Eurasian Journal of Educational Research 87 (2020) 137-156

Eurasian Journal of Educational Research
www.ejer.com.tr

Analysis of Human Performance in the Solution of Traveling Salesman Problem*

Kenan KARAGUL[1], Yusuf SAHIN[2], Necdet GUNER[3], Aykut ORAL[4]

ARTICLE INFO

Article History:
Received: 22 Aug. 2019
Received in revised form: 03 Dec. 2019
Accepted: 23 Feb. 2020
DOI: 10.14689/ejer.2020.87.7

Keywords
problem solving, optimization, cognitive researches

ABSTRACT

Purpose: Traveling Salesman Problem (TSP) that can be extended and modified in various ways, is a practical and realistic type of problem and forms the basis for the visual and spatial solution of many optimization problems. In this study, 15, 25 and 35 nodes Travelling Salesman Problems were solved by secondary school, high school and undergraduate students in order to examine human performance in the solution of TSP. In addition to this assessment, whether gender and education level had an impact on the quality of the solution was analyzed.
Research Methods: The categorical comparisons of solutions, male-female, and educational level were examined with the help of nonparametric statistical methods. In addition, for the three levels of education, the Kruskal-Wallis Test was applied to determine whether the difference between the education levels was significant. On the other hand, the performance of human solutions was compared with the heuristic methods found in the literature.
Findings: As a result, it was seen that the gender difference was not statistically significant for all problems. On the other hand, it was determined that the education level had a significant effect on the solutions. It can be concluded for the given problems that the human solutions produced as good results as the solutions obtained with other heuristic methods in the literature.
Implications for Research and Practice: The findings of the study confirm previous studies. By examining the effect of the factors that affect optimization strategies, it is possible to produce human-based TSP heuristic solutions that surpass all existing heuristic algorithms.

* This study was partly presented at the International Conference on Artificial Intelligence and Applied Mathematics in Engineering (ICAIAME 2019) in Antalya, 20–22 April, 2019.
[1] Pamukkale University, e-mail: kkaragul@pau.edu.tr, TURKEY, ORCID: 0000-0001-5397-4464
[2] Corresponding Author: Burdur Mehmet Akif Ersoy University, e-mail: ysahin@mehmetakif.edu.tr, TURKEY, ORCID: 0000-0002-3862-6485
[3] Pamukkale University, e-mail: nguner@pau.edu.tr, TURKEY, ORCID: 0000-0003-3338-7929
[4] Pamukkale University, e-mail: aykuthatay@gmail.com, TURKEY, ORCID: 0000-0003-3626-2136

Introduction

In the field of optimization, the performance of the developed methods is tested by solving classical and best-known problems. The Traveling Salesman Problem (TSP), one of the most studied optimization problems in the world, is an important classical optimization problem that is traditionally difficult to solve, although it seems to be a very simple problem (Jati, 2011, p. 393). In general, the main purpose of the problem is to find the shortest route for the salesman to visit a number of cities only once and return to the city where he lives. From a theoretical point of view, TSP is the problem of finding the shortest Hamilton cycle or round in an undirected finite network without multiple edges and cycles (Potvin, 1996, p. 339). This network is called G=(*N*, *E*) where the shortest Hamilton cycle is searched. In this network, *N* refers to a set of cities, and *E* refers to a set of paths that have a certain length that concatenates these cities (nodes) (Míča, 2015, p. 161). It consists of a network connection to each other of all nodes within the network. The aim is to find the shortest path to be followed while moving all the nodes back to the starting point.

After mathematical modeling by Dantzig et al. (1954), TSP has been an inspiration for modeling a number of integrated optimization problems such as order picking (Ratliff & Rosenthal, 1983), crew scheduling (Hoffman & Padberg, 1993), the assembly of printed circuit boards (Burke et al., 1999), path planning (Yu et al., 2002), and vehicle routing (Kim et al., 2010; Mazzeo & Irene, 2004) problems (Sahin & Karagül, 2019, p. 106). The time required for the most efficient algorithm to solve the TSP is an exponential function of the number of nodes in the problem. Therefore, it is one of the problems of NP-Hard class (Best & Simon, 2000, p.42). While small size problems can be solved easily with the help of analytical models, it is very difficult to solve large-scale problems within an acceptable period of time. With the Concorde software using the Lin-Kernighan-Helsgaun algorithm, it took 22 years to find the optimal results for Germany's 15.112 cities (Joines et al., 2017, p. 214).

In cases where the problem size is large, metaheuristic methods such as tabu search (Fiechter, 1994; Gendreau et al. 1998), genetic algorithm (Aytekin & Kalaycı, 2010; Chowdhury et al. 2013; Freisleben & Merz, 1996; Zhao et al. 2009), simulated annealing (Malek et al. 1989; Wang et al., 2013), ant colony optimization algorithm (Alaykıran & Engin, 2005; Dikmen et al. 2014; Montgomery & Randall, 2003; Mavrovouniotis & Yang, 2013; Stüzle & Hoss, 1997), particle swarm optimization (Dorigo & Gambardella, 1997; Wang et al., 2003), harmony search (Karagül et al. 2016), fluid genetic algorithm (Şahin & Karagül, 2019), and kangaroo algorithm (Erdem & Keskinturk, 2010) are used as a solution method to solve the problem in acceptable times.

Optimization studies can also be used for the analysis of human abilities in the context of problem-solving. In addition, decision making, engine control, and detection can also be modeled as optimization tasks. It can be said that using optimization tasks can be an effective way of examining human cognition in general and problem-solving in particular. Insight problems can be seen as a special kind of non-routine problem in which the problem solver is not familiar with the solution procedure. Verbal, mathematical, and spatial types of insight problems are included in the literature (Dow & Mayer, 2004, p.389). Another feature of the TSP is that it is a problem used for analyzing problem-solving performances of human subjects. From this point of view, it is obvious that the TSP can be used as a problem of spatial insight. Despite the computational complexity of TSP, previous studies show that human solvers produce near-optimal solutions for this problem within acceptable times (Dry & Fontaine, 2014, p. 84).

Macgregor and Ormerod (1996) found that human solvers found solutions better than other heuristics, and closer to the optimal for traveling salesman problems consisting of 10 and 20 cities. After this pioneering study, a lot of studies have been carried out in this field. Ormerod and Chronicle (1999) presented strong evidence that human TSP solution performance is based on global perceptual processing of the problem array. Best and Simon (2000) collected data by tracking the mouse and individual movements to analyze human performance in the solution of the TSP. The simulation and the data obtained suggest a solution method that includes a fast-global approximation followed by a local exact solution. Graham et al. (2000) compared the TSP solution performance of human subjects with heuristics methods and the solution performance of a new algorithm. The performance of the proposed new algorithm produced very similar results to the solution performance of the subjects.

Cutini et al. (2005) presented a computational model including the bottom-up and top-down effects, symbolizing human performance observed during the execution of a variant of the TSP task. Macgregor et al. (2006) compared the convex hull, the nearest neighbor and crossing avoidance heuristics and human performance in terms of path length, the overlap between solutions, and the number of crossings in solving open versions of the TSP. It is the convex hull method which shows the most similarity with the human solutions among the heuristic methods. Kong and Schunn (2007) investigated the relative role of global and local computing in solving the TSP. Within the scope of the study, an experiment was performed to measure the importance of global knowledge and possible constraints of global information processing in search. Haxhimusa et al. (2011) conducted two psychophysical experiments in which subjects solved TSP problems on the real and simulated ground, as well as a 3D volume. The results showed that the performance of the subjects and the performance on the computer screen were quite similar. Liew (2012) likened to social insect behavior and suggested convex layers to TSP based on the claim that the knowledge of uneducated people could help the TSP. In order to prove this idea, tour improvement algorithms were used in convex layers to find the most suitable tour for the 13-cites problem.

Blaser and Wilber (2012) compared the performance of the figural version of the TSP with navigation version of the same task. It was determined that there was no general difference in performance between figural and navigational task modes, as the number of nodes increased and performance decreased, while the NN strategy developed the most appropriate way. Dry et al. (2012) analyzed the spatial distribution factor of the human performance stimuli related to the TSP and the Minimum Spanning Tree Problem. The results of this study showed that the participants produced better quality solutions when the stimuli were highly clustered and highly regular. Dry and Fontaine (2014) presented participants with four different sets of TSP stimulants with relative solution challenges and asked them to indicate which of the four stimuli they would prefer to solve. The results showed that easy-to-dissolve stimuli were chosen at a higher frequency than those that were difficult-to-solve. Kyritsis et al. (2018) developed the cost-functionality within the nearest neighbor algorithm for heuristic scanning based on human processing. The results obtained show that the relation between the node to node and the distance from node-to-center can be used to closely model the average human performance in a series of ETSP (Euclidean TSP) graphs.

When the studies conducted to date are examined, it is seen that the subjects are more interested in their mental characteristics and problem-solving abilities, and the effect of characteristics such as education level, age and gender on problem solving performance is not investigated. The problem addressed in the study is also used for the analysis of the mental performance of students. Three randomly generated TSP datasets with 15, 25 and 35 nodes were used to evaluate students' problem-solving performances at different educational level and gender situations and the results were statistically analyzed. The aim of the research was to find answers to the following questions:

1. Does gender have an impact on problem-solving skills?
2. Does the level of education have an impact on problem-solving skills?
3. Are human solutions as effective as other heuristics?

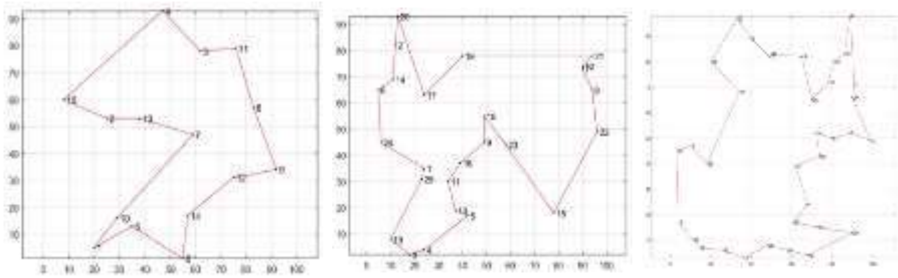
Method

Research Design

In this study, statistical comparisons were made with the data belonging to human solutions of TSP problems with 15, 25 and 35 nodes, respectively. The problems were solved by secondary school (SS), high school (HS), and undergraduate (UG) students. The categorical comparisons of solutions, male-female, and educational level were examined with the help of nonparametric statistical methods. The Mann-Whitney U test was used to determine whether the difference between genders was significant. In addition, for the three levels of education, the Kruskal-Wallis Test was applied to determine whether the difference between the education levels was significant.

Research Sample

For the solution of the data sets used, a tool which shows the position of the nodes on the paper for three problems was preferred. The graphical views of the problems are shown in Figure 1. A total of 320 volunteer students who did not have any prior knowledge of the TSP gave valid answers to the problems. The distribution of genders was 164 males and 156 females and, details are shown in Table 1. In the studies conducted to date, data obtained from 81 subjects were used (Macgregor & Ormerod, 1996; Vickers et al. 2003 etc.).



(a) 15-nodes problem (b) 25-nodes problem (c)35-nodes problem

Figure 1: Graphical Representation of Problems

Table 1.

Distribution of Students by Gender and Education Level

Gender	SS	HS	UG	Total
Female (F)	58	77	21	156
Male (M)	64	58	42	164
Total	122	135	63	

Research Instruments and Procedures

Three different TSP data sets were used in the study. The details of the problems used in the study are shown in Table 2 and Figure 1, respectively. The problems were designed as a network to enable students to respond to problem sets. Descriptive statistics related to the answers are shown in Table 3.

Table 2.

Characteristics of Problems

Problem	Number of nodes	Optimal solution
P1N15	15	340
P1N25	25	411
P1N35	35	462

Table 3.

Descriptive Statistics of the Solutions

Item	Pr.-Lev.-Gen.	Vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
1	**P1N15 – HS-FM**	1	77	374.52	69.57	350.00	358.71	13.34	340.00	780.00	440.00	3.78	16.25	7.93
2	**P1N15 – HS-M**	1	58	394.45	84.79	363.00	378.35	34.10	340.00	780.00	440.00	3.25	11.90	11.13
3	**P1N15 – SS- FM**	1	58	379.03	65.08	361.50	366.81	31.88	340.00	780.00	440.00	4.27	22.52	8.55
4	**P1N15 - SS - M**	1	64	374.69	79.79	349.50	356.71	13.34	340.00	780.00	440.00	4.18	17.99	9.97
5	**P1N15 – UG - FM**	1	21	389.14	99.38	348.00	366.29	11.86	340.00	780.00	440.00	2.90	8.48	21.69
6	**P1N15 – UG-M**	1	42	363.26	69.05	346.50	349.32	9.64	340.00	780.00	440.00	5.25	28.64	10.65
7	**P1N25 – HS-FM**	1	77	466.82	90.07	458.00	453.57	44.48	412.00	1170.00	758.00	6.22	45.39	10.26
8	**P1N25 – HS-M**	1	58	479.03	112.58	454.50	457.27	41.51	411.00	1170.00	759.00	4.44	22.83	14.78
9	**P1N25 – SS- FM**	1	58	665.59	329.22	477.00	639.33	80.06	411.00	1170.00	759.00	0.86	-1.25	43.23
10	**P1N25 - SS - M**	1	64	705.17	340.29	477.50	684.23	69.68	416.00	1170.00	754.00	0.62	-1.61	42.54
11	**P1N25 – UG - FM**	1	21	436.14	22.54	434.00	433.47	23.72	411.00	488.00	77.00	0.84	-0.53	4.92
12	**P1N15 – UG-M**	1	39	440.28	22.90	436.00	438.27	25.20	412.00	503.00	91.00	0.75	-0.12	3.67
13	**P1N35 – HS-FM**	1	77	553.52	177.74	512.00	521.57	34.10	462.00	1949.00	1487.00	6.40	46.54	20.26
14	**P1N35 – HS-M**	1	58	566.93	198.85	522.00	532.10	48.93	462.00	1949.00	1487.00	5.86	37.37	26.11
15	**P1N35 – SS- FM**	1	58	667.43	441.71	509.50	553.96	38.55	472.00	1949.00	1477.00	2.48	4.35	58.00
16	**P1N35 - SS - M**	1	64	672.88	452.76	504.00	548.17	25.20	475.00	1949.00	1474.00	2.40	3.92	56.59
17	**P1N35 – UG - FM**	1	20	502.20	37.85	491.00	495.50	17.05	462.00	611.00	149.00	1.56	1.54	8.46
18	**P1N35 – UG-M**	1	40	502.28	38.37	487.00	494.81	18.53	466.00	630.00	164.00	1.67	2.14	6.07
19	**P1N15 – HS-FM**	2	77	15.23	3.26	16.00	15.76	1.48	0.00	18.00	18.00	-3.92	15.72	0.37
20	**P1N15 – HS-M**	2	58	16.14	1.36	16.00	16.25	1.48	11.00	18.00	7.00	-1.28	2.83	0.18
21	**P1N15 – SS- FM**	2	58	12.17	1.77	12.00	12.33	0.00	0.00	14.00	14.00	-5.53	35.80	0.23
22	**P1N15 - SS - M**	2	64	12.58	0.77	12.00	12.48	0.00	12.00	14.00	2.00	0.86	-0.82	0.10
23	**P1N15 – UG - FM**	2	21	18.81	4.45	20.00	19.53	1.48	0.00	23.00	23.00	-3.54	12.32	0.97
24	**P1N15 – UG-M**	2	42	21.02	4.41	20.00	21.15	2.97	0.00	29.00	29.00	-2.18	9.91	0.68
25	**P1N25 – HS-FM**	2	77	15.23	3.26	16.00	15.76	1.48	0.00	18.00	18.00	-3.92	15.72	0.37
26	**P1N25 – HS-M**	2	58	16.14	1.36	16.00	16.25	1.48	11.00	18.00	7.00	-1.28	2.83	0.18
27	**P1N25 – SS- FM**	2	58	12.17	1.77	12.00	12.33	0.00	0.00	14.00	14.00	-5.53	35.80	0.23
28	**P1N25 - SS - M**	2	64	12.58	0.77	12.00	12.48	0.00	12.00	14.00	2.00	0.86	-0.82	0.10
29	**P1N25 – UG - FM**	2	21	18.81	4.45	20.00	19.53	1.48	0.00	23.00	23.00	-3.54	12.32	0.97
30	**P1N25 – UG-M**	2	39	20.82	4.48	20.00	20.97	2.97	0.00	29.00	29.00	-2.16	9.62	0.72
31	**P1N35 – HS-FM**	2	77	15.23	3.26	16.00	15.76	1.48	0.00	18.00	18.00	-3.92	15.72	0.37
32	**P1N35 – HS-M**	2	58	16.14	1.36	16.00	16.25	1.48	11.00	18.00	7.00	-1.28	2.83	0.18
33	**P1N35 – SS- FM**	2	58	12.17	1.77	12.00	12.33	0.00	0.00	14.00	14.00	-5.53	35.80	0.23
34	**P1N35 - SS - M**	2	64	12.58	0.77	12.00	12.48	0.00	12.00	14.00	2.00	0.86	-0.82	0.10
35	**P1N35 – UG - FM**	2	20	19.75	1.12	20.00	19.56	1.48	18.00	23.00	5.00	1.33	1.77	0.25
36	**P1N35 – UG-M**	2	40	20.95	4.50	20.00	21.06	2.97	0.00	29.00	29.00	-2.12	9.40	0.71

Because, as can be seen from the Figure 2, the distributions of the solution times are skewed to the right. This creates a problem of not being suitable for normal distribution. Therefore, it will not be possible to test the results with parametric hypothesis tests. For this reason, nonparametric hypothesis tests were used for testing hypotheses. In non-parametric hypothesis tests, the mass parameters to be tested do not have to conform to a distribution but are assumed to be distributed continuously. In addition, these methods allow easy calculation and fast results. In the statistical analyzes, R-Project program was performed with "psych" package. Histogram graphs were generated using the "ggplot2" package.

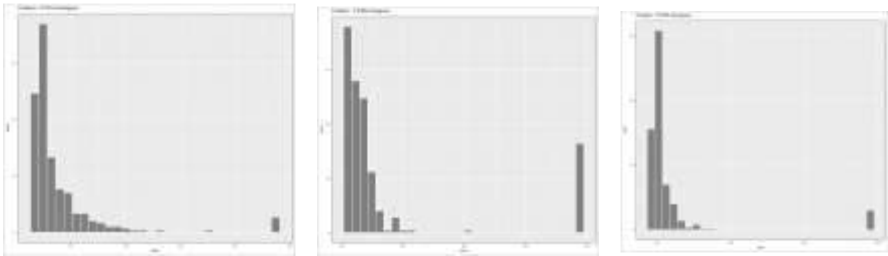


Figure 2: Solutions of Students (by Gender)

Results

Differences between Genders

The first analysis was performed on the basis of genders. The data do not conform to the normal distribution. For this reason, the non-parametric Mann-Whitney-Wilcoxon Test was used for the analysis. The hypothesis and the alternative hypothesis are as follows;

H_0: $The\ difference\ between\ the\ genders\ is\ not\ important.$

H_a: $The\ difference\ between\ the\ genders\ is\ important$

The results of the test are shown in Table 4. The level of education was not taken into account when analyzing by gender for this test. According to the analysis without considering the level of education, it is seen that gender has no effect on the quality of the solution.

Table 4.

Test Statistics by Gender

Problem	W.stat	p.Value	Results
P1N15	12581	0.79855	H_0 cannot be rejected.
P1N25	13145.5	0.47128	H_0 cannot be rejected.
P1N35	12404.5	0.85408	H_0 cannot be rejected.

Comparison of Genders on the Basis of Education Level

For each education level, the average of the gender-based solution was compared separately. For these comparisons, the training groups were tested with the Mann-Whitney U Test. The following hypothesis was used to test whether there is a gender difference for each level of education.

H_0: $The\ difference\ between\ the\ genders\ for\ each\ level\ of\ education\ is\ not\ significant.$

H_a: $The\ difference\ between\ the\ genders\ for\ each\ level\ of\ education\ is\ significant.$

Table 5.

Test Statistics Based on Educational Level

Level	Problem	W.stat	p.Value	Results
Secondary School	P1N15	1614	0.21473	H_0 cannot be rejected.
	P1N25	2028	0.37131	H_0 cannot be rejected.
	P1N35	1859	0.98977	H_0 cannot be rejected.
High School	P1N15	2724	0.02891	H_0 can be rejected.
	P1N25	2268.5	0.87635	H_0 cannot be rejected.
	P1N35	2494.5	0.24588	H_0 cannot be rejected.
Undergraduate	P1N15	389	0.44672	H_0 cannot be rejected.
	P1N25	465.5	0.3891	H_0 cannot be rejected.
	P1N35	386	0.83224	H_0 cannot be rejected.

When the results in Table 5 are analyzed, it is seen that gender had no effect on the solution for middle school and undergraduate students. On the other hand, it can be mentioned that there was an effect of gender at the high school level for only 15 node TSP. The details of the solutions' statistical analysis results for each level of education are presented in Table 6. For instance, as a result of the solutions made with the P1N15 data set, the average solution of males was 374.7 and the average of the women was 379.

Table 6.
Detail of the Statistics for Each Educational Level

Level	Groups	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
Secondary School	**P1N15 (M)**	64	374.7	79.79	349.5	356.71	13.3	340	780	440	4.18	17.99	9.97
	P1N15 (F)	58	379.0	65.08	361.5	366.81	31.9	340	780	440	4.27	22.52	8.55
	P1N25 (M)	64	705.2	340.3	477.5	684.23	69.7	416	1170	754	0.62	-1.61	42.5
	P1N25 (F)	58	665.6	329.2	477	639.33	80.1	411	1170	759	0.86	-1.25	43.2
	P1N35 (M)	64	672.9	452.8	504	548.17	25.2	475	1949	1474	2.4	3.92	56.6
	P1N35 (F)	58	667.4	441.7	509.5	553.96	38.6	472	1949	1477	2.48	4.35	58
High School	**P1N15 (M)**	58	394.5	84.79	363	378.35	34.1	340	780	440	3.25	11.9	11.1
	P1N15 (FM)	77	374.5	69.57	350	358.71	13.3	340	780	440	3.78	16.25	7.93
	P1N25 (M)	58	479.0	112.6	454.5	457.27	41.5	411	1170	759	4.44	22.83	14.8
	P1N25 (FM)	77	466.8	90.07	458	453.57	44.5	412	1170	758	6.22	45.39	10.3
	P1N35 (M)	58	566.9	198.9	522	532.1	48.9	462	1949	1487	5.86	37.37	26.1
	P1N35 (FM)	77	553.5	177.7	512	521.57	34.1	462	1949	1487	6.4	46.54	20.3
Undergraduate	**P1N15 (M)**	42	363.3	69.05	346.5	349.32	9.64	340	780	440	5.25	28.64	10.7
	P1N15 (FM)	21	389.1	99.38	348	366.29	11.9	340	780	440	2.9	8.48	21.7
	P1N25 (M)	39	440.3	22.9	436	438.27	25.2	412	503	91	0.75	-0.12	3.67
	P1N25 (FM)	21	436.1	22.54	434	433.47	23.7	411	488	77	0.84	-0.53	4.92
	P1N35 (M)	40	502.3	38.37	487	494.81	18.5	466	630	164	1.67	2.14	6.07
	P1N35 (FM)	20	502.2	37.85	491	495.5	17.1	462	611	149	1.56	1.54	8.46

Another analysis of the solutions obtained relates to the amount of deviation from the optimal solution values. Table 7 shows the deviation values for all problems. The deviation amounts were divided into 4 groups. For example, when the solutions of the secondary school students were examined for the first data set, it was found that 54.1% of the answers deviated from 0% to 5% of the optimal solution. The deviation values in the table are summarized in Figure 4. As can be seen from the table and figure, undergraduate students found the solution with the smallest deviation from the optimal.

Table 7.
Deviation of the Solutions from the Optimal Solution

Problem	Education level	0%-5%	5%-10%	10%-15%	>15%
P1N15	Secondary School (SS)	54.10%	16.40%	9.00%	20.50%
P1N15	High School (HS)	54.80%	14.80%	3.70%	26.70%
P1N15	Undergraduate (UG)	71.40%	6.30%	7.90%	14.30%
P1N25	Secondary School	20.50%	10.70%	16.40%	52.50%
P1N25	High School	31.10%	14.10%	23.70%	31.10%
P1N25	Undergraduate	46.70%	25.00%	21.70%	6.70%
P1N35	Secondary School	18.00%	36.90%	14.80%	30.30%
P1N35	High School	15.60%	28.10%	18.50%	37.80%
P1N35	Undergraduate	46.70%	28.30%	8.30%	16.70%

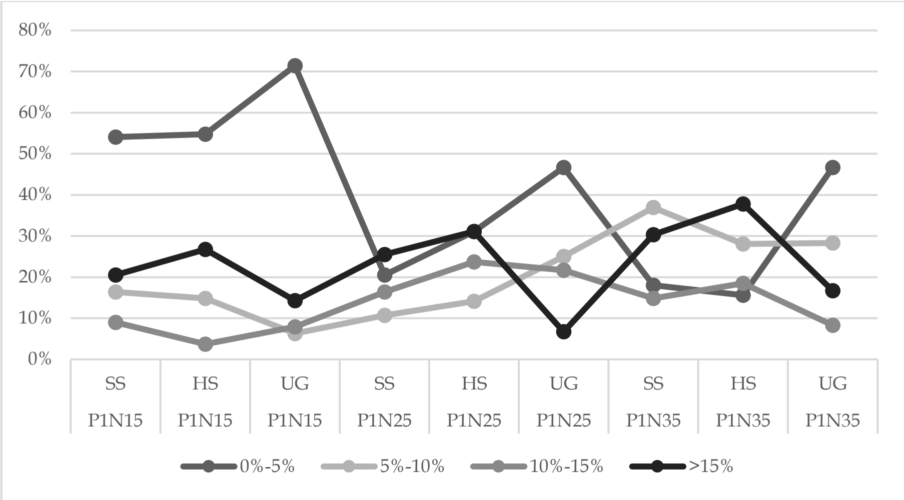


Figure 3: Comparing the Solutions According to the Level of Education and Gender

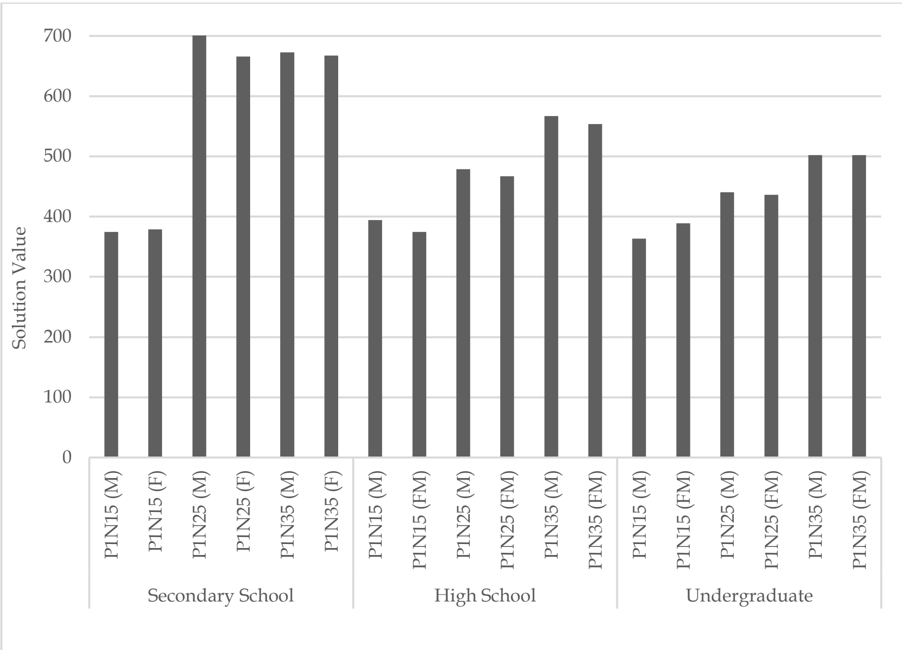


Figure 4: Solutions of Students (by Gender)

Analysis of the Difference between Education Groups

In this section, the effect of education level on the quality of solutions was analyzed. The hypothesis that the level of education has no effect on the quality of the solution has been tested with the Kruskal-Wallis test. Kruskal-Wallis test was used for non-parametric statistical methods to control the significance of the difference between the education groups. Accordingly, it was concluded that the difference between education levels was significant. The test statistics are shown in Table 8.

Table 8.
Test Results

Problem	Chisq	Df	p.value	Result
P1N15	9.12	2	0.01	H_0 can be rejected.
P1N25	45.14	2	0.00	H_0 can be rejected.
P1N35	23.36	2	0.00	H_0 can be rejected.

The significance level of the difference between education levels is shown in Table 9. As can be seen from Table 9, it was determined that there was no difference between the solutions of secondary and high school students in terms of education level for all problems, and the difference between the educational level of the undergraduate and the other education levels was significant.

Table 9.
Significance Level of the Difference between Levels of Education

Problem	Level	High School	Secondary School
P1N15	Secondary School	0.7616	-
	Undergraduate	0.0116	0.0646
P1N25	Secondary School	0.0000	-
	Undergraduate	0.0095	0.0000
P1N35	Secondary School	0.6049	-
	Undergraduate	0.0000	0.0005

The Comparison of Human Performance with Different Heuristics

In this section, the human solutions obtained are compared with the solutions obtained with the heuristic methods in the literature. For the comparison, the Convex Hall Insertion (CHI), the Nearest Neighbor (NN) and the Space-Filling Curve (SFC) methods were used. For the nearest Neighbor heuristic, two different approaches were used, where the beginning node was the first node (NN-1) and any node (NN-any). Logistics Engineering Matlab Toolbox (Kay, 2014) is used for these methods. Solutions obtained by heuristic methods and human solutions according to educational level are shown in Table 10.

Table 10.
Comparison of Human Solutions with Heuristic Algorithms

		Heuristic Methods				Average Solution Values		
Data Set	**Optimal**	**CHI**	**NN-1**	**NN-Any**	**SFC**	**SS**	**HS**	**UG**
P1N15	340	342.0	378.1	347.7	366.9	377	383	378
P1N25	411	519.9	470.5	444.2	484.6	684	472	439
P1N35	462	501.2	618.1	532.6	528.0	669	560	502

The deviations of the solution values from the optimal solution are shown in Table 11 and Figure 5. When the average deviation values were examined, it was seen that the deviation of the solutions provided by undergraduate students was lower than other students and heuristic methods. The highest deviation occurred in middle school students' solutions.

Table 11.
Deviation of the Solutions

Data Set	**CHI**	**NN-1**	**NN-Any**	**SFC**	**SS**	**HS**	**UG**
P1N15	0.60	11.20	2.26	7.93	10.88	12.65	11.18
P1N25	26.50	14.47	8.07	17.90	66.42	14,84	6.81
P1N35	8.48	33.79	15.29	14.29	44.81	21.21	8.66
Avarage	11.86	19.82	8.54	13.37	40.70	16.23	8.88

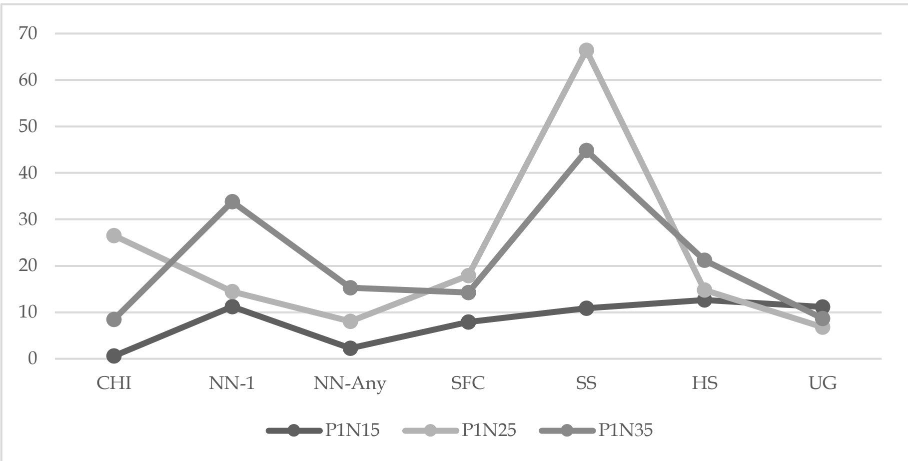


Figure 5: Deviation of the Solutions

Discussion, Conclusion and Recommendations

The analysis of human performance in the solution of optimization problems is a subject of intense interest from academics who have been working in the field of psychology over the past twenty-five years. The assessments prove that human subjects can produce good solutions even if they did not receive any training on the problem previously addressed, as in this study. However, the increase in the problem size leads to a decrease in the solution performance. At this point, although the solution performance decreases, the ability to produce good solutions to such a problem which is a very alternative solution in a short time shows that human beings have sufficient mental infrastructure for solving complex problems. From this point of view, the use of insight problems to explore human abilities and conduct research on cognitive processes will become more common.

The main purpose of this study was to analyze human performance in the solution of TSP problems. In previous studies (Mcgregor & Ormerod, 1996; Vickers et al., 2003 *etc.*), a small number of subjects were generally chosen among university students and did not evaluate whether different educational levels and gender had any effect on the solution. In this study, the effect of education level and gender was examined using the data of 320 subjects. From this point of view, analysis and comparisons were made for 4 different situations. First, it was evaluated whether the gender had an impact on the quality of the solution, regardless of the level of education. As a result of the non-parametric Mann-Whitney-Wilcoxon test which is applied because human solutions did not show a normal distribution , it has been determined that gender has no effect on solution performance (see Table 4). The second analysis was made to determine whether gender had an impact when considering the education levels. As a result of the analysis, it was determined that gender had an effect only among high school students for P1N15 data set and no such effect for others (See Table 5). The third comparison was made between educational levels. While there was no significant difference between the solutions of middle and high school students, the solutions of university students varied. It was concluded that the level of education affected the quality of the solution. The latest comparison was made between the solutions of heuristic methods in the literature and human solutions. The Convex Hull Insertion, the Nearest Neighbor (NN-1 and NN-Any) and the Space-Filling Curve methods were coded using Matlog Tool Box. The nearest neighbor was used in two different ways. The first version used was the NN-1 method, which started with the first node. The second version was the NN-Any method, which started from different nodes and provided the best solution as the final solution. When the average deviation from the optimal solution was examined, it was determined that university students produced very good solutions. These results also confirm the results of previous studies (Best & Simon, 2000; Haximusa et al. 2011; Macgregor & Ormerod, 1996; Ormerod & Chronicle, 1999; *etc*.). It is seen that human subjects are quite good at solving the traveling salesman problem. The ability of human subjects to solve the networked GSP is not affected by gender, but by education level. As the number of nodes increases, the impact of education on solution performance becomes more pronounced.

The present study was the first study conducted in Turkey in the relevant field. On the other hand, more subjects were studied compared to the previous studies. In future studies, it is considered that different insight problems can be applied to people for different gender and education level, and moreover, different school types can be included in the study. Developing healthy policies for the education system of the country can be ensured through the expansion of educational research. It is considered that these and similar studies can provide data that can guide education.

References

Alaykıran, K., & Engin, O. (2005). Ant colony metaheuristic and an application on traveling salesman problem. Journal of the Faculty of Engineering and Architecture of Gazi University, 20(1), 69-76. https://dergipark.org.tr/en/pub/gazimmfd/issue/6663/88878

Best, B. J., & Simon, H. A. (2000, March). Simulating human performance on the traveling salesman problem. In *Proceedings of the Third International Conference on Cognitive Modeling* (pp. 42-49).

Blaser, R. E., & Wilber, J. (2013). A comparison of human performance in figural and navigational versions of the traveling salesman problem. *Psychological Research*, 77(6), 761-772. https://doi.org/10.1007/s00426-012-0470-8

Burke, E. K., Cowling, P. I., & Keuthen, R. (1999). New models and heuristics for component placement in printed circuit board assembly. In *Proceedings 1999 International Conference on Information Intelligence and Systems (Cat. No. PR00446)* (pp. 133-140). IEEE.

Chowdhury, S., Tong, W., Messac, A., & Zhang, J. (2013). A mixed-discrete particle swarm optimization algorithm with explicit diversity-preservation. *Structural and Multidisciplinary Optimization*, 47(3), 367-388. https://doi.org/10.1007/s00158-012-0851-z

Cutini, S., Di Ferdinando, A., Basso, D., Bisiacchi, P. S., & Zorzi, M. (2005, July). A computational model of planning in the Traveling Salesman Problem. In *Proceedings of the twenty-seventh annual conference of the cognitive science society. Erlbaum, Mahwah*.

Dantzig, G.B., Fulkerson, D.R. & Johnson, S.M. (1954). Solution of a large-scale traveling salesman problem. *Operations Research*, 2(4), 393–410. https://doi.org/10.1287/opre.2.4.393

Dikmen, H., Dikmen, H., Elbir, A., Eksi, Z., & Çelik, F. (2014). Optimization and Comparison of Travelling Salesman Problem Using Ant Colony and Genetic Algorithms. Suleyman Demirel University Journal of Natural and Applied Science, 18(1), 8-13. https://dergipark.org.tr/tr/download/article-file/193799

Dorigo, M., & Gambardella, L. M. (1997). Ant colony system: a cooperative learning approach to the traveling salesman problem. *IEEE Transactions on evolutionary computation*, *1*(1), 53-66. https://doi.org/10.1109/4235.585892

Dow, G. T., & Mayer, R. E. (2004). Teaching students to solve insight problems: Evidence for domain specificity in creativity training. *Creativity Research Journal*, *16*(4), 389-398. https://doi.org/10.1080/10400410409534550

Dry, M. J., & Fontaine, E. L. (2014). Fast and Efficient Discrimination of Traveling Salesperson Problem Stimulus Difficulty. *The Journal of Problem Solving*, *7*(1), 84-93. https://doi.org/10.7771/1932-6246.1160

Dry, M., Preiss, K., & Wagemans, J. (2012). Clustering, randomness, and regularity: Spatial distributions and human performance on the traveling salesperson problem and minimum spanning tree problem. *The Journal of Problem Solving*, *4*(1), 1-17. https://doi.org/10.7771/1932-6246.1117

Erdem, Y., & Keskintürk, T. (2011). Kanguru Algoritması Ve Gezgin Satıcı Problemine Uygulanması. *İstanbul Ticaret Üniversitesi Fen Bilimleri Dergisi*, 10(19), 51-63. http://acikerisim.ticaret.edu.tr/xmlui/bitstream/handle/11467/608/M00434.pdf?sequence=1&isAllowed=y

Freisleben, B., & Merz, P. (1996, May). A genetic local search algorithm for solving symmetric and asymmetric traveling salesman problems. In *Proceedings of IEEE international conference on evolutionary computation* (pp. 616-621). IEEE.

Graham, S. M., Joshi, A., & Pizlo, Z. (2000). The traveling salesman problem: A hierarchical model. *Memory & cognition*, *28*(7), 1191-1204. https://doi.org/10.3758/BF03211820

Haxhimusa, Y., Carpenter, E., Catrambone, J., Foldes, D., Stefanov, E., Arns, L., & Pizlo, Z. (2011). 2D and 3D traveling salesman problem. *The Journal of Problem Solving*, *3*(2), 167-193. https://doi.org/10.7771/1932-6246.1096

Hoffman, K. L., & Padberg, M. (1993). Solving airline crew scheduling problems by branch-and-cut. *Management science*, *39*(6), 657-682. https://doi.org/10.1287/mnsc.39.6.657

Jati, G. K. (2011, September). Evolutionary discrete firefly algorithm for travelling salesman problem. In *International Conference on Adaptive and Intelligent Systems* (pp. 393-403). Springer, Berlin, Heidelberg.

Joines A., Kay, M.G., Karagul K., Tokat S. (2017). Performance analysis of Genetic Algorithm Optimization Toolbox via Traveling Salesperson Problem. In W. Sayers (Eds.) *Contemporary Issues in Social Sciencesand Humanities* (pp. 213-221), Landon, UK, AGP Research.

Karagul, K., Aydemir, E., & Tokat, S. (2016). Using 2-Opt based evolution strategy for travelling salesman problem. *An International Journal of Optimization and Control: Theories & Applications (IJOCTA)*, *6*(2), 103-113. http://dx.doi.org/10.11121/ijocta.01.2016.00268

Kay, M. (2014). *Matlog: Logistics Engineering Matlab Toolbox*. Retrieved from www.ise.ncsu.edu/kay/matlog/ Accessed 15.03.2018

Kim, B. I., Koo, J., & Park, J. (2010). The combined manpower-vehicle routing problem for multi-staged services. *Expert Systems with Applications*, *37*(12), 8424-8431. https://doi.org/10.1016/j.eswa.2010.05.036

Kong, X., & Schunn, C. D. (2007). Global vs. local information processing in visual/spatial problem solving: The case of traveling salesman problem. *Cognitive Systems Research*, *8*(3), 192-207. https://doi.org/10.1016/j.cogsys.2007.06.002

Kyritsis, M., Gulliver, S. R., Feredoes, E., & Din, S. U. (2018). Human behaviour in the Euclidean Travelling Salesperson Problem: Computational modelling of heuristics and figural effects. *Cognitive Systems Research*, *52*, 387-399. https://doi.org/10.1016/j.cogsys.2018.07.027

Liew, S. (2012). Introducing convex layers to the Traveling Salesman Problem. *arXiv preprint arXiv:1204.2348*.

MacGregor, J. N., & Ormerod, T. (1996). Human performance on the traveling salesman problem. *Perception & Psychophysics*, *58*(4), 527-539. https://doi.org/10.3758/BF03213088

MacGregor, J. N., Chronicle, E. P., & Ormerod, T. C. (2006). A comparison of heuristic and human performance on open versions of the traveling salesperson problem. *The Journal of Problem Solving*, *1*(1), 33-43. https://doi.org/10.7771/1932-6246.1005

Malek, M., Guruswamy, M., Pandya, M., & Owens, H. (1989). Serial and parallel simulated annealing and tabu search algorithms for the traveling salesman problem. *Annals of Operations Research*, *21*(1), 59-84. https://doi.org/10.1007/BF02022093

Mavrovouniotis, M., & Yang, S. (2013). Ant colony optimization with immigrants' schemes for the dynamic travelling salesman problem with traffic factors. *Applied Soft Computing*, *13*(10), 4023-4037. https://doi.org/10.1016/j.asoc.2013.05.022

Mazzeo, S., & Loiseau, I. (2004). An ant colony algorithm for the capacitated vehicle routing. *Electronic Notes in Discrete Mathematics*, *18*, 181-186. https://doi.org/10.1016/j.endm.2004.06.029

Míča, O. (2015, November). Comparison metaheuristic methods by solving travelling salesman problem. In *The international scientific conference INPROFORUM*, České Budějovice, Czech Republic (pp. 161-165).

Montgomery, J., & Randall, M. (2003). The accumulated experience ant colony for the traveling salesman problem. *International Journal of Computational Intelligence and Applications*, *3*(02), 189-198. https://doi.org/10.1142/S1469026803000938

Ormerod, T. C., & Chronicle, E. P. (1999). Global perceptual processing in problem solving: The case of the traveling salesperson. *Perception & Psychophysics*, *61*(6), 1227-1238. https://doi.org/10.3758/BF03207625

Potvin, J. Y. (1996). Genetic algorithms for the traveling salesman problem. *Annals of Operations Research*, *63*(3), 337-370. https://doi.org/10.1007/BF02125403

Ratliff, H. D., & Rosenthal, A. S. (1983). Order-picking in a rectangular warehouse: a solvable case of the traveling salesman problem. *Operations Research*, *31*(3), 507-521. https://doi.org/10.1287/opre.31.3.507

Sahin, Y., & Karagul, K. (2019). Solving travelling salesman problem using hybrid fluid genetic algorithm (HFGA). *Pamukkale University Journal of Engineering Sciences*, *25*(1), 106-114. https://doi.org/10.5505/pajes.2018.81084

Stützle, T., & Hoos, H. (1997, April). The MAX-MIN ant system and local search for the traveling salesman problem. In *Proceedings of IEEE international conference on evolutionary computation* (pp. 309-314).

Vickers, D., Bovet, P., Lee, M. D., & Hughes, P. (2003). The perception of minimal structures: Performance on open and closed versions of visually presented Euclidean travelling salesperson problems. Perception, 32(7), 871-886. https://journals.sagepub.com/doi/abs/10.1068/p3416

Wang Y., Tian D., Li Y. (2013) An Improved Simulated Annealing Algorithm for Traveling Salesman Problem. In Lu W., Cai G., Liu W., Xing W. (eds), Proceedings of the 2012 International Conference on Information Technology and Software Engineering. Lecture Notes in Electrical Engineering, vol 211. Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-642-34522-7_56

Wang, K. P., Huang, L., Zhou, C. G., & Pang, W. (2003, November). Particle swarm optimization for traveling salesman problem. In *Proceedings of the 2003 International Conference on Machine Learning and Cybernetics, 3, 1583-1585,* Xi'an, China.

Yu Z., Jinhai L., Guochang, G., Rubo Z., Haiyan, Y. (2002, June). An implementation of evolutionary computation for path planning of cooperative mobile robots. Proceedings of the 4th World Congress on Intelligent Control and Automation, Shanghai, China, (pp. 1798-1802). https://doi.org/10.1109/wcica.2002.1021392

Zhao F, Li S, Sun J, Mei D. (2009). Genetic algorithm for the one-commodity pickup-and-delivery traveling salesman problem. *Computers & Industrial Engineering*, 56(4), 1642-1648. https://doi.org/10.1016/j.cie.2008.10.014

Gezgin Satıcı Probleminin Çözümünde İnsan Performansının Analizi

Atıf:

Karagul, K., Sahin, Y., Guner, N., & Oral, A. (2020). Analysis of human performance in the solution of traveling salesman problem. *Eurasian Journal of Educational Research, 87,* 137-156. DOI: 10.14689/ejer.2020.87.7

Özet

Problem Durumu: Gezgin Satıcı Sorunu (GSP), bir dizi şehri ziyaret edecek satıcı tarafından kullanılacak en kısa rotayı belirleyen bir en uygun şekle sokma problemidir. Çeşitli şekillerde genişletilip değiştirilebilen GSP, pratik ve gerçekçi bir problem türü olmakla beraber birçok optimizasyon probleminin görsel ve mekânsal çözümünün temelini oluşturur. Optimizasyon alanında yoğun olarak çalışılan GSP insan yeteneklerinin problem çözme bağlamında analizi için de kullanılmaktadır. Diğer taraftan bu problem, karar verme, motor kontrolü ve algılama çalışmaları için de içgörü (insight) problemi olarak modellenebilmektedir. İçgörü problemleri, problem çözücünün çözüm prosedürüne aşina olmadığı özel ve rutin olmayan problemlerdir. Literatürde sözlü, matematiksel ve mekânsal içgörü problemlerinin kullanıldığı çalışmalar mevcuttur. Çalışma kapsamında deneklerin çözmesi istenen GSP insan deneklerin problem çözme performanslarını analiz etmek için kullanılan bir problemdir. Bu açıdan GSP'nin mekânsal bir içgörü problemi olarak kullanılabileceği aşikârdır. GSP'nin hesaplama karmaşıklığına rağmen, önceki çalışmalar insan çözücülerin kabul edilebilir zamanlarda bu sorun için en uygun çözümlere yakın olduklarını göstermektedir (Dry ve Fontaine, 2014, s.84).

Araştırmanın Amacı: Çalışma kapsamında üç soruya cevap aranmaktadır. Birinci aşamada, eğitim seviyesi dikkate alınmadan cinsiyetin problem çözme performansına bir etkisinin olup olmadığı araştırılmıştır. İkinci aşamada ise öğrencinin eğitim seviyesinin elde edilen çözüme etki edip etmediği analiz edilmiştir. Son olarak ise insan çözümlerinin bilimsel yazında bulunan ve GSP'nin çözümünde kullanılan sezgisel yöntemlerin çözümlerine kıyasla en iyi çözüme ne derece yaklaştığı belirlenmeye çalışılmıştır.

Araştırmanın Yöntemi: Çalışma kapsamında istatistiksel yöntemler ile sezgisel yöntemler kullanılmaktadır. İlk olarak farklı eğitim seviyelerinde bulunan öğrencilere 15, 25 ve 35 düğümlü GSP ağ şeklinde ifade edilerek çözmeleri istenmiştir. Öğrencilerden alınan cevaplar kullanılarak eğitim seviyesinin ve cinsiyetin çözüm performansına etkisini analiz etmek için parametrik olmayan Mann-Whitney-Wilcoxon ve Mann-Whitney-U testleri kullanılmıştır. Elde edilen insan çözümlerinin kalitesinin belirlenebilmesi için sezgisel yöntemlerle elde edilen çözümler kullanılmıştır. GSP'nin çözümü için bilimsel yazında birçok sezgisel ve metasezgisel yöntem olmakla birlik, çalışma kapsamında Dış Bükey Örtü Ekleme (Convex Hull Insertion), En Yakın Komşu ve Uzay Doldurma Eğrisi (Space Filling Curve) yöntemleri ile 15, 25 ve 35 düğümlü problemler çözülmüştür.

Araştırmanın Bulguları: Çalışmanın ana amacı GSP'nin çözümünde insan performansının analiz edilmesidir. Bu noktadan hareketle 4 farklı durum için analiz

ve karşılaştırmalar yapılmıştır. İlk aşamada eğitim seviyesi ve cinsiyet farkının çözüm kalitesi üzerinde bir etkisinin olup olmadığı analiz edilmiştir. İnsan çözümlerinin normal dağılım göstermemesi nedeniyle parametrik olmayan Mann-Whitney-Wilcoxon testi uygulanmış ve eğitim seviyesi dikkate alınmadığı durumda cinsiyetin çözüm kalitesi üzerinde anlamlı bir etkiye sahip olmadığı sonucuna ulaşılmıştır (bakınız Tablo 4). İkinci durumda ise cinsiyetin etkisi eğitim seviyesi dikkate alınarak analiz edilmiş ve cinsiyetin sadece lise düzeyindeki öğrencilerin çözümleri üzerinde P1N15 veri seti için etkili olduğu, diğer veri setleri ve eğitim seviyeleri için herhangi bir etkisinin olmadığı belirlenmiştir (bakınız Tablo 5). Üçüncü analiz sadece eğitim seviyeleri dikkate alınarak yapılmış ve üniversite öğrencilerinin yapmış oldukları çözümlemenin ortaokul ve lise seciyesindeki öğrencilere kıyasla anlamlı düzeyde farklılık gösterdiği belirlenmiştir. Buna göre eğitim seviyesi çözüm kalitesine etki etmektedir. Nihai ve son karşılaştırma ise sezgisel yöntemlerle elde edilen çözümler ve insan çözümleri arasında gerçekleştirilmiştir. Çalışma kapsamında kullanılan problemler Matlog Araç Kutusu (Kay, 2014) yardımıyla Dış Bükey Örtü Ekleme, En Yakın Komşu ve Uzay Doldurma Eğrisi yöntemleri ile çözülmüş ve elde edilen sonuçlar insan çözümleri ile kıyaslanmıştır. En Yakın Komşu yöntemi iki farklı versiyon olarak çalışmaya dahil edilmiştir. İlk versiyonda (NN-1) çözüme birinci düğümden başlanırken diğerinde (NN-Any) herhangi bir düğümden çözüme başlanabilmektedir. Her bir problem için optimal çözümden sapma değerlerinin ortalamaları dikkate alındığında lisans öğrencilerinin çözümlerinin oldukça iyi olduğu görülmektedir.

Araştırmanın Sonuçları ve Öneriler: Optimizasyon problemlerinin çözümünde insan performansının analizi, geçtiğimiz yirmi beş yıllık dönemde psikoloji alanında çalışmalar yapan akademisyenlerin yoğun şekilde ilgisi çeken bir konudur. Yapılan değerlendirmeler, bu çalışmada olduğu gibi daha önceden ele alınan problem ile ilgili bir eğitim almamış olsa bile insan deneklerin iyi çözümler üretebildiğini kanıtlar niteliktedir. Macgregor ve Ormerod (1996) tarafından yapılan ve 10 ile 20 düğümden oluşan problemde insan denekler iyi çözümler üretebilmiştir. Ancak yapılan bu çalışmada olduğu gibi problem boyutunun büyümesi çözüm performansında azalmayı da beraberinde getirmektedir. Bu noktada, böyle bir probleme kısa sürelerde iyi çözümler üretebilmesi insanoğlunun karmaşık problemlerin çözümünde yeterli zihinsel alt yapıya sahip olduğunu göstermektedir. Bu açıdan bakıldığında, insan yeteneklerini keşfetmek, bilişsel süreçlere ilişkin araştırmalar yapmak için içgörü problemlerinin kullanımı daha da yaygın hale gelecektir.

Yapılan kıyaslamalar neticesinde elde edilen sonuçlar geçmiş yıllarda yapılan çalışmaları (Macgregor ve Ormerod, 1996; Ormerod ve Chronicle, 1999; Best and Simon, 2000) doğrulamaktadır. İnsan deneklerin ağ şeklinde gösterilmiş GSP'yi çözme becerileri cinsiyetten etkilenmemekle beraber eğitim seviyesinden etkilenmektedir. Sunulan çalışma ilgili alanda Türkiye'de yapılan ilk çalışmadır. Gelecekte yapılacak çalışmalarda farklı içgörü problemlerinin de benzer şekilde farklı cinsiyet ve eğitim seviyesindeki kişilere uygulanabileceği, dahası farklı okul türlerinin çalışmaya dâhil edilebileceği değerlendirilmektedir.

Anahtar Sözcükler: Problem çözme, optimizasyon, bilişsel araştırmalar