JISTA

Journal of Intelligent Systems: Theory and Applications

JUNE 2018 WWW.JISTA.INFO

VOL 1 NO 1

ARTIFICIAL INTELLIGENT > MACHINE LEARNING > MULTI-AGENTS

WWW.JISTA.INFO

Journal of Intelligent Systems: Theory and Applications 1(1) 2018: 1-4.

Significance of Artificial Intelligence in Science and Technology

Zekâi Şen [1*]

[1] *Istanbul Medipol University, Engineering and Natural Sciences Faculty, Civil Engineering Department, Kavacık, Istanbul, Turkey*

Abstract

Intelligence is composed of harmonious and proportional connection of different human abilities among which are mind, cleverness, rationality, intuition, ambition, interest, culture, belief, scientific information treatment and alike gifts given by Allah. Every individual has intelligence level at different scales and levels; there is no one who is immune of these abilities. The intellectual intelligence might be at the static level without any research and development for the betterment of human beings in the society. Although natural human intelligence has been in existence since the creation of man and woman (Adam and Eve), but it took centuries to reach todays intellectual level after a series of philosophical thinking and logical propositions. Unfortunately, today, in many disciplines and societies human intelligence reflection to science and technology has been overlooked and consequently such societies are lacking behind well developed countries. This paper provides brief review and suggestions for artificial intelligence significance through the historical perspective and methodological (models and machines) aspects. It is advised that for innovative inventions or at least partial modification of existing scientific and technologically available methodologies human intelligence must shed light rather than classical, repetitive and imitative approaches.

Keywords: Artificial, intelligence, logic, machine, model, philosophy, robot.

Bilim ve Teknolojide Yapay Zekanın Önemi

Öz

Zeka; Allah'ın verdiği zihin, akıl, sezgi, hırs, ilgi, kültür, inanç, bilimsel bilgi davranışları olmak üzere farklı insan yeteneklerinin ahenkli ve orantılı bağlantısından oluşur. Her birey farklı ölçek ve seviyelerde zeka seviyesine sahiptir; Bu yeteneklerden etkilenmeyen kimse yoktur. Entelektüel zeka, toplumdaki insanları iyileştirmek için hiçbir araştırma ve geliştirme yapılmaksızın statik seviyede olabilir. Doğal insan zekası, erkek ve kadının (Adem ve Havva) yaratılmasından bu yana var olmasına rağmen, bir dizi felsefi düşünce ve mantıksal önermeden geçerek günümüzün entelektüel seviyesine ulaşması yüzyıllar boyu sürdü. Ne yazık ki günümüzde pek çok disiplin ve toplumda insan zekasının bilim ve teknolojiye yansıması göz ardı edilmekte ve dolayısıyla bu toplumlar iyi gelişmiş ülkelerin gerisinde kalmaktadır. Bu makale, tarihsel perspektif ve metodolojik (modeller ve makineler) yönleriyle yapay zeka önemi için kısa bir değerlendirme ve öneriler sunmaktadır. Yenilikçi buluşlar veya mevcut bilimsel ve teknolojik olarak mevcut metodolojilerin en azından kısmen değiştirilmesi için insan zekasının klasik, kendini tekrar eden yaklaşımlar yerine bu konulara ışık tutması gerektiği önerilmiştir.

Anahtar Kelimeler: Yapay, zeka, mantık, makine, model, felsefe, robot.

1. Introduction

Artificial intelligence can be thought of Allah (Creator) given human natural soft abilities transition to some gadgets, software, robots and machines.

Human beings have been wondering about artificial intelligence, even though it may be unconsciously, right from the antiquity times. The initial thoughts and their mechanical instrumentations were either in the form of ideas that have not been materialized or as simple weapons, gadgets and instruments or drawings, which have not been put into application stages. The fundamentals of artificial intelligence were born in the philosophical thinking during Old Greek period (Archimedes, B.C. ~ 159), verbal descriptive writings during early Roman period (Heron, A.C. ~ 50) and actual and today like robotic mechanical drawings and explanations during Medieval Islamic civilization period (Abo-l Iz Al-Jazari, ~ 1200). In general, artificial intelligence born thoughts have their bases in

* Corresponding Author.
E-mail: zsen@medipol.edu.tr

Recieved : 01.02.2018
Revision :
Accepted : 24.02.2018

the reduction and conversion of rather complex problems to human graspable levels with its consequent simple linguistic, symbolistic, mathematical, algorithmic and logistic solutions. Artificial intelligence works does not necessitate formal education only, but it may depend on personal of group experiences, which may be expressed in linguistic terms that can later be converted to mechanical movements through various purpose machines. Today artificial intelligence searches for human brain and mind functionality, machine learning and improvement machines and robots so as their main objectives are service to men.

Modern artificial intelligence works had started right after the Second World War and had their origin with the emergence of computer technology and engineering sprout out during 1950s. Digital computers provided a domain for simulation of natural events in different disciplines (social, economy, engineering, etc.), and hence, these initial works triggered the human thought towards the artificial intelligence direction. A brief history of these recent developments is presented by Russel and Norvig (1995).

Artificial intelligence theoretical and practical studies and applications are increasing since the appearance of digital computers and these studies deal with uncertain, vague, incomplete and missing data cases through approximate reasoning models. Computers help to visualize and apply artificial intelligence configurations provided that human intelligence can be translated to computer software through a set of assumptions and simplifications. Linguistic knowledge and information can be represented by modeling, reasoning and decision making procedures in addition to numerical data treatments. The main source of artificial intelligence is the human brain functionalities leading to clever gadgets, instruments and machines for social and economic life improvement purposes. Human intelligent is the main source of artificial intelligence not only in clever gadgets, instruments and machines only but also in any basic or applicable science and technology studies. Scientific and technological developments cannot be achieved without transformation of human intelligence to artificial intelligence, which may appear in the forms of formulations, equations, algorithms, software, models and machines. This paper provides a brief explanation by touching on these forms from artificial intelligence point of view.

2. Human and Intelligence

Any activity in this world cannot be thought without the human thinking, work, application and process. These activities may be mental, social, educational, research and development, economic, environmental, military, health, etc. Each individual has to engage him (her) self with some of these activities and perhaps with several of them to achieve a personal goal in the society or as a service to men for betterment and improvement of life standards. Although human have gifts as five sensitive organs that help to take inside outside knowledge and information, but their processing in some subjective or objective manner provides better or improved outputs. Figure 1 is a simple model for a human being existence in the environment that is physical and also to some extend spiritual.

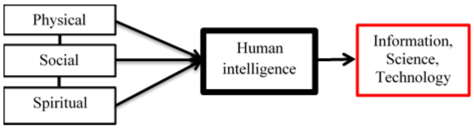


Figure 1 Human activity model

The final goal is to generate useful information, scientific knowledge and technological gadgets that help human to have easier life without difficulties. As shown in the initial part of this figure among the three components, namely, physical, social and spiritual aspects of human life the most effected part lies within the physical realities of life. For instance, washing machines, dish washers, natural gas and many alike are for the relief of physical overburdens and partially also for the social activities. Today, intelligence is taken for granted to express the physical improvements of the life neglecting other aspects of life like social, cultural and spiritual dimensions. Anyone who will be the most satisfied with the artificial intelligence will also have satisfaction with other supportive aspects of the life. It has been shown in Figure 1 that physical, social and spiritual components of human existence are related with each other and one cannot be exterminated from others. In case of a balance among these three components the artificial intelligence can emerge with peace and generative manner of enlightenment.

Apart from the above mentioned facts the other most two important software within that are parts of human intelligence are philosophy and logic. One can gather tremendous amount of knowledge, information and know-how practical abilities, which may remain in his (her) daily life as non-generative agents without any innovative developments. This is especially true if the philosophical and logical aspirations are missing from human thoughts. Without especially science philosophy and logic the knowledge and information accumulation is like concrete without reinforcement. However, on these and future days each society seeks and urges for individual that are empowered with innovative idea and brilliant generations at least as improvements and developments of existing facilities, whatever they may be. Artificial intelligence cannot be without science philosophical and logical thinking ingredients. Furthermore, artificial intelligence needs “suspicion” from the behavior of gadget that is around us.

3. Models and Intelligence

Models are description, imitation, and replacement of human thoughts into a sequence of logical statements and first to geometrical shapes and then translation to mathematics and finally the solutions with their verification according to real life observations and, if possible, measurements. Each model digests human intelligence to a certain extend under the light of idealizations, hypothesis, theorems, assumptions and other sort of simplifications to reflect the real-world problems (social, environmental, economy, health, energy, education, etc.) on the graspable level such that the human intelligence can approach the reality. During the long history of modeling various probabilistic, statistical, analytical, chaotic and artificial intelligence alternatives took place. All type of models is based on human intelligence, which are expressible in terms of rational sentences that are convertible to mathematical signs and consequently mathematical analytical, empirical and differential equations. The rational and logical expressions are very helpful to communicate with computers through well-established models. The historic evolution of models has also started in applications after the digital computer entrance into scientific and technological research domain. The first intelligent models were in the form of "black box" type, where the input and output numerical data are available in the form of measurement records. This caused researchers to look for "data bases" to initiate the model estimations. The first classical black box model has three components as input, output and transfer unit as in Figure 2.

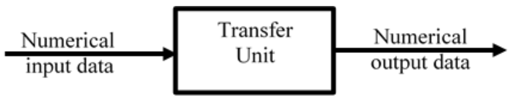


Figure 2 Black box model components

After having obtained input and output data bases the researchers think about the transfer system to replicate the output pattern from the input data. The transfer unit needs artificial intelligence thoughts for desired match between two sets of data. Unfortunately, at this stage many researchers dive into existing methodologies without his (her) own intelligence contribution for the formation of transfer unit. In general, the transfer unit is in the form of probability, statistics, stochastic processes, analytical formulations, empirical equations, Fourier series, artificial neural networks, genetic algorithms, analytical hierarchical methods and many other similar approaches. Such a way does not activate the human intelligence but provides ready answers under a certain error limits.

On the other hand, active human intellect after knowing the philosophical and logical bases of each classical methodologies may try to bring another innovative modeling technique or at least suggest some modifications, which implies the contribution of his (her) intellectual ability. Such an implementation of human intelligence provides artificial intellect in the model construction.

Another artificial intelligence methodology after around 1970s is the fuzzy logic modeling (Zadeh, 1965, 1968), which depends completely on the individual or group intelligence, because it requires the scientific philosophical basis with rational inferences leading to a set of constructive rule base" instead of "data base". Herein, approximate reasoning plays the most active role for artificial intelligence implications under the light of human intelligence. The general parts of fuzzy modeling take the form as shown in Figure 3.

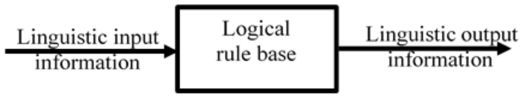


Figure 3. Fuzzy model components

The bases of the model in Figure 3 are completely linguistic, which requires verbal rational logical prepositions with antecedent and consequent parts within a set of the following statements.

Rules: IF…. (antecedent, linguistic input) ……… THEN ……. (Consequent, linguistic output)

Any natural, social, economic and engineering problem can be expressed linguistically for its science philosophical fundamentals and then a set of logic rules like the proposition can be set for its linguistical description. In any artificial intelligence or even analytical approaches in any aspect of scientific research rather than "1data base" "logical rule base" is important. The logical rules can best be set down by human intelligence, but unfortunately rather ready formulations, equations, software and algorithms are considered in numerous studies without any bother. Artificial neural networks (Şen, 2002) are among the most used modeling technique, because one does not need to ponder and pump human intelligence after all the architecture is known and by means of trial and error methodology the best suitable one can be identified.

For better, improved and innovative research activities it is advised that the researcher should criticize each method with suspicion and bring it to his (her) intelligence level.

4. Machine and intelligence

Human intelligence can be transferred to machines as robots and such intelligence systems are in existence throughout the science history. Although there have been some thoughts on artificial intelligence through machines and machine like robotic visualization during Old Greek and Early Hellenistic civilizations, but the first crisp and vivid examples have been suggested by Muslim thinkers through pictures and in geometric shapes. The first of automatic robotic is presented in the following figure where water power is used to raise the left and right hands of a robotic man on an elephant. He has expressed his ideas, opinions and views not in a subjective manner as many ancient Greek philosophers have done, but on objective grounds with drawings that can be convinced by everybody even today. Perhaps, his engineering side is more significant than his philosophical and scientific sides. For instance, Figure 4 is the first historical example provided by Al-Jazari, who lived during the 12th century in the southeastern part of present Turkey.

Figure 4 The first robotic gadget based on human intelligence

Machine learning provides effective data mining procedures whereby one can deduce significantly applicable techniques.

5. Conclusions

This paper presented a brief description of artificial intelligence significance in the human life at present with emphasis that these techniques are bound to gain more significance in the future. Even though everyone has natural intelligence, but in recent decades, s/he wants to load the intelligence activities to models through which the computers can deal with artificial intelligence, but more appropriately through the machines that are directed by computer software. Any software whether simple of complex can be disintegrated down to logical rule set, because without logical propositions about the problem concerned, one cannot write computer programs. It is stated in the paper that the first objective, physical and mechanical artificial drawings and explanations emerged from the Islamic civilization although there were some early versions only in the form of general writings without mind and intellectual triggering. Artificial intelligence originates from natural human intellect first in the form of models and finally machines including robots.

References

Russel, S.J. and Norvig, P., 1995, “Artificial Intelligence A Modern Approach”, Contributing writers: John F. Canny, Jitendra M. Malik, Douglas D. Edwards , Prentice Hall, Englewood Cliffs, New Jersey 07632, ISBN 0-13-103805-2.

Şen, Z., 2004. Yapay Sinir Ağları İlkeleri. Su Vakfı Yayınları, 183 sayfa.

Zadeh, L. A., 1965. Fuzzy sets. Informat. And Control, 8, pp. 338-353.

Zadeh, L. A., 1968. Fuzzy algorithms. Informat. and Control. 12, no. 2, pp.94-102.

Journal of Intelligent Systems: Theory and Applications 1(1) 2018: 5-15.

Solving Economic Load Dispatch problem with Multiple Fuels using Teaching Learning based Optimization and Salp Swarm Algorithm

Y. V. Krishna Reddy[1], Dr. M. Damodar Reddy[2]

[1] *Research scholar, Dept. of Electrical and Electronics Engineering, Sri Venkateswara University, Tirupati, India.*

[2] *Professor, Dept. of Electrical and Electronics Engineering, Sri Venkateswara University, Tirupati, India.*

Abstract

This paper bestows the implementation of bio-inspired algorithms like Teaching-learning Based Optimization (TLBO) and Salp Swarm Algorithm (SSA) for the solution of Economic Load Dispatch (ELD) problem with multiple set of fuels. To obtain the optimal solution, the proposed algorithms are validated on test system consists of ten thermal units with four different load demands. Results have been obtained using SSA and TLBO and they are compared with the results of recently published methods. The study has been done without valve-point effect as well as with valve-point effect for four different load demands. Both the mentioned algorithms are described and presented in this paper. The optimization which has been done taking total fuel cost as the fitness function. The results are simulated for both the cases and analyzed and then presented in this paper. The results reveal the effectiveness and applicability of the proposed algorithms to ELD problem.

Keywords: Salp Swarm Algorithm, Teaching-learning Based Optimization, Valve-point effect, Economic load dispatch, multiple fuels, and Valve-point effect.

1. Introduction

In the present scenario the electric power demand is growing due to the advances in both industrial and public sector. The major source for this electric power is mainly thermal plants and they are expected to satisfy the load demand. For any thermal plant in general the generation cost will be proportional to the fuel cost. So, in order to provide lower generation cost proper load sharing of generating units are required. For this purpose, Economic Load Dispatch (ELD) problem is considered to obtain optimal allocation of generation by all the generating units that minimize the total fuel cost, while satisfying equality constraint and a set of inequality constraints. Usually, the ELD problem is complex due to the design and operation constraints of the generating units such as transmission network losses, valve-point effects, prohibited operating zones and multiple fuel options. In conventional ELD problem, the cost function is approximated by a single quadratic function and the valve-point effects are ignored.

Usually Lambda Iteration method [1] is used to solve the ELD problem for the proper allocation of thermal units with minimum fuel cost. But it is difficult to obtain proper allocation of generating units for large system. To overcome this problem researchers are trying new methods similar to Evolutionary Programming Techniques [2], Genetic Algorithm (GA) [3] and Particle Swarm Optimization (PSO) [4]. In practical power systems, an ELD problem is non-convex due to the valve-point effect, so the application of the classical methods is restricted. In order to solve ELD problem with valve-point effect improved differential evolution (IDE) [5], Tournament-based harmony search (THS) [6] and Oppositional based grey wolf optimization (OGWO) [7] algorithms are used.

Present operating conditions of many thermal units, the generation cost functions for thermal plants be segmented as piecewise quadratic functions. The reasons for this partitioning of the cost curves are many thermal units supplied with multiple fuels like coal, oil and natural gas. Hence, there is a dilemma for some generating units to determining which fuel is most economical to burn. A single unit poses the problem of at least two cost curves for a single unit, these curves are not parallel. Intersecting curves implies that it may be more efficient to burn oil for some MW outputs and natural gas for others. Additionally, varying heat contents of natural gas from multiple suppliers could result in cost curves which are not parallel when compared to each other.

* Corresponding Author. Phone: 9618074754
E-mail:yvkrishnareddy36@gmail.com

Recieved : 09 Feb. 2018
Revision : 12 Apr. 2018
Accepted : 7 May 2018

The notion of multiple cost curves is not limited to applications with multiple fuels. To solve this problem, many methods have been proposed such as hierarchical economic dispatch [8], Hopfield neural network (HNN) [9-10] and PSO [11] without considering the valve-point effect.

A non-convex ELD problem considering the multiple fuels with valve-point effect is more realistic. In recent years, many researchers put effort to solve the realistic ELD problem by applying various search techniques. Biogeography-based optimization (BBO) [12], Improved PSO [13], Improved Random Drift PSO [14], hybrid algorithm consisting of distributed sobol PSO, tabu search algorithm (DSPSO-TSA) [15], backtracking search algorithm (BSA) [16], Lighting Flash algorithm (LFA) [17], new adaptive PSO (NAPSO) [18] and multiple algorithms [19] consisting of modified shuffled frog leaping algorithm (MSFLA), global-best harmony search algorithm (GHS), hybrid algorithm such as SFLA-GHS and shuffled differential evolution (SDE) are committed to the solve ELD problem with valve-point loading and multiple fuel options.

In this paper, implementation and application of some nature inspired algorithms like Teaching-Learning Based Optimization (TLBO) [20] and Salp Swarm algorithm (SSA) [21] for a constrained ELD problem. They are applied on a ten unit thermal system with multiple fuel quadratic cost function as first case and including valve-point effect as second case to test the efficiency of the suggested algorithms.

2. PROBLEM FORMULATION

2.1. *ELD problem formulation*

In order to minimize the cost of operation, Economic Load Dispatch (ELD) is the process of optimal allocation of available generation units to satisfy the required load demand. In general, the generation cost function represented as a second order function, as shown in Eqn. (1).

$$F_k(P_{Gk}) = a_k P_{Gk}^2 + b_k P_{Gk} + c_k \tag{1}$$

Where a_k, b_k and c_k are coefficients of generator k.

The objective function is minimizing to generation cost as shown in Eqn. (2).

$$F = \min f = \sum_{k=1}^{n} F_k(P_{Gk}) \quad (\$/h) \tag{2}$$

Where F_k denotes total generation cost for the generator unit k, which is defined in Eqn. (1).

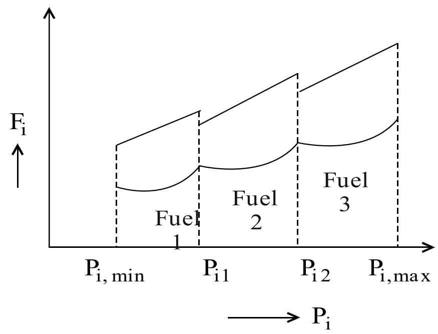


Figure 1. Incremental cost function with multiple fuels

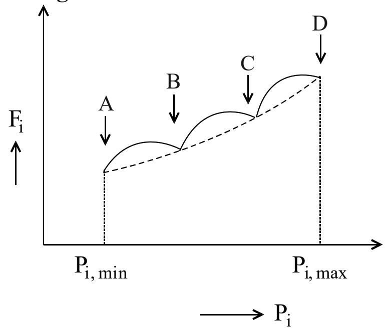


Figure 2. Fuel cost function with valve-point effect.

2.2. *ELD problem with multiple fuels*

Practically the generating units are supplied with multiple fuels like oil, gas and coal. In general fuel cost represent as single quadratic function even though supplied with multiple fuels. But it's not accurate longer than, hence the fuel cost function with multiple fuels should be represented as several piecewise quadratic functions as shown in Fig. 1 reflecting the effects of fuel changes and the generator must identify the most economic fuel to burn. Practically the fuel cost function should be expressed as shown in Eqn. (3).

2.3. *ELD problem with valve-point effect*

In practical power system cost function is non-convex, because of multi-valve steam turbines in generating units. Due to the valve-point effect cost function contains higher order non-linearity as shown in Fig. 2. Hence to simulate the valve-point effect added sinusoidal terms to the second order cost functions as follows Eqn. (4).

Where e_{ck} and f_{ck} are constants of the unit-k due to discontinuities of generating unit.

2.4. *ELD problem with multiple fuels including valve-point effect*

In practical operation, generating units are supplied with multiple fuels and also including valve-point effect to the cost functions in order to get accurate ELD solution. The generation cost function with multiple fuels (3) should be combined with valve-point effect (4), and can be practically expressed as Eqn. (5).

$$F = F_C(P_{Gk}) = \begin{cases} a_{k1}P_{Gk}^2 + b_{k1}P_{Gk} + c_{k1} & P_{Gk}^{min} \le P_{Gk} \le P_{Gk1} \\ a_{k2}P_{Gk}^2 + b_{k2}P_{Gk} + c_{k2} & P_{Gk1} \le P_{Gk} \le P_{Gk2} \\ . & \\ ..a_{kn}P_{Gk}^2 + b_{kn}P_{Gk} + c_{kn} & P_{Gk(n-1)} \le P_{Gk} \le P_{Gk}^{max} \end{cases} \quad (\$ / h) \tag{3}$$

$$F_2 = F_C(P_G) = \sum_{k=1}^{N_G} (a_k P_{Gk}^2 + b_k P_{Gk} + c_k) + \left| e_{ck} \times \sin(f_{ck} \times (P_{Gk}^{min} - P_{Gk})) \right| \quad (\$ / h) \tag{4}$$

$$F = F_C(P_{Gk}) = \begin{cases} a_{k1}P_{Gk}^2 + b_{k1}P_{Gk} + c_{k1} + \left| e_{ck1} \times \sin(f_{ck1} \times (P_{Gk}^{min} - P_{Gk})) \right| & P_{Gk}^{min} \le P_{Gk} \le P_{Gk1} \\ a_{k2}P_{Gk}^2 + b_{k2}P_{Gk} + c_{k2} + \left| e_{ck2} \times \sin(f_{ck2} \times (P_{Gk}^{min} - P_{Gk})) \right| & P_{Gk1} \le P_{Gk} \le P_{Gk2} \\ . & \\ a_{kn}P_{Gk}^2 + b_{kn}P_{Gk} + c_{kn} + \left| e_{ckn} \times \sin(f_{ckn} \times (P_{G}^{min} - P_{Gk})) \right| & P_{Gk(n-1)} \le P_{Gk} \le P_{Gk}^{max} \end{cases} \tag{5}$$

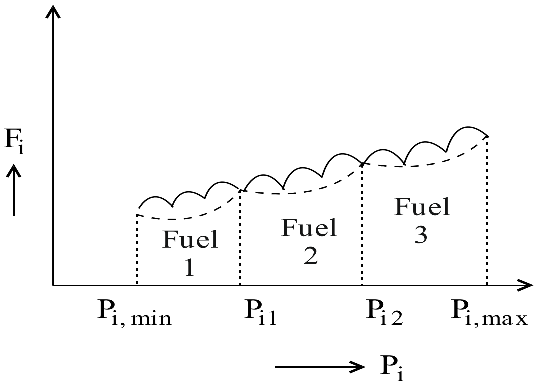


Figure 3. Fuel cost function with multiple fuels including valve-point effect.

Complication of the practical ELD problem is due to the involvement of valve-point effect and multiple fuels to the fuel cost function which is graphically shown in Fig.3.

2.4.1. Equality constraint

Total generation of any power system must meet the required load demand and losses occur in the transmission lines, as shown in Eqn. (6).

$$\sum_{k=1}^{N_G} P_{Gk} = P_D + P_L \tag{6}$$

Where P_L denotes power losses and P_D denotes the power demand. The power loss can be computed using B-coefficient method expressed as a second order function shown in Eqn. (7).

$$P_L = \sum_{j=1}^{n}\sum_{k=1}^{n} P_{Gj}B_{jk}P_{Gk} + \sum_{j=1}^{n} B_{0j}P_{Gj} + B_{00} \quad (MW) \tag{7}$$

2.4.2. Power limit constraint

Any generator output can be varied between minimum and maximum power limits as follows Eqn. (8).

$$P_{Gk}^{min} \le P_{Gk} \le P_{Gk}^{max} \tag{8}$$

3.TLBO ALGORITHM

Based on the influence of a teacher on learners, Ravipudi Venkata Rao proposed Teaching-Learning based optimization technique (TLBO) [20]. This method works on the effect of teacher on the learners in a class, and consequently, learning by interaction between learners which helps in their grades. In this algorithm a number of solutions which is considered as the population or a group of students in a class. Learners' different subjects are represented as design parameters in TLBO, and the learners' grades is similar to the ''fitness''. The best solution in, TLBO is similar to teacher because teacher is the most learned person in the society. TLBO divided into two parts, among the first part is ''teacher phase'' and the second part is ''learner phase''. The learners learning from teachers means ''teacher phase'' and the learners learning through the interaction between learners in a class means ''learner phase''. Now, implementation of TLBO is described below.

3.1. Initialization

The population **X** is randomly initialized which is bounded by matrix of N **(no. of learners)** rows and **D (no.of subjects)** columns. The j^{th} parameter of the i^{th} learner is assigned values randomly using the Eqn. (9).

$$X_{i,j}^0 = X_j^{min} + rand * (X_j^{max} - X_j^{min}) \tag{9}$$

Where rand represents a random variable within the range (0, 1), X_j^{min} and X_j^{max} represents the minimum and maximum value for j^{th} parameter.

3.2. Teacher Phase

The mean result of each subject of the learners in the class at generation **p** is given as Eqn. (10).

$$M^p = [m_1^p, m_2^p, m_3^p, ..., m_j^p, ...m_D^p] \tag{10}$$

The minimum objective function of learner is represented as the 'Teacher' (X_T). The teacher tries to improve the grades of other learners (X_L) by updating the mean result (M^p) of the classroom towards X_T position. New position of student is given by Eqn. (11).

$$Xnew_L^p = X_L^p + rand(X_T^p - TF * M^p) \quad (11)$$

Here the valve of TF (teaching factor) either 1 or 2, it is evaluated using Eqn. (12).

$$TF = round[1 + rand(0,1)\{2-1\}] \quad (12)$$

Where TF valve is randomly decided by the algorithm using above Equation.

If $Xnew_L^p$ is found to be lesser than X_L^p in generation p, than it interchanges on X_L^p otherwise it remains X_L^p.

3.3. Learner Phase

In this phase, the learners increase their knowledge with help of other learners. Therefore, each learner learns new knowledge if the other learners have more knowledge than him/her. For a learner X_L^p, randomly select other learner X_{randL}^p as $L \neq randL$. New position of each learner is given by Eqn. (13) and Eqn. (14).

$$Xnew_L^p = X_L^p + rand * (X_L^p - X_{randL}^p) \text{ if } f(X_L^p) < f(X_{randL}^p) \quad (13)$$

$$Xnew_L^p = X_L^p + rand * (X_{randL}^p - X_L^p) \text{ if } f(X_L^p) > f(X_{randL}^p) \quad (14)$$

When MAXIT (maximum iteration) is completed, and then the TLBO algorithm is stop, otherwise 'Teacher Phase' repeated. The flowchart of TLBO algorithm shown in Fig. 4.

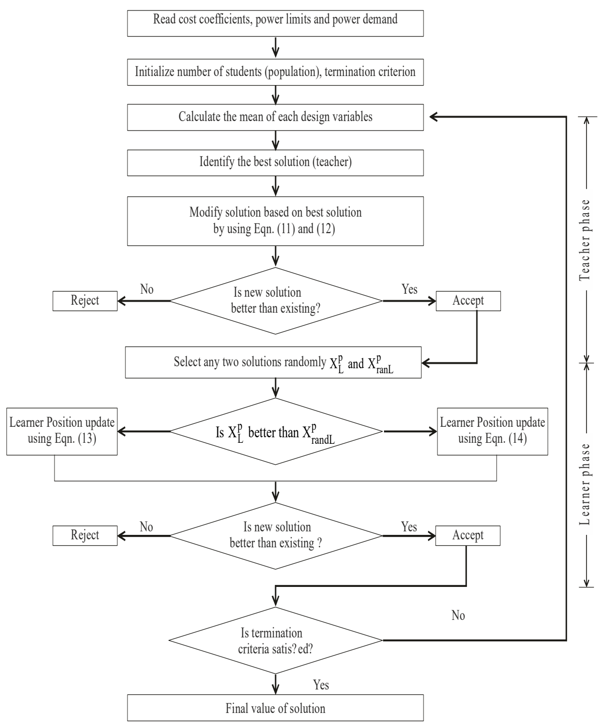


Figure 4. Flowchart of TLBO algorithm

Execution of TLBO algorithm for ELD

The steps for solving ELD problem using TLBO algorithm as follows:

Step 1: Read cost coefficients of generators, minimum/maximum power limits and load demand.

Step 2: Set time count t=1 and repeat the next steps up to maximum iterations.

Step 3: Start "teacher phase", teacher is selected to minimize the cost.

Step 4: In teacher phase new generator matrix is formed using Eqn. (10) and Eqn. (11).

Step 5: Start "learner phase", generation is upgraded by collaboration with different learners.

Step 6: Random learner is selected for an individual learner to interact each other using Eqn. (13) and Eqn. (14).

Step 7: The process is terminated when maximum iteration reached. Otherwise repeat from teacher phase.

4. SALP SWARM ALGORITHM

4.1 Inspiration

Salp Swarm Algorithm (SSA) [21] is a novel optimization algorithm for solving optimization problem. The main inspiration of SSA is the swarming behaviour of salps when navigating and foraging in oceans. Salps belong to the family of Salpidae and have transparent barrel-shaped body. Their tissues are highly similar to jelly fishes. Salps move similar to jelly fish, in which the water is pumped through body as propulsion to move forward. In deep oceans, salps often form a swarm called salp chain. This is done for achieving better locomotion using rapid coordinated changes and foraging.

4.2. Proposed mathematical model for moving salp chains

The population is first divided to two groups: leader and followers. The leader is the salp at the front of the chain, whereas the rest of salps are considered as followers. As the name of these salps implies, the leader guides swarm and the followers follow each other (and leader directly or indirectly). To update the position of the leader the following Eqn. (15) is proposed.

$$x_j^1 = \begin{cases} F_j + c_1((ub_j - lb_j)c_2 + lb_j) & c_3 \geq 0.5 \\ F_j - c_1((ub_j - lb_j)c_2 + lb_j) & c_3 < 0.5 \end{cases} \quad (15)$$

Where x_j^1 shows the position of the first salp (leader), F_j is the position of the food source, c_1, c_2 and c_3 are random numbers. Equation (15) shows that the leader only updates its position with respect to the food source. The coefficient C_1 is the most important parameter in SSA it defined using Eqn. (16).

$$c_1 = 2e^{-(\frac{4l}{L})^2} \quad (16)$$

Where l is the current iteration and L is the maximum number of iterations.

The parameter C_2 and C_3 are random numbers uniformly generated in the interval of [0, 1]. In fact, they dictate if the next position in *j*th dimension should be towards positive infinity or negative infinity as well as the step size. To update the position of the followers, the following Eqn. (17) is utilized (Newton's law of motion):

$$x_j^i = \frac{1}{2}at^2 + v_0 t \tag{17}$$

Where $i \geq 2$, x_j^i shows the position of *i*th follower salp in *j*th dimension, t is time, V_0 is the initial speed, and $a = \frac{v_{final}}{v_0}$ where $v = \frac{x - x_0}{t}$.

Because the time in optimization is iteration, the discrepancy between iterations is equal to 1 and considering

$V_0 = 0$, this equation can be expressed as follows:

$$x_j^i = \frac{1}{2}(x_j^i + x_j^{i-1}) \tag{18}$$

Where $i \geq 2$ and x_j^i shows the position of *i*th follower salp in *j*th dimension.

When maximum iteration is reached, and then the SSA algorithm is stop, otherwise from leader section algorithm repeated. The flowchart of SSA algorithm shown in Fig. 5.

5. NUMERICAL RESULTS

To prove the efficacy and superiority of present approaches, a ten unit system is considered with multiple fuels in first case and valve-point effects are considered along with multiple fuels in second case. The input data available in reference [19]. In this ELD problem, generators are supplied with three types of fuels, namely 1, 2 and 3. The total ten units are categorized into three subsystems, where the 1st subsystem consists of four thermal units and remaining two subsystems consists of three thermal units. Among the ten thermal units unit-1 supplied with only two types fuels (1 and 2), unit-9 is a different, even though fuel 2 is available but uneconomical to burn and when fuels 1 and 3 are not available then fuel 2 can be utilized instantly.

The parameters require to implementing the TLBO and SSA algorithms are as follows. The population (no.of students in class or no. of salps) and maximum iteration (termination criteria) are set as 40 and 1500. To reduce the statistical errors, test system repeated 50 times and all simulations are developed in MATLAB 2014a.

5.1. ELD problem with multiple fuels

ELD problem with multiple fuels is considered as first case. This case, the 10-unit system data, such as fuel types and its cost coefficients are taken from Ref. [11]. Initially load demand considered as 2400 MW and later with increment of 100 MW, load demand increases upto 2700 MW. The best results of the proposed TLBO and SSA algorithms are shown in Tables 1-4 for different load demands of 2400 MW to 2700 MW respectively. The comparisons of results after 50 trials for the ten unit system with multiple fuels are given in Table 5. Furthermore, the average and maximum values obtained by proposed algorithms are equal to minimum value, which proves the robustness of the proposed algorithms. But the time require for TLBO is more compared with SSA algorithm.

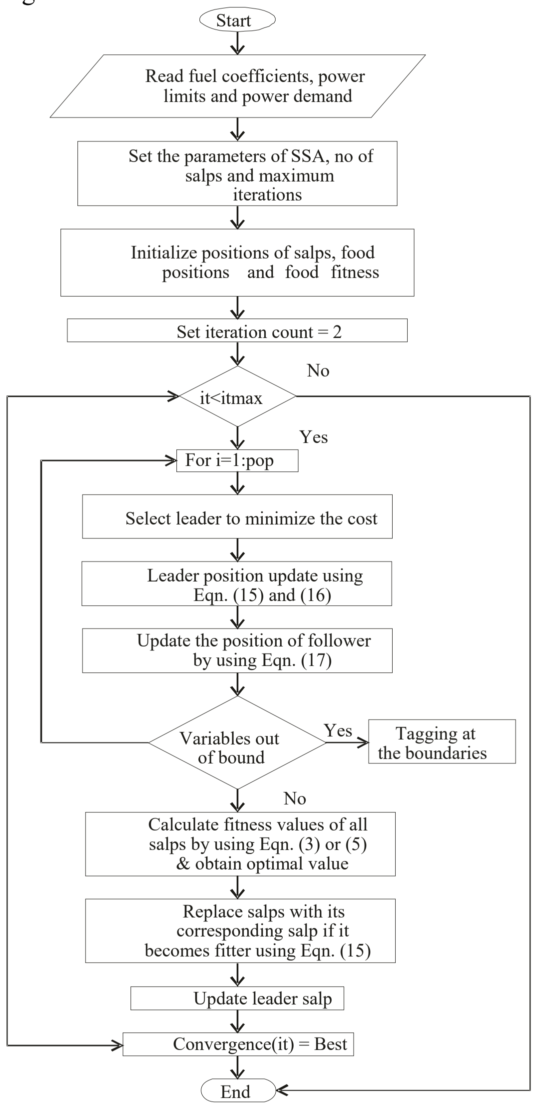


Fig. 5. Flowchart of SSA algorithm

For this ten unit test system, the optimal solution attained from the methods informed in the literature namely, hierarchical economic dispatch [8], HNN [9-10], PSO [11] and the proposed algorithms are listed in Table 1-4 for a demand of 2400 MW to 2700 MW respectively. From the results it can be concluded that the proposed methods obtain optimal results as compare with other methods informed in the literature. The convergence characteristics of the suggested algorithms are shown in Fig. 6-9 for different load demands.

Table 1: Simulation and Comparisons results of proposed algorithms with demand = 2400 MW.

Unit	HM [8]		MHNN [9]		AHNN [10]		MPSO [11]		TLBO		SSA	
	Fuel type	GEN (MW)	Fuel type	GEN (MW)	Fuel type	GEN (MW)	Fuel type	GEN (MW)	Fuel type	GEN (MW)	Fuel type	GEN (MW)
P_1(MW)	1	193.2	1	192.7	1	189.1	1	189.7	1	189.7405	1	189.7406
P_2(MW)	1	204.1	1	203.8	1	202.0	1	202.3	1	202.3427	1	202.3427
P_3(MW)	1	259.1	1	259.1	1	254.0	1	253.9	1	253.8953	1	253.8952
P_4(MW)	3	234.3	2	195.1	3	233.0	3	233.0	3	233.0456	3	233.0456
P_5(MW)	1	249.0	1	248.7	1	241.7	1	241.8	1	241.8297	1	241.8296
P_6(MW)	3	195.5	3	234.2	3	233.0	3	233.0	3	233.0456	3	233.0456
P_7(MW)	1	260.1	1	260.3	1	254.1	1	253.3	1	253.2750	1	253.2750
P_8(MW)	3	234.3	3	234.2	3	232.9	3	233.0	3	233.0456	3	233.0455
P_9(MW)	1	325.3	1	324.7	1	320.0	1	320.4	1	320.3832	1	320.3831
P_{10}(MW)	1	246.3	1	246.8	1	240.3	1	239.4	1	239.3969	1	239.3970
PT(MW)	2401.2		2399.8		2400.0		2400		2400		2400	
FC($/h)	488.500		487.87		481.700		481.723		481.7226		481.7226	
Time(sec)	-----		-----		-----		-----		9.1955		4.6413	

Table 2: Simulation and Comparisons results of proposed algorithms with demand = 2500 MW.

Unit	HM [8]		MHNN [9]		AHNN [10]		MPSO [11]		TLBO		SSA	
	Fuel type	GEN (MW)	Fuel type	GEN (MW)	Fuel type	GEN (MW)	Fuel type	GEN (MW)	Fuel type	GEN (MW)	Fuel type	GEN (MW)
P_1(MW)	2	206.6	2	206.1	2	206.0	2	206.5	2	206.5190	2	206.5190
P_2(MW)	1	206.5	1	206.3	1	206.3	1	206.5	1	206.4573	1	206.4573
P_3(MW)	1	265.9	1	265.7	1	265.7	1	265.7	1	265.7391	1	265.7392
P_4(MW)	3	236.0	3	235.7	3	235.9	3	236.0	3	235.9531	3	235.9532
P_5(MW)	1	258.2	1	258.2	1	257.9	1	258.0	1	258.0177	1	258.0177
P_6(MW)	3	236.0	3	235.9	3	235.9	3	236.0	3	235.9531	3	235.9531
P_7(MW)	1	269.0	1	269.1	1	269.6	1	268.9	1	268.8635	1	268.8635
P_8(MW)	3	236.0	3	235.9	3	235.9	3	235.9	3	235.9531	3	235.9531
P_9(MW)	1	331.6	1	331.2	1	331.4	1	331.5	1	331.4877	1	331.4877
P_{10}(MW)	1	255.2	1	255.7	1	255.4	1	255.1	1	255.0562	1	255.0561
PT(MW)	2501.1		2499.8		2500.0		2500.0		2500.0		2500.0	
FC($/h)	526.700		526.13		526.2300		526.239		526.2388		526.2388	
Time(sec)	-----		-----		-----		-----		8.7299		4.5864	

Table 3: Simulation and Comparisons results of proposed algorithms with demand = 2600 MW.

Unit	HM [8]		MHNN [9]		AHNN [10]		MPSO [11]		TLBO		SSA	
	Fuel type	GEN (MW)	Fuel type	GEN (MW)	Fuel type	GEN (MW)	Fuel type	GEN (MW)	Fuel type	GEN (MW)	Fuel type	GEN (MW)
P_1(MW)	2	216.4	2	215.3	2	215.8	2	216.5	2	209.7880	2	209.7880
P_2(MW)	1	210.9	1	210.6	1	210.7	1	210.9	1	207.9079	1	207.9079
P_3(MW)	1	278.5	1	278.9	1	279.1	1	278.5	1	269.9146	1	269.9146
P_4(MW)	3	239.1	3	238.9	3	239.1	3	239.1	3	236.9782	3	236.9782
P_5(MW)	1	275.4	1	275.7	1	276.3	1	275.5	1	263.7247	1	263.7247
P_6(MW)	3	239.1	3	239.1	3	239.1	3	239.1	3	236.9782	3	236.9782
P_7(MW)	1	285.6	1	286.2	1	286.0	1	285.7	1	274.3591	1	274.3591
P_8(MW)	3	239.1	3	239.1	3	239.1	3	239.1	3	236.9782	3	236.9782
P_9(MW)	1	343.3	1	343.5	1	342.8	1	343.5	1	402.7945	1	402.7945
P_{10}(MW)	1	271.9	1	272.6	1	271.9	1	272.0	1	260.5767	1	260.5767
PT(MW)	2600.0		2599.8		2600.00		2600.00		2600.00		2600.00	
FC($/h)	574.030		574.26		574.370		574.381		573.7413		573.7413	
Time(sec)	-----		-----		-----		-----		8.9296		4.5722	

Table 4: Simulation and Comparisons results of proposed algorithms with demand = 2700 MW.

Unit	HM [8]		MHNN [9]		AHNN [10]		MPSO [11]		TLBO		SSA	
	Fuel type	GEN (MW)	Fuel type	GEN (MW)	Fuel type	GEN (MW)	Fuel type	GEN (MW)	Fuel type	GEN (MW)	Fuel type	GEN (MW)
P_1(MW)	2	218.4	2	224.5	2	225.7	2	218.3	2	209.7880	2	209.7880
P_2(MW)	1	211.8	1	215.0	1	215.2	1	211.7	1	207.9079	1	207.9079
P_3(MW)	1	281.0	3	291.8	1	291.8	1	280.7	1	269.9146	1	269.9146
P_4(MW)	3	239.7	3	242.2	3	242.3	3	239.6	3	236.9782	3	236.9782
P_5(MW)	1	279.0	1	293.3	1	293.7	1	278.5	1	263.7247	1	263.7247
P_6(MW)	3	239.7	3	242.2	3	242.3	3	239.6	3	236.9782	3	236.9782
P_7(MW)	1	289.0	1	303.1	1	302.8	1	288.6	1	274.3591	1	274.3591
P_8(MW)	3	239.7	3	242.2	3	242.3	3	239.6	3	236.9782	3	236.9782
P_9(MW)	3	429.2	3	355.7	3	355.1	3	428.5	3	402.7945	3	402.7945
P_{10}(MW)	1	275.2	1	289.5	1	288.8	1	274.9	1	260.5767	1	260.5767
PT(MW)	2702.2		2699.7		2700.00		2700.00		2700.00		2700.00	
FC($/h)	625.180		626.12		626.240		623.809		622.8092		622.8092	
Time(sec)	-----		-----		-----		-----		9.1236		4.3085	

Table 5: Statistical comparison of proposed algorithms for 50 trials.

Load (MW)	Cost ($/h)	SDE [19]	SFLA-GHS [19]	TLBO	SSA
2400	Minimum cost	481.7226	481.7226	481.7226	481.7226
	Average cost	481.7226	481.7226	481.7226	481.7226
	Maximum cost	481.7226	481.7226	481.7226	481.7226
2500	Minimum cost	526.2388	526.2388	526.2388	526.2388
	Average cost	526.2388	526.2388	526.2388	526.2388
	Maximum cost	526.2388	526.2388	526.2388	526.2388
2600	Minimum cost	574.3808	574.3808	573.7413	573.7413
	Average cost	574.3808	574.3808	573.7413	573.7413
	Maximum cost	574.3808	574.3808	573.7413	573.7413
2700	Minimum cost	623.8092	623.8092	622.8092	622.8092
	Average cost	623.8092	623.8092	622.8092	622.8092
	Maximum cost	623.8092	623.8092	622.8092	622.8092

From the convergence characteristics the results presented in the tables are ratified. From the graphs observed that TLBO algorithm get convergence with less number of iterations as compare with SSA algorithm, but the amount of time require for (each trial) TLBO algorithm is more as compared with SSA algorithm. For statistical analysis proposed algorithms are repeated 50 times and corresponding convergence curves for 50 trials are presented in Fig. 10 and Fig. 11 for the load demand of 2700 MW.

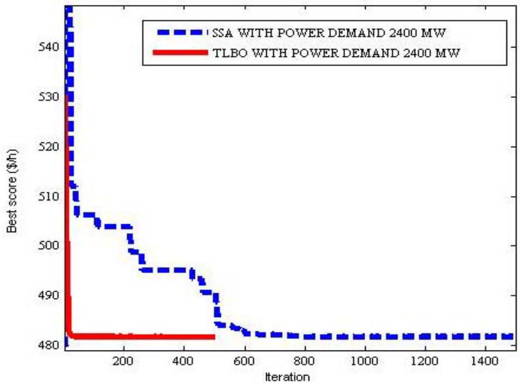


Figure 6. Convergence characteristics of 10 unit system with power demand = 2400 MW for case 1.

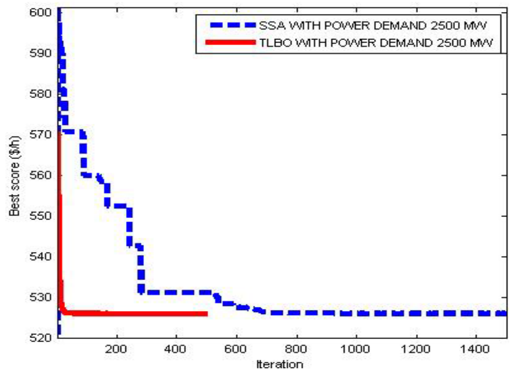


Figure 7. Convergence characteristics of 10 unit system with power demand = 2500 MW for case 1.

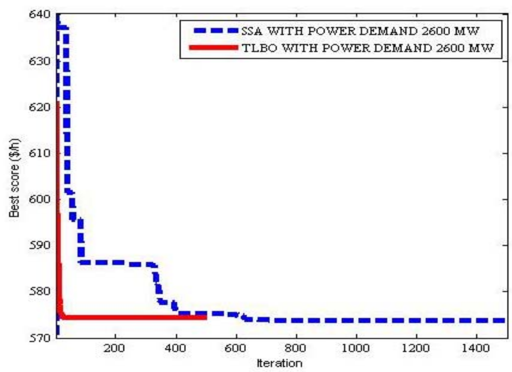


Figure 8. Convergence characteristics of 10 unit system with power demand = 2600 MW for case 1.

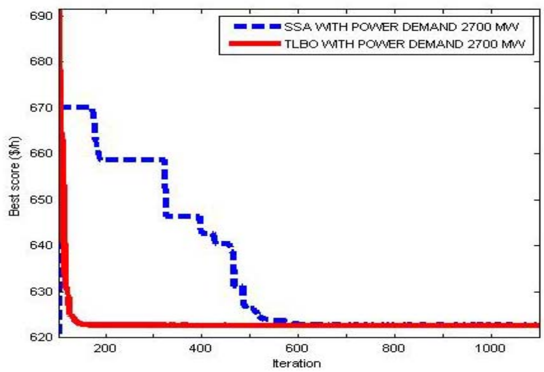


Figure 9. Convergence characteristics of 10 unit system with power demand = 2700 MW for case 1.

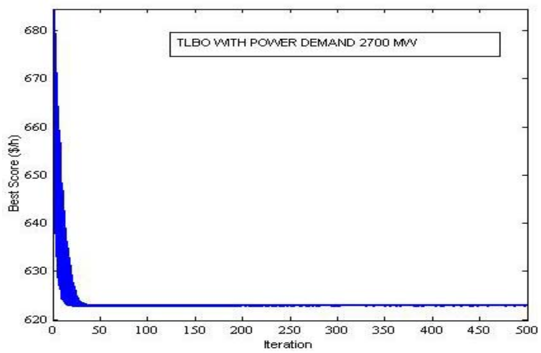


Figure 10. TLBO characteristics of 10 unit system with power demand = 2700 MW for 50 trials for case 1.

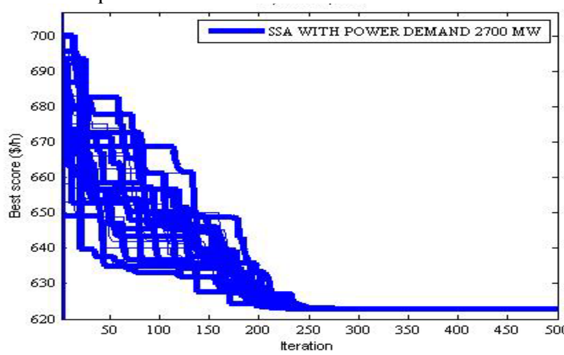


Figure 11. SSA characteristics of 10 unit system with power demand = 2700 MW for 50 trials for case 1.

5.2. ELD problem with multiple fuels including Valve-Point effect

ELD problem with multiple fuels including valve-point effect is considered as second case. This case, the 10-unit system data, such as fuel types and its cost coefficients are taken from Ref. [17]. Load demands are consider as similar to previous case like 2400 MW to 2700 MW with increment of 100 MW. The best results of the proposed TLBO and SSA algorithms are shown in Tables 6-9 for different load demands of 2400 MW to 2700 MW respectively. The comparisons of results after 50 trials for the ten unit thermal system with multiple fuels with valve-point effect are given in Table 10. Furthermore, the average and maximum values obtained by proposed algorithms are approximately same as minimum value because due to the effect of valve-point effect.

Table 6: Simulation and Comparisons results of proposed algorithms with demand = 2400 MW.

Unit	SDE [19]		MSFLA[19]		GHS [19]		SFLA-GHS [19]		TLBO		SSA	
	Fuel type	GEN (MW)	Fuel type	GEN (MW)	Fuel type	GEN (MW)	Fuel type	GEN (MW)	Fuel type	GEN (MW)	Fuel type	GEN (MW)
P_1(MW)	1	190.09	1	184.57	1	189.31	1	188.52	1	190.0426	1	189.7406
P_2(MW)	1	202.3	1	204.78	1	202.55	1	203.54	1	201.7834	1	202.3427
P_3(MW)	1	254.44	1	244.36	1	253.43	1	254.44	1	254.1962	1	253.8952
P_4(MW)	3	233.05	3	231.85	3	233.05	3	234.53	3	233.0582	3	233.0456
P_5(MW)	1	240.36	1	254.55	1	243.96	1	239.93	1	240.6335	1	241.8296
P_6(MW)	3	233.05	3	29.29	3	234.13	3	232.78	3	231.2827	3	233.0456
P_7(MW)	1	252.16	1	257.11	1	252.18	1	254.54	1	253.1148	1	253.2750
P_8(MW)	3	233.05	3	234.53	3	233.45	3	231.71	3	232.8416	3	233.0455
P_9(MW)	1	320.39	1	323.16	1	319.28	1	322.05	1	322.6016	1	320.3831
P_{10}(MW)	1	241.06	1	235.79	1	238.63	1	237.3	1	240.4456	1	239.3970
PT(MW)	2400.0		2400.0		2400.0		2400.0		2400.0		2400.0	
FC($/h)	481.7305		482.278		481.75043		481.7754		481.7489		481.6420	
Time(sec)	-----		-----		-----		-----		60.1740		15.5595	

Table 7: Simulation and Comparisons results of proposed algorithms with demand = 2500 MW.

Unit	SDE [19]		MSFLA[19]		GHS [19]		SFLA-GHS [19]		TLBO		SSA	
	Fuel type	GEN (MW)	Fuel type	GEN (MW)	Fuel type	GEN (MW)	Fuel type	GEN (MW)	Fuel type	GEN (MW)	Fuel type	GEN (MW)
P_1(MW)	2	207.29	2	208.32	2	207.30	2	206.22	2	212.1764	2	207.1101
P_2(MW)	1	206.26	1	206.01	1	206.76	1	206.76	1	205.2873	1	203.5421
P_3(MW)	1	265.53	1	266.54	1	265.53	1	265.53	1	265.5651	1	265.3599
P_4(MW)	3	236.01	3	237.08	3	235.60	3	234.26	3	236.6921	3	236.2802
P_5(MW)	1	258.34	1	254.37	1	258.27	1	258.49	1	252.2533	1	254.9352
P_6(MW)	3	236.01	3	236.95	3	235.20	3	235.07	3	235.0916	3	234.5333
P_7(MW)	1	268.75	1	266.49	1	268.75	1	271.17	1	269.9148	1	273.6039
P_8(MW)	3	236.01	3	236.68	3	236.28	3	233.86	3	233.8608	3	239.2363
P_9(MW)	1	332.02	1	328.69	1	332.56	1	334.23	1	331.4671	1	333.1278
P_{10}(MW)	1	253.74	1	258.82	1	253.71	1	254.37	1	257.6916	1	252.2711
PT(MW)	2500.0		2500.0		2500.0		2500.0		2500.0		2500.0	
FC($/h)	526.24266		526.33166		526.26547		526.32577		526.2762		526.1032	
Time(sec)	-----		-----		-----		-----		54.3198		12.8801	

Table 8: Simulation and Comparisons results of proposed algorithms with demand = 2600 MW.

Unit	SDE [19]		MSFLA[19]		GHS [19]		SFLA-GHS [19]		TLBO		SSA	
	Fuel type	GEN (MW)	Fuel type	GEN (MW)	Fuel type	GEN (MW)	Fuel type	GEN (MW)	Fuel type	GEN (MW)	Fuel type	GEN (MW)
P_1(MW)	2	216.53	2	218.59	2	209.34	2	214.48	2	216.8075	2	212.0521
P_2(MW)	1	210.72	1	203.04	1	207.99	1	212.70	1	210.4631	1	208.4934
P_3(MW)	1	278.64	1	271.58	1	269.62	1	277.63	1	282.6441	1	272.5263
P_4(MW)	3	238.83	3	236.41	3	236.95	3	239.63	3	239.3174	3	236.1458
P_5(MW)	1	276.31	1	276.43	1	265.48	1	275.03	1	276.4376	1	263.5184
P_6(MW)	3	238.96	3	241.92	3	235.87	3	241.25	3	238.4607	3	236.8176
P_7(MW)	1	285.35	1	287.72	1	273.51	1	282.98	1	282.9223	1	277.0237
P_8(MW)	3	238.83	3	240.84	3	237.75	3	239.37	3	238.4305	3	237.2208
P_9(MW)	1	343.09	1	344.19	1	403.32	1	344.19	1	342.0667	1	395.7819
P_{10}(MW)	1	272.70	1	27.22	1	260.11	1	272.69	1	272.4502	1	260.4200
PT(MW)	2600.0		2600.0		2600.00		2600.00		2600.00		2600.00	
FC($/h)	574.3839		574.89446		574.78857		574.4561		573.7620		573.5663	
Time(sec)	-----		-----		-----		-----		54.1888		13.4834	

For this ten unit test system, the optimal solution attained from the methods informed in the literature namely, SDE [19], MSFLA [19], GHS [19], SFLA-GHS [19] and the proposed algorithms are listed in Table 6-8 for a demand of 2400 MW, 2500 MW and 2600 MW respectively. For 2700 MW power demand optimal solution compared with DPSO-TSA [15], BSA [16], NAPSO [18], SFLA-GHS [19] and the proposed algorithms are listed in Table 9. From the results it can be concluded that the suggested methods obtain best results as compare with other methods informed in the literature. The convergence characteristics of the suggested algorithms are shown in Fig. 12-15 for different load demands.

Table 9: Simulation and Comparisons results of proposed algorithms with demand = 2700 MW.

Unit	DPSO-TSA [15]		BSA [16]		NAPSO [18]		SFLA-GHS [19]		TLBO		SSA	
	Fuel type	GEN (MW)	Fuel type	GEN (MW)	Fuel type	GEN (MW)	Fuel type	GEN (MW)	Fuel type	GEN (MW)	Fuel type	GEN (MW)
P_1(MW)	2	217.55	2	218.57	2	219.06	2	218.59	2	219.7690	2	221.6360
P_2(MW)	1	211.21	1	211.21	1	211.16	1	212.20	1	210.9383	1	209.7312
P_3(MW)	1	279.64	3	279.56	1	279.65	1	279.64	1	278.8449	1	280.6238
P_4(MW)	3	240.04	3	239.50	3	239.41	3	239.90	3	239.1031	3	240.5800
P_5(MW)	1	279.94	1	279.97	1	280.09	1	279.95	1	277.9823	1	276.8772
P_6(MW)	3	239.77	3	241.11	3	239.52	3	239.77	3	237.0181	3	239.2363
P_7(MW)	1	287.73	1	289.79	1	287.73	1	290.09	1	285.2918	1	294.9909
P_8(MW)	3	239.50	3	240.57	3	240.08	3	239.50	3	238.9219	3	239.5051
P_9(MW)	3	428.70	3	426.88	3	428.17	3	427.45	3	439.2320	3	423.6788
P_{10}(MW)	1	275.86	1	272.79	1	275.07	1	272.84	1	272.8986	1	273.1406
PT(MW)	2700.0		2700.0		2700.00		2700.00		2700.00		2700.00	
FC($/h)	623.8375		623.9016		623.62170		623.84065		622.8490		622.7174	
Time(sec)	-----		-----		-----		-----		52.0099		22.8867	

Table 10: Statistical comparison of proposed algorithms for 50 trials.

Load (MW)	Cost ($/h)	TLBO	SSA
2400	Minimum cost	481.7489	481.6420
	Average cost	481.8118	481.9565
	Maximum cost	481.8655	482.1060
2500	Minimum cost	526.2762	526.3032
	Average cost	526.3337	527.9598
	Maximum cost	526.4121	526.5349
2600	Minimum cost	573.7620	573.5663
	Average cost	574.1227	574.2088
	Maximum cost	574.5190	574.7104
2700	Minimum cost	622.8490	622.7174
	Average cost	622.8836	622.9975
	Maximum cost	622.9424	623.1005

From the results conclude that proposed methods produce better results as compared with other methods proposed in the literature. For given different load demands proposed method SSA produce better result as compare with TLBO Method and also the computational time for SSA is less as compared with TLBO method. The convergence characteristics for TLBO and SSA are shown in below figures.

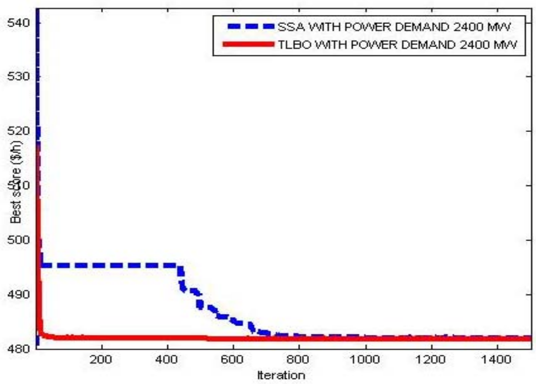


Figure. 12. Convergence characteristics of 10 unit system with power demand = 2400 MW for case 2.

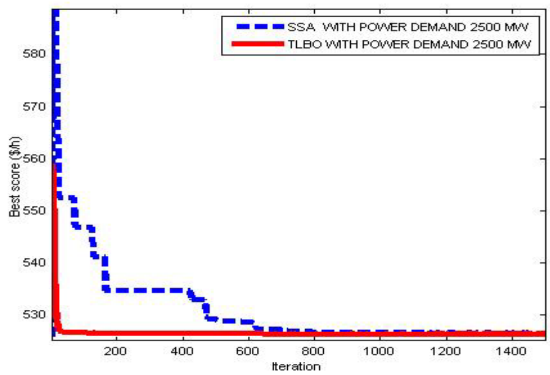


Figure. 13. Convergence characteristics of 10 unit system with power demand = 2500 MW for case 2.

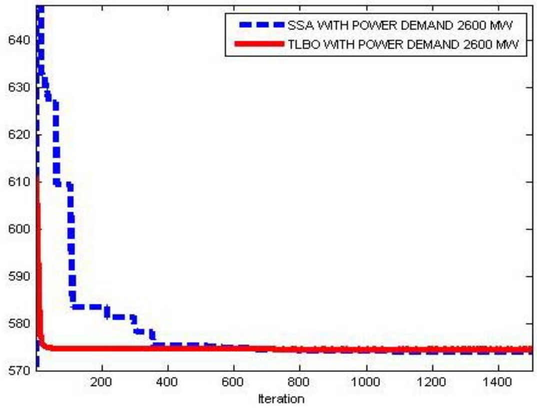


Figure 14. Convergence characteristics of 10 unit system with power demand = 2600 MW for case 2.

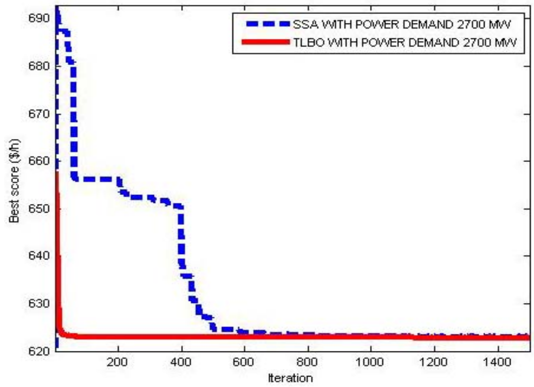


Figure 15. Convergence characteristics of 10 unit system with power demand = 2700 MW for case 2.

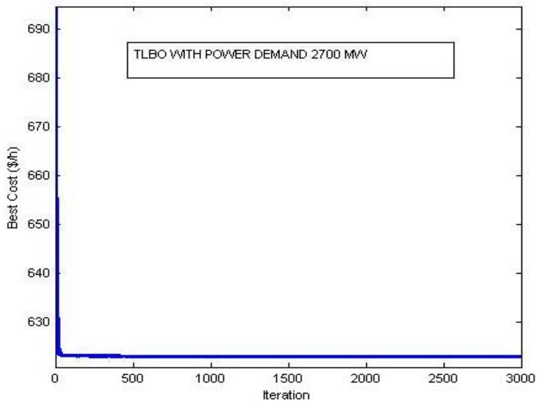


Figure 16. TLBO characteristics of 10 unit system with power demand = 2700 MW for 50 trials for case 2.

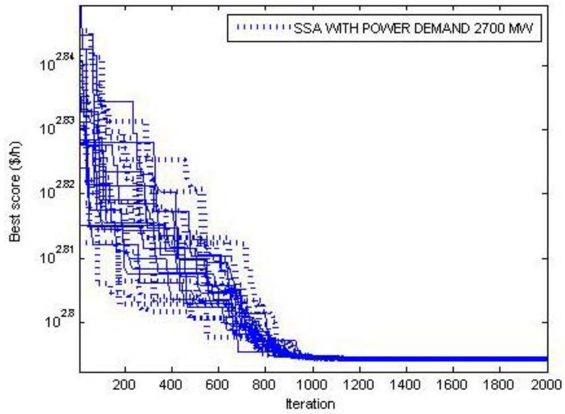


Figure 17. SSA characteristics of 10 unit system with power demand = 2700 MW for 50 trials for case 2.

From the convergence characteristics the results presented in the tables are ratified. From the graphs observed that TLBO algorithm get convergence with less number of iterations as compare with SSA algorithm, but the amount of time require for (each trial) TLBO algorithm is more as compared with SSA algorithm. For statistical analysis proposed algorithms are repeated 50 times and corresponding convergence curves for 50 trials are presented in Fig. 16 and Fig. 17 for the load demand of 2700 MW.

6. CONCLUSIONS

In this paper, we attempt to use recently developed Teaching-Learning Based Optimization (TLBO) and Salp Swarm Algorithm (SSA) to solve the realistic Economic Load Dispatch (ELD) problem. In this work, we address the 10-unit system with multiple fuel option as first case and non-convex ELD problem with multiple fuel options as second case. The proposed methods exhibits same result during first case, but for second case SSA method exhibits better result as compare with TLBO method. The suggested algorithms found optimal results for the 10 unit thermal system than the other results found so far in the literature. The results clearly indication that the suggested methods can be used as an effective optimizer providing better results for real power system ELD problems.

REFERENCES

[1]. Prateek K. Singhal, R. Naresh. 2014, Enhanced Lambda Iteration Algorithm for the Solution of Large Scale Economic Dispatch Problem. ICRAIE-2014, May 09-11, Jaipur, India.

[2]. R. Gnanadass, K. Manivannan. 2002, Application of Evolutionary Programming Approach to Economic Load Dispatch Problem. National Power Systems Conference, NPSC.

[3]. Satyendra Pratap Singh. 2014, Genetic Algorithm for Solving the Economic Load Dispatch. International Journal of Elctronic and Electrical Engineering. ISSN 0974-2174, Volume 7,Number 5, pp. 523-528.

[4]. Shubham Tiwari, Ankit Kumar. 2013, Economic Load Dispatch Using Particle Swarm Optimization. IJAIEM, ISSN 2319 - 4847 Volume 2, Issue 4,

[5]. Dexuan Zou, Steven Li. 2016, An improved differential evolution algorithm for the economic load dispatch problems with or without valve-point effects. Applied Energy 181 375–390.

[6]. Mohammed Azmi Al-Betar, Mohammed A. Awadallah. 2016, Tournament-based harmony search algorithm for non-convex economic load dispatch problem. Applied Soft Computing.

[7]. Moumita Pradhan, Provas Kumar Roy, Tandra Pal. 2017, Oppositional based grey wolf optimization algorithm for economic dispatch problem of power system. Ain Shams Engineering Journal

[8]. C.E. Lin, G.L. Viviani. 1984, Hierarchical Economic Dispatch for Piecewise Quadratic Cost Functions. IEEE Transactions on Power Apparatus and Systems, Vol. PAS-103, No. 6.

[9]. J.H.Park, Y.S. Kim, K.Y.Lee. August 1993, Economic Load Dispatch for Piecewise Quadratic Cost Function using Hopfield Neural Network. IEEE Transactions on Power System, Vol. 8, No. 3.

[10]. Kwang Y. Lee and Arthit Sode-Yome, June Ho Park. May 1998, Adaptive Hopfield Neural Networks for Economic Load Dispatch. IEEE Transactions on Power Systems, Vol. 13, No. *2.*

[11]. Jong-Bae Park, Ki-Song Lee, Joong-Rin Shin. FEB 2005, A Particle Swarm Optimization for Economic Dispatch with Nonsmooth Cost Functions. IEEE Transactions on Power Systems, VOL. 20, NO. 1.

[12]. Aniruddha Bhattacharya and Pranab Kumar Chattopadhyay. May 2010, Biogeography-Based Optimization for Different Economic Load Dispatch Problems. IEEE Transactions On Power Systems, Vol. 25, No. 2.

[13]. Jong-Bae Park, Yun-Won Jeong, Joong-Rin Shin. Feb 2010, An Improved Particle Swarm Optimization for Nonconvex Economic Dispatch Problems. IEEE Transactions On Power Systems, Vol. 25, No. 1,

[14]. Wael Taha Elsayed, Yasser G. Hegazy. June 2017, Improved Random Drift Particle Swarm Optimization with Self-Adaptive Mechanism for solving the Power Economic Dispatch Problem. IEEE Transactions On Industrial Informatics, Vol. 13, No. 3.

[15]. S. Khamsawang, S. Jiriwibhakorn. 2010, DSPSO–TSA for economic dispatch problem with nonsmooth and noncontinuous cost functions. Energy Conversion and Management 51 365–375.

[16]. Mostafa Modiri-Delshad, S. Hr. Aghay Kaboli. 2017, Backtracking search algorithm for solving economic dispatch problems with valve-point effects and multiple fuel options. Energy 116 (2016) 637e649. Energy 129 , 1e15.

[17]. Mostafa Kheshti, Xiaoning Kang. 2017, An effective Lightning Flash Algorithm solution to large scale non- convex economic dispatch with valve-point and multiple fuel options on generation units. Energy 129, 1e15.

[18]. Taher Niknam, Hasan Doagou Mojarrad. 2011, Non-smooth economic dispatch computation by fuzzy and self adaptive particle swarm optimization. Applied Soft Computing 11 2805–2817.

[19]. K. Vaisakh, A. Srinivasa Reddy. 2013, MSFLA/GHS/SFLA-GHS/SDE algorithms for economic dispatch problem considering multiple fuels and valve point loadings. Applied Soft Computing.

[20]. R. Venkata Rao. 2016, Review of applications of TLBO algorithm and a tutorial for beginners to solve the unconstrained and constrained optimization problems. Decision Science Letters 5 1–30.

[21]. Seyedali Mirjalili, Amir H. Gandomi. 2017, Salp Swarm Algorithm: A bio-inspired optimizer for engineering design problems. Advances in Engineering Software ,1–29.

Journal of Intelligent Systems: Theory and Applications 1(1) (2018) 16-25

Process Planning and Scheