	Error %	Result(state2)	Error %	Result(state3)	Error %
1992	67,217	76	13,750666	76	13,3301168	68	1,755218035
1993	73,432	78	6,7902607	73	0,3993447	72	1,934245057
1994	77,783	83	7,344982	91	16,5624388	78	0,049111845
1995	85,552	84	1,4071128	86	0,38639482	87	1,660233849
1996	94,789	98	2,8717127	86	8,87114211	95	0,546922132
1997	105,517	105	0,6098695	105	0,0548555	106	0,340278536
1998	114,023	115	0,7401371	118	3,1271778	118	3,515771466
1999	118,485	110	6,7993912	121	1,8217928	109	8,032168478
2000	128,276	113	11,870979	123	4,03510227	116	9,423535327
2001	126,871	128	1,2723127	127	0,11768867	117	7,537607004
2002	132,553	121	8,4077162	127	4,27258772	123	6,880203923
2003	141,151	130	7,547164	142	0,29946566	134	4,982794206
2004	150,018	150	0,2470101	152	1,12604286	152	1,055083397
2005	160,794	161	0,4032913	155	3,52466996	161	0,42707484
2006	174,637	174	0,3383503	181	3,45338055	172	1,309908166
2007	190	193	1,6294206	184	3,25110846	192	0,886661028
2008	198,085	219	10,50319	211	6,65273852	220	10,83969019
2009	194,079	198	2,2381921	216	11,095175	195	0,226930737
2010	210,434	207	1,5096242	211	0,32994913	206	2,241810805
2011	230,306	231	0,2824315	206	10,3898195	231	0,503045163
MAPE			**4,328191**		**4,65505**		**3,20741471**

The error between the actual value and the value obtained by TSp was calculated by absolute percentage error, and mean absolute percent error (MAPE) was chosen as the performance criterion of the algorithm (Equation 6).

$$\text{MAPE}=\frac{1}{N}\sum\left|\frac{actual-targeted}{actual}\right|*100 \quad (6)$$

As can be seen from the table, the smallest value of MAPE is observed in case 3. Therefore, for TSp, the function set F3 = {+, -, /, *, cos, sin, log, exp} was selected.
To evaluate the performance of TSp in electrical energy modeling, its results are compared with those obtained from applying GP to the same problem. In addition, the k-fold cross-validation method was applied to better evaluate the performance of both algorithms. For this purpose, the data between 1992 and 2016 were divided into 5 layers and one of them was held for testing and the remaining layers were used for training. Each program was run once and the results of the first model were recorded. Table 14 shows MAPE results for each algorithm in each layer.

Table 14. Comparison of TSp and GP

Error of Layers	TSp		GP	
	training	test	training	test
k1 (MAPE)	**4.0494**	7.34919	5.828	**6.29223**
k2 (MAPE)	**7.71094**	**7.63107**	10.9263	25.9011
k3 (MAPE)	**5.49096**	**3.05628**	6.34631	5.644
k4 (MAPE)	**4.41305**	**8.84297**	6.51932	9.40058
k5 (MAPE)	**5.10258**	**3.62744**	6.95984	8.61886
Mean of Error	5.35339	6.10139	7.31595	11.1714

The electrical energy models obtained by TSp and GP in each k layer are shown as follows:

The models produced by TSp

k1: (X4 + ((log ((X4 + X4)) + (X2 - (X4 - X4))) * (X2 / (X4 + ((log (X4) + (X2 - (X4 + ((log (X4) + (X2 - ((X4 + X2) - X4))) * (X2 / X4))))) * (X2 / X4))))))

k2: ((X2 + (X1 / log (((log (X2) + (X1 / log ((X2 * (X1 * X1))))) + (X2 + X2))))) + sin((X1 / (sin((X1 / (X1 / log ((X2 + (log (X2) + (X1 / log ((X2 * (X2 * X1)))))))))) / log ((X2 + (log (X2) + (X1 / log ((X2 * (X2 * X1))))))))))

k3: (((X2 + (X4 + X4)) - X3) + exp (exp (sin(exp ((X4 + X4))))))

k4: (((X2 + ((((X4 - sin((X4 - X3))) - sin((X4 - X3))) - sin((X4 - X3))) + (X4 - X3))) + (X1 / X2)) + cos((X3 + (X3 + X2))))

k5: ((sin((X3 - (X4 + X2))) + (sin((X3 - (X4 + X2))) + X4)) + (log ((((X4 + sin(((X3 - (X4 + (X4 - (X3 - X2)))) + sin(X4)))) + sin(((X3 - (X4 + X2)) + sin(X4)))) + X2)) - (X3 - (((X4 + sin(((X3 - (X4 + X2)) + sin(X4)))) + sin(((X3 - (X4 + X2)) + sin(X4)))) + X2))))

