

A CRITICAL APPROACH TO THE PARTICLE SWARM OPTIMIZATION METHOD FOR FINDING MAXIMUM POINTS

Mine SERTSÖZ & Mehmet FİDAN***

** Assist. Prof. Dr., Eskisehir Technical University,
TURKEY, e-mail: msertsoz@eskisehir.edu.tr
ORCID: <https://orcid.org/0000-0003-1641-9191>*

*** Assoc. Prof. Dr., Eskisehir Technical University,
TURKEY, e-mail: mfidan@eskisehir.edu.tr
ORCID: <https://orcid.org/0000-0003-2883-9863>*

Received: 8 January 2020, Accepted: 22 April 2020

ABSTRACT

Particle Swarm is an optimization method that is used for solving industrial problems and is highly preferred due to its ease of use and it's ability to find accurate results rapidly in recent years. In this study, it was used to optimize the resistance value of train sets.

There are many types of resistance in train sets and the train can't start moving until the traction motors overcome the resistances. Run resistance, ramp resistance, and curve resistance are the resistances that the train must overcome at a constant speed. However, it is known that the acceleration of high-speed trains is very high and the resistance that the train sets must overcome for the change in speeds is acceleration resistance.

This study aimed to calculate the acceleration, time, curve, ramp and distance, under certain constraints, for the total resistance value of YHT 65000 train by using the Particle Swarm Method as to obtain the minimum and maximum. Although, the results showed that the Particle Swarm Method returned very successful results for the minimum resistance, the same cannot be said for the maximum resistance.

Key Words: *Railway Systems, Energy Efficiency, Optimization, Particle Swarm Method.*

1. INTRODUCTION

Efficient use of energy is an important research topic in recent years. Efficient use of depleted resources, in spite of the increasing world population, is a precaution against a lack of energy in the future. Considering the sectoral productivity in Turkey, it was determined that there exists the potential for significant energy savings. The distribution is as follows: 30% in the building sector, 20% in the industrial sector, 15% in the transportation sector [1]. This study is an optimization problem for the energy efficiency of rail systems, which is an important part of the transportation sector.

Optimization of the rail system has many subheadings. These are the design of the train, the use of auxiliary equipment, (such as ventilation, the door opening and closing system), efficient driving, regenerative braking energy, route planning, energy storage, signaling, the construction phase etc. In fact, the aim of optimization in rail transport is to reduce energy consumption without compromising quality and reliability as in all optimization problems. In this section, some of the main studies in this field are given.

According to the efficient driving theory, it is seen that electricity savings will be between 15-35% [2], [3], [4], [5], [6], [7], [8], [9]. Another case study was carried out and a slight improvement in travel time was envisaged but energy savings rose by up to 6% in any subway [10]. It is important to know the energy consumption along curves, slopes, and at different speed, etc. for efficient driving. Optimization looks to achieve the best combination of all these parameters.

When it comes to the resistance of the train sets, and to examine the subject in more detail, the optimization process can be traced back to the oldest periods of development in the railways. Many researchers have made investigations in this field and have reached the empirical equations shared in the findings section. Studies in literature are mainly based on cruise resistance and their prediction models. Travel resistance was reported by Davis [11] in 1926 as follows:

$$R_s = AV^2 + BV + C$$

A is a constant which changes proportionally to the square of the speed and represents aerodynamic resistance caused by air pressure and friction.

B, is a constant which is responsible for mechanical resistances and HVAC (Heating, Ventilating and Air Conditioning).

C, is a constant which is not fixed to the vehicle speed, but is a function of weight.

In the past, detailed tests have been conducted to determine these constants. The cruise resistance coefficients of different trains were found for the Shinkansen. [12] In addition, different tests and cruise resistance tests were applied to the passenger cars and locomotives of Eurofim [13]. However, since the tests are very costly, different empirical equations have been developed in the past for estimating the resistance of certain trains. An overview of the methods adopted by the main national railways (up to 2000) and a calculation tool, to calculate cruise resistance, in which the effects of various characteristics of the train's architecture can be taken into account, are presented; these results are compared with the results of other equations for calculating train resistance [14].

More recently, Lukaszewicz has proposed a method that allows the determination of train resistance coefficients by measuring only train speed and position from full-scale cruise tests [15]. In this study, resistance was determined by the change in kinetic and potential energy of a train traveling between successful measurement points. Using this method [16], the same authors shared experimental results to determine the travel resistance of different trains and the

effect of variables such as speed, number of axles, number of wagons, axle load, road type and train length. Since 2005, a CEN (European Committee for Standardization) standard [17] has described methodologies for evaluating the coefficients of Davis's formula starting from a predictive formula, numerical simulations and reduced-scale tests from full-scale test measurements, but no strictly accepted methods have been obtained.