The models produced by GP

k1: (((X2 + X4) - (((X3 - sin(X3)) - (X4 / X3)) / log ((X2 * (X2 - log ((X2 * (((X2 + X4) - (X3 / X4)) / log ((X2 * (((X2 + X4) - (((X2 + X4) - (sin(X3) / (X2 / X2))) / X3)) - cos(X2))))))))))) - cos(X3))

k2: (X3 + ((X2 / log ((X1 / X2))) / log (log ((X1 / (X1 / (log (((log (X3) + cos(sin(cos(((X3 + (X2 / log (X3))) - X2))))) + (X3 + (X3 + X2)))) + X3)))))))

k3: (exp ((sin(X2) / (X4 - sin((X3 / X1))))) + (log ((sin((((X2 - X3) + X4) / X1)) / X4)) + ((X2 - exp (log ((X1 / (X2 - exp (log ((X1 / ((X2 - X3) + X3))))))))) + (X4 - sin(((((sin(X2) / X1) - X3) + X3) / X2))))))

k4: ((X4 + X2) + ((exp (cos((cos(cos(X2)) - (cos((X4 + X2)) - X3)))) - log (X3)) - log (X3)))

k5: (((X4 + X2) - log ((X4 + X4))) - log (X3))

As can be seen from the tables, except for the results on test data in k1, TSp shows better results in both training and test data in all layers. In addition, both algorithms attained successful results in the test data as well as in the training data (except GP in layer 2). In order to find the final model of electrical energy, TSp was run 4 times on 25 data (1992-2016) using the same control parameters and the models giving the results in Table 15 were obtained. The model in the 4th experiment with the smallest error was chosen as the electrical energy consumption model (Equation 7). The actual energy demand and estimated values are also figured in Fig. 4.
The estimation model of electrical energy is as follows:

$$
\begin{aligned}
&((\sin(X4) + \\
&((\cos(\cos(\log(((\cos(\cos(\log((X4 + \\
&(\cos(\cos(\log(X4))) + X4))))) * X4) + \\
&(\cos(\cos(\log(X3))) * \\
&(\cos(\cos(\log(((\cos(\cos(\log((X4 + X2)))) * \\
&X4) + (\cos(\cos(\cos(\log(X4)))) * X4))))) * \\
&X4)))))) * X4) + X2)) + \\
&\log((\cos(\cos(\log(((\cos(\cos(\log((X4 + X2)))) * \\
&X4) + (\cos(\cos(\cos(\log(X4)))) * X4))))) * X4)))
\end{aligned} \tag{7}
$$

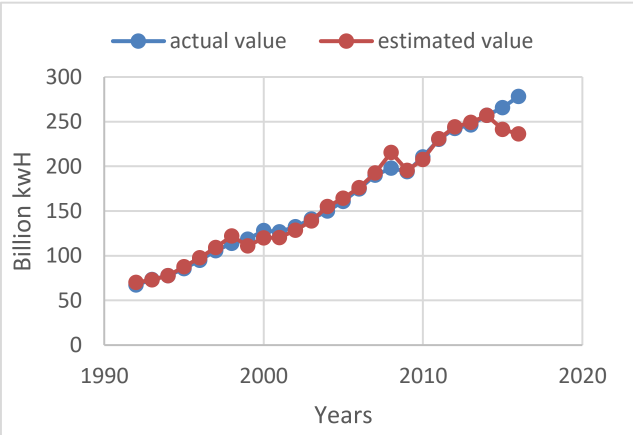

Figure 4. Comparison of the values of the energy model with the actual values

Table 15. Selection of electrical energy model

Years	Actual value	1st run	Error %	2nd run	Error %	3rd run	Error %	4th run	Error %
1992	67,217	73,79321	9,783555	76,719151	14,1365292	77,48925	15,28222	70,10921	4,302791
1993	73,432	74,53599	1,503417	76,332202	3,9495065	80,19131	9,204861	72,86392	0,773612
1994	77,783	88,30436	13,52655	87,08603	11,9602359	84,28706	8,3618	77,78017	0,003638
1995	85,552	86,98876	1,6794	85,387323	0,19248746	90,75864	6,085938	87,68983	2,49887
1996	94,789	92,5772	2,33339	94,017723	0,81367817	96,80561	2,127476	97,67912	3,048999
1997	105,517	100,5375	4,719152	102,93402	2,44792931	104,8485	0,633573	109,2529	3,54061
1998	114,023	120,4028	5,595145	123,90718	8,66858749	115,0729	0,920801	121,9863	6,983912
1999	118,485	108,7137	8,246906	116,01133	2,08775244	107,7147	9,089984	110,8598	6,435543
2000	128,276	113,3343	11,64808	114,43897	10,7869198	113,8604	11,23795	120,1053	6,369649
2001	126,871	126,4232	0,352975	126,75583	0,09077551	115,0129	9,346604	120,414	5,089397
2002	132,553	131,9636	0,444662	131,74367	0,61056872	120,7212	8,926076	128,3761	3,151088
2003	141,151	136,3915	3,371931	139,08063	1,46677955	131,7462	6,66296	139,0001	1,523849
2004	150,018	152,9454	1,951372	150,31242	0,19625358	152,6597	1,760918	154,8756	3,237981
2005	160,794	157,3068	2,168735	158,10301	1,67356513	164,8698	2,534819	164,2592	2,155084
2006	174,637	170,8324	2,178582	166,99749	4,37451005	177,4055	1,585287	176,1227	0,850735
2007	190	189,2901	0,37361	182,94721	3,71199467	196,2792	3,30482	192,7347	1,439323
2008	198,085	218,9496	10,53317	216,94516	9,52124634	217,2484	9,674308	215,7009	8,893095
2009	194,079	213,955	10,2412	219,80586	13,2558696	200,5961	3,35795	195,4969	0,730601
2010	210,434	204,8317	2,662282	199,18319	5,34647992	210,7516	0,150924	207,8536	1,226233
2011	230,306	213,5514	7,27494	199,38472	13,4261726	229,5447	0,330554	231,0135	0,307198
2012	242,37	248,5788	2,561687	244,22555	0,76558458	242,6216	0,103799	244,0538	0,694703
2013	246,357	242,8202	1,435643	236,83788	3,86395359	247,857	0,608892	249,3612	1,219443
2014	257,22	269,1014	4,61914	265,95208	3,39478998	255,2862	0,751812	257,0188	0,078212
2015	265,724	262,2066	1,323695	260,6869	1,89561301	248,4848	6,487628	241,2638	9,205133
2016	278,345	250,9333	9,848098	248,84692	10,597668	244,4952	12,16111	236,3904	15,07288
			4,815093		5,16941805		5,227722		3,553303

6. Estimation of electrical energy

In this section, it is aimed to find the estimated values of electricity between 2017-2025 by using the obtained electricity energy consumption model. For this purpose, the data in Table 11 is prepared for the estimation problem under different scenarios. Scenario 1 indicates that GDP increased by 0.7%, population by 1.6%, imports by 6.2%, exports by 4.8%, while scenario 2 shows that GDP increased by 8.8%, population by 1.5%, imports by 11.1%, exports by 10%. Forecasted values for electrical energy in 2017-2025 are given in Table 16 and Fig.5.

Table 16. Estimated values for electrical energy

Years	Scenario1 Electricity consumption	Scenario2 Electricity consumption
2017	242,714634	251,1928615
2018	252,6439915	265,3401234
2019	259,2632887	281,8077973
2020	269,3086822	296,4210462
2021	278,3193847	307,8388044
2022	285,9812313	319,7838084
2023	293,836533	328,2871161
2024	301,9541565	336,9941503
2025	310,27674	349,7675897

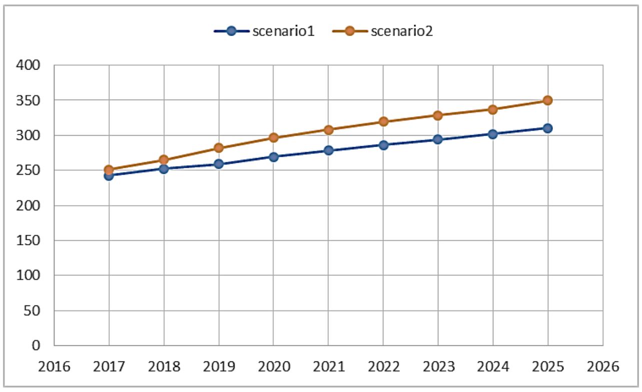

Figure 5. Estimation of electricity demand according to scenarios

As can be seen in Table 16 and Fig. 5, in both scenarios, close values for electricity consumption were estimated and these values increased gradually and reached 310,277 10^9 kWh in scenario 1 , 349,768 10^9 kWh in scenario 2 for 2025

7. Conclusion and Future Works

Energy has an important place in the economic, social, and technological development of a country. For this reason, many studies are done on energy modeling. Considering that the obtained reliable model allows predicting future energy consumption, this may prevent over-expenditure of energy resources, cost, or lack of energy.

In this study, as a technique for modeling Turkey's electricity consumption, the new version of TSA presented for automatic programming was used. TSA is a population-based, heuristic algorithm based on the relationship between a tree and its seeds. As an extended version of TSA, TSp is an automated programming approach that uses tree-based crossover for solution representation. In order to obtain the electrical energy model, the indicators affecting the consumption of electrical energy were determined and their historical data between 1992-2016 were used. GDP, population, import, and export were selected as indicators. The new TSp method was applied to 10 symbolic regression problems before applying it to the energy modeling problem. TSp, which has achieved good results on some functions, has shown that it is an applicable approach for different problems. GP was applied to the same problem in order to investigate the performance of TSp in energy modeling. To better evaluate the performance of both algorithms, the k-fold cross-validation method was used, GP and TSp results were compared in each layer. According to the results, TSp performed better on both test and training data. In order to obtain the electrical energy model to be used in the estimation problem, TSp was applied to all data in 1992-2016. This model has a 3.6% error and produced estimated electricity consumption under 2 scenarios for 2017-2025. For future works, it is planned that the programming version of TSA will be applied to the different problems.

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