Cruise tests are performed to determine the speed dependent terms (A and B) according to CEN Standards. There is a need for a special test for term C, which means that the train is traveling at a very low speed. In order to find the coefficients A and B in the CEN standard, the regression method and the velocity history identification method were used. The first cruise test is based on the combination of all available experimental data and the second is based on the combination of the equation of motion. Both methods require a very good knowledge of the test section properties (slopes and curve radiuses).

In another study in the literature, the standard methods for determining Davis' coefficients were compared to new methods. In particular, it has been shown that the three coefficients of the Davis' formula can be estimated by two tests only, the first is a very low speed test on a high altitude slope section (without having to perform a traction test), and the second is a travel test starting at the train's maximum speed. It also proposed a regression method, which is a new method to define the A and B coefficients in the Davis equation. The main advantage of this method is that it does not need to know the characteristics and coefficient C of the railway line. Starting from experimental full-scale tests (characterized by a mass of 450 tonnes) scaled for a general ideal train; the entire procedure for determining travel resistance coefficients is described. The comparison of the results obtained by different methods for estimating the coefficients A and B of the Davis equation is presented and analyzed [18].

In this study, different from the above-mentioned studies, a single mathematical model was used to determine total resistance by using empirical equations which were accepted for all resistances. Then, it was determined how much acceleration, time, curve, ramp and distance are required for the minimum and maximum conditions of this model. For this purpose, the Particle Swarm Optimization (PSO) method is used.

2. METHOD

The method to find the optimum working point is the PSO method because, in both linear and non-linear problems, finding the roots of equations and solving industrial problems, (as in this study), are just some of the areas in which it is used. From a performance standpoint, both for speed and simplicity, it has advantages over other optimization techniques. PSO is one of the types of algorithms that respond well to intuitive and stochastic processes. It was named because it was inspired by the adaptation of living beings to their living conditions and by acting on intuition.

Details of this method are given below.

2.1 PSO Method

There are many algorithms which have been produced that reflect the behavior of living beings in nature. These include the Ant System [19], the Max-Min Ant System [20], Particle Swarm Optimization [21], Artificial Bee Colony [22], the Fruit Fly Optimization Algorithm [23], Cuckoo optimization based on Levy Flight [24], the Krill Herd Optimization Algorithm [25], Bakeri Foraging Behavior [26], the Bat Algorithm [27], the Firefly Algorithm [28], the Lion Algorithm [29], the Gray Wolf Algorithm [30], the Dolphin Algorithm [31], the Bush Colony Algorithm [32], the Artificial Algae Algorithm [33], the Virus Colony Search Algorithm [34], the Shark Olfaction Optimization Algorithm [35] and the Social Spider Algorithm [36].

Among all these algorithms, particle swarm optimization is the most cited intuitive intelligence algorithm with the cited number is 5721 [37]. This method was developed by a social psychologist and an electrical engineer about thirty years ago [21]. In fact, it is an algorithm developed entirely by studying the random behavior of fish and birds in order to survive. PSO is based on social information sharing among individuals in the swarm. The search is performed by the generation number as in the genetic algorithm. Here, in fact, individuals are called particles, and the community of these particles is called the swarm. This optimization, based on the experience of the previous position of the particle, each individual tries to approach the individual which is in the best position in the swarm. The speed of this approach is random and the assumption is that the next step is better than the previous one. This approach continues until it reaches the goal (i.e. the best position). Although it is similar to the genetic algorithm (GA) method, it is easier to use than GA and responds better in some studies.

In a PSO, a sequence of particles with random positions and velocities is initiated at size D. Dimension D is also equal to the unknown number in the conformity function. The goal here is to find the best value by updating its generations. At each iteration, each particle is updated according to the two “best” values. In fact there are two aspects to the best value. The first is the best suitability value a particle has ever found. This value is stored in memory for use later and is referred to as “pbest”, the best value of the particle. The second best value is the best fitness value that any particle in the swarm has ever achieved. This value is the global best value for the swarm and is called “gbest”. The speeds and positions are changed according to these new assigned values. The swarm particle matrix is nxD in size. where n is the number of particles.

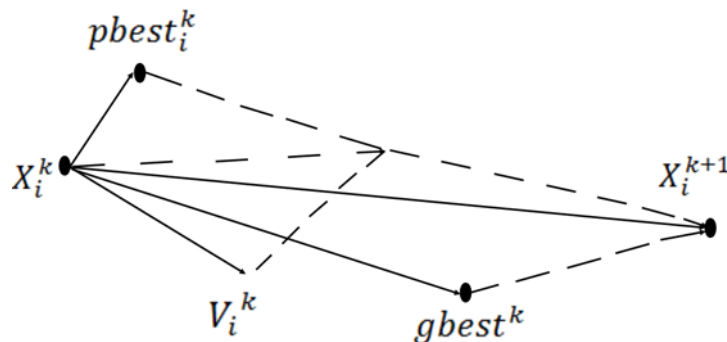
$$X = \begin{bmatrix} X_{11} & \cdots & X_{1D} \\ \vdots & \ddots & \vdots \\ X_{n1} & \cdots & X_{nD} \end{bmatrix} \quad (1)$$

Particle updates velocity (amount of change of position in each size) and position according to the following statements:

$$V_i^{k+1} = V_i^k + c1 * rand_1^k(pbest_i^k - x_i^k) + c2 * rand_2^k(gbest^k - x_i^k) \quad (2)$$

$$X_i^{k+1} = X_i^k + V_i^{k+1} \quad (3)$$

Figure 1. Working Principle of Particle Swarm Optimization (Eberhart, 1995)



Particle number: There are 20 to 40. For many problems it is enough to use 10 particles, while for some difficult or special problems it may be necessary to use 100 or 200 particles.

Particle dimension: It depends on the problem to be optimized.

Particle spacing: Particles of different sizes and ranges can be identified, depending on the problem to be optimized.

Vmax: In an iteration, it determines the maximum change (velocity) in a particle. It is usually determined by particle spacing.

Learning Factors: c_1 and c_2 are generally selected as 2. But different values can also be selected.

Stop Condition: The algorithm can be stopped when the maximum number of iterations is reached or the value function reaches the desired level. For multiple model problems, the PSO algorithm often fails to achieve satisfactory results due to early convergence [38], [39]. The solutions obtained using the standard PSO algorithm are also unsatisfactory for some single model problems. Since PSO is not guaranteed to approach the local optimum [40], solutions are often developed using finely tuned local search methods [41], [42], [43]. Therefore, neither the search nor the search mechanism in the standard PSO algorithm is sufficient for different types of problems. In order to improve research efficiency and address the shortcomings in the standard algorithm, researchers have proposed some changes to the PSO method [44].

3. YHT 65000 FAST TRAIN

This train is a high-speed train model that is currently used in Turkey. It is a high speed train set produced by the Spanish railway manufacturer Construcciones y Auxiliar de Ferrocarriles (CAF).

YHT 65000 trains are based on the trains that RENFE (Red Nacional De Ferrocarriles Espanoles) Class with 120 trains use in Spain. A set consists of 6 cars as standard. In this study, it was thought that there were 6 cars. However, it has a modular structure and 2 more cars can be added if desired. In addition, 2 sets can be combined to form a total of 12 cars. Before this study, the technical information of the high-speed train used in the study is given in Table 1.

Table 1. Technical Information of High Speed YHT 65000 Train *

Main Characteristics	YHT 65000
Power	38400 kW
Lokomotive Load	297,25 Ton
Axle Load	17 Ton
Axle Type	-
Maximum Velocity	275 km/h
Line Gap	1435 mm
Catenary Type	AC 25 kV, 50 Hz
Traction Motor Power	AC 4800 kW

*Obtained from TCDD (Turkish State Railways).

Figure 2. YHT 65000 High Speed Train (<https://sites.google.com>)



4. RESULTS

In this study, four resistances which prevent the movement of high speed trains were calculated. These were cruise resistance (car resistance and locomotive resistance, not as a separate resistance in high-speed train sets (one resistance)), curve resistance, ramp resistance and acceleration resistance. Since wind resistance is a chaotic resistance, it was not taken into account. It should be noted that these resistors directly affect power consumption. In this case, it is possible to express the total resistance (RT) equation as follows (G is the total load carried in tonnes):

Cruise Resistance:

$$R_s = (1,3953 - 0,0071 * V + 0,0006 * V^2)G \quad (1)$$

Since cruise resistance exists for a high-speed train set, it consists of a single resistance provided by the manufacturer, which is inseparable as car and locomotive resistance.

Curve Resistance:

$$R_k = \left(\frac{650}{k-55}\right)G \quad (2)$$

This curve resistance formula is known as the Röcki formula and is used for 1435 mm line length. The k value in the equation is the curvature radius of the line in m.

Ramp Resistance:

$$R_r = rG \quad (3)$$

r is the ramp value in ‰. This value is taken as positive when climbing the ramp and negative when descending.

In order for the train set to move, it must overcome these resistances. A train can only move with "Steady" velocity after overcoming these resistances. At steady velocity, there is no

acceleration (a) (it is equal to zero) according to Newton's 1st Law. There is one more resistance must be overcome when the train wants to change its velocity. This resistance is called as acceleration resistance.

Acceleration Resistance:

$$R_a = \left(\frac{4V^2}{S}\right)G \tag{4}$$

The acceleration resistance given above is the acceleration resistance of the train set. S refers to the line.

While there is no acceleration in the first three resistance types, but in the fourth one, there is a rise in acceleration resistance when the speed changes. The power consumption is determined by applying the PSO method to the total resistance formula given below.

$$R = R_s + R_k + R_r + R_a \tag{5}$$

The equation in full is written as:

$$R = \left(V^2 \left(0.0006 + \frac{4}{S}\right) - 0.0071V + 1.3953 + \frac{650}{K-55} + r\right)G \tag{6}$$

$$V = at \tag{7}$$

In this study, resistance was minimized and maximized in 20 iterations with the Particle Swarm Optimization Method. Constraints and results (Table 2.) are given below.

Constraints:

$-28\text{m/s}^2 < a < 28\text{ m/s}^2$ (acceleration)

$1\text{ s.} < t < 3600\text{ s.}$ (time)

$-\%26 < r < \%26$ (ramp)

$130\text{ m.} < k < 530\text{ m.}$ (curve)

$0\text{ m.} < S < 300\text{ km.}$ (distance)

Table 2. Values Found Using the Swarm Particle Method

	a	t	r	k	S
Situations for the Least Resistance	10 m/s ²	0 s.	-%26	530 m.	300 km.
Situations for the Highest Resistance	-18.2 m/s ²	3163 s.	-%19.2	206 m.	10 m.

Table 2 shows that the total resistance is the smallest gave quite reasonable results. Resistance values are the smallest values except for acceleration resistance. However, in cases where resistance is the highest different results have been obtained instead of expected upper limits.

5. CONCLUSION

By means of the PSO method used, the points where the least power was consumed, so the minimum resistance, were found in the extreme constraints given, with the exception of acceleration. However, the acceleration, time, curve, ramp and distance values make the highest resistance not be obtained correctly with the PSO method. This is due to the fact that the number of iterations, 20, was not sufficient to find the parameters that make the lowest resistance value, but not enough to find the highest resistance.

Two solutions can be proposed here. The first one is that the number of iterations can be increased and more accurate results can be obtained. when the number of iterations is 1000, the results are more accurate, but this greatly extends the test runtime and it becomes impractical. While 20 iterations were 1.88 s, it was 795 s for 1000 iterations. So the time increased almost 422.87 times.

A second way is to keep the number of iterations of the particle swarm optimization method at 20 again while finding the maximum resistance, but by hybridizing the optimization method with a different method to eliminate the disadvantages of the rapid convergence of PSO. Thus, the right result can be achieved and save time. The authors plan to create such a method as a second step.

REFERENCES

- [1] DOĞAN, H., YILANKIRKAN, N., “Türkiye’nin Enerji Verimliliği Potansiyeli ve Projeksiyonu”, Gazi Üniversitesi Fen Bilimleri Dergisi Part:C, Tasarım Ve Teknoloji GU J Sci Part:C 3(1):375-383 (2015).
- [2] RSSB. T618 technical report: improving the efficiency of traction energy use. London: RSSB; 2007.
- [3] ANDERSON, R., MAXWELL, R., HARRIS, N. “Maximizing the potential for metros to reduce energy consumption and deliver low-carbon transportation in cities”, Working paper for the CoMET and Nova Metro Benchmarking Groups; 2009.
- [4] KOKKEN, K. “The reduction of energy consumption in EMU trains”, 6th World congress on railway research (WCRR), Edinburgh; 2003.
- [5] BOCHARNIKOV, Y., TOBIAS, A., ROBERTS, C., HILLMANSEN, S., GOODMAN, C. “Optimal driving strategies for traction energy saving on DC suburban railways”, IEEE Electr Power Appl 2007;1:675–82.
- [6] CORAPI, G., DE MARTINIS, V., PLACIDO, A., DE LUCA, G. “Impacts of energy saving strategies (ESSs) on rail services and related effects on travel demand”, WIT transactions on the built environment, Rome; 2014.
- [7] HULL, G., ROBERTS, C., HILLMANSEN, S. “Simulation of energy efficiency improvement on commuter railways”, IET conference on railway traction systems, Birmingham; 2010.
- [8] HU, W., SUN, Q., LV, J. “Research on subway trains’ energy conservation running based on PSO”, International conference on information science, electronics and electrical engineering (ISEEE), Sapporo; 2014.
- [9] RODRIGO, E., TAPIA, S., MERA, JM., SOLER, M. “Optimizing electric rail energy consumption using the lagrange multiplier technique”, J Transp Eng 2013;139(3):321–9.
- [10] XIN, T., ROBERTS, C., HE, J., HILLMANSEN, S., ZHAO, N., CHEN, L., ve diğerleri “Railway vertical alignment optimisation at stations to minimise energy”, IEEE 17th international conference on intelligent transportation systems, Qingdao; 2014.
- [11] DAVIS Jr., W.J., “The tractive resistance of electric locomotives and cars”, Gen. Electr. Rev, 29, 2-24, 1926.
- [12] HARA, T., OHKUSHI, J., NISHIMURA, B., “Aerodynamic drag of trains”, Q. Rep. RTRI, 8 (4), 226-229, 1967.
- [13] Report ERRI C, 179/RP 9, Utrecht, April, 1993.
- [14] ROCHARD, B.P., SCHMID, F., “A review of methods to measure and calculate train resistances”, Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit, 214(4), 185-199, 2000.
- [15] LUKASZEWICZ, P., “A simple method to determine train running resistance from full-scale measurements”, Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit, 221(3), 331-337, 2007.
- [16] LUKASZEWICZ P., “Running resistance - Results and analysis of full-scale tests with passenger and freight trains in Sweden”, Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit, 221 (2), 183-193, 2007.

- [17] EN 14067-4 (2005) - A1 (2009). Railway applications - Aerodynamics – Part 4: Requirements and test procedures for aerodynamics on open track.
- [18] SOMASCHINI, C., ROCCHI, D., TOMASINI G. and SCHITO P. “Simplified Estimation of Train Resistance Parameters: Full Scale Experimental Tests and Analysis”, Proceedings of the Third International Conference on Railway Technology: Research, Development and Maintenance 2016; Paper 58.
- [19] DORIGO, M., MANIEZZO, V., COLORNI A., “The Ant System: Optimization by a colony of cooperating agents”, IEEE Transactions on Systems, Man, and Cybernetics– Part B, Vol.26, No.1, 1996, pp.1-13. DOI: 10.1109/3477.484436.
- [20] STUTZLE, T. ve HOOS, HH, “The Max-Min ANT System and Local Search for Combinatorial Optimization Problems”, June 2000 Future Generation Computer Systems 16. DOI: 10.1007/978-1-4615-5775-3_22.
- [21] EBERHART, R. C. and KENNEDY, J., “A new optimizer using particle swarm theory”, Proceedings of the Sixth International Symposium on Micro Machine and Human Science, Nagoya, Japan, 39-43. Piscataway, NJ: IEEE Service Center, 1995.
- [22] KARABOGA, D., BASTURK, B., “Sayısal fonksiyon optimizasyonu için güçlü ve verimli bir algoritma: Yapay arı kolonisi (ABC) algoritması”, Journal Of Global Optimazition 39(3) (2007).
- [23] PAN, W., “A new Fruit Fly Optimization Algorithm”, Taking the financial distress model as an example”, Knowledge-Based Systems, Volume 26, February 2012, Pages 69-74. DOI: 10.1016/j.knosys.2011.07.001
- [24] YANG, X.S. DEB, S., “Cuckoo Search via Lévy flights”, 2009 World Congress on Nature & Biologically Inspired Computing (NaBIC), 9-11 Dec. 2009, DOI:10.1109/NABIC.2009.5393690.
- [25] GANDOMI, A.H., ALAVI A.H., “Krill Herd: A new bio-inspired optimization algorithm”, Communications in Nonlinear Science and Numerical Simulation Volume 17, Issue 12, December 2012, Pages 4831-4845. DOI: 10.1016/j.cnsns.2012.05.010.
- [26] PASSINO, K.M., “Biomimicry of bacterial foraging for distributed optimization and control”, IEEE Control Systems Magazine, Volume: 22 , Page(s): 52 - 67 Issue: 3 , June 2002. DOI: 10.1109/MCS.2002.1004010.
- [27] YANG, X.S., “A New Metaheuristic Bat-Inspired Algorithm”, International Workshop on Nature Inspired Cooperative Strategies for Optimization (NICSO 2008), Tenerife Spain, (2008).
- [28] YANG X.S., “Lecture Notes in Computer Science ”, 5792 (2009) 169-178.
- [29] RAJAKUMAR B.R., Procedia Technology 6 (2012) 126-135.
- [30] MIRJALILI, S., MIRJALILI, S.M., LEWIS A., “Grey Wolf Optimizer”, Advances in Engineering Software Volume 69, March 2014, Pages 46-61. DOI: 10.1016/j.advengsoft.2013.12.007.
- [31] KAVEH, A., FARHOUDI, N., “A new optimization method: Dolphin echolocation”, May 2013 Advances in Engineering Software 59:53–70. DOI: 10.1016/j.advengsoft.2013.03.004.
- [32] MEHRABIAN, A.R., LUCAS C., “A novel numerical optimization algorithm inspired from weed colonization”, Ecological Informatics 1 (4): 355-366 (2006) DOI:10.1016/j.ecoinf.2006.07.003.

- [33] UYMAZ, S.A., TEZEL, G., YEL E., “Artificial algae algorithm with multi-light source for numerical optimization and applications”, *Biosystems*. 2015 Dec;138:25-38. DOI: 10.1016/j.biosystems.2015.11.004. Epub 2015 Nov 10.
- [34] LI, M.D., ZHAO, H., WENG, X.W., HAN T., “A novel nature-inspired algorithm for optimization: Virus colony search”, *Advances in Engineering Software* 92:65-88, February 2016. DOI: 10.1016/j.advengsoft.2015.11.004.
- [35] ABEDINIA, O., AMJADY, N., GHASEMI, A., “A new metaheuristic algorithm based on shark smell optimization”, *Complexity* Volume 21, Issue 5, 2014. DOI: 10.1002/cplx.21634.
- [36] YU, J.J.Q., LI, V.O.K., “A Social Spider Algorithm for Global Optimization”, *Applied Soft Computing*, 2015, v. 30, p. 614-627. DOI: 10.1016/j.asoc.2015.02.014.
- [37] ERDOĞMUŞ, P., “Doğadan Esinlenen Optimizasyon Algoritmaları ve Optimizasyon Algoritmalarının Optimizasyonu”, *Düzce Üniversitesi Bilim ve Teknoloji Dergisi*, 4 (2016) 293-304.
- [38] LIANG, J.J., QIN, A.K., SUGANTHAN, P.N., BASKAR, S., “Comprehensive learning particle swarm optimizer for global optimization of multimodal functions, *IEEE Transaction on Evolutionary Computation*, Vol. 10(3), pp. 281-295, 2006.
- [39] SEVKLI, Z., SEVILGEN, E., “A Hybrid Particle Swarm Optimization Algorithm for Function Optimization”, *EvoWorkshop'08. LNCS* Vol. 4974, pp. 585-595, 2008.
- [40] VAN DEN BERG, F., ENGELBRECHT, A., “A new locally convergent particle swarm optimizer”, *Proceeding of IEEE Conference on System, Man and Cybernetics*, pp. 96-101, 2002.
- [41] FAN, S.K., ZAHARA, E. “A hybrid simplex search and particle swarm optimization for unconstrained optimization”, *European Journal of Operational Research*, Vol. 181, pp. 527-548, 2007.
- [42] LIU, B., WANG, L., JIN, Y-H., TANG, F., HUANG, D.X., “Improved particle swarm optimization combined with chaos”, *Chaos Solutions & Fractals* Vol.25, pp. 1261-1271, 2005.
- [43] SHELOKAR, P.S., SIARRY, P., JAYARAMAN, V.K. KULKARNI, B.D., “Particle swarm and ant colony algorithms hybridized for improved continuous optimization”, *Applied Mathematics and Computation*, Vol.188, pp.129-142, 2007.
- [44] SEVKLI, A.Z., SEVILGEN F.E., “StPSO: Strengthened particle swarm optimization”, *Turk J. Elec. Eng & Comp Sci*, Vol.18, No.6, 2010, TÜBİTAK. doi:10.3906/elk-0909-18.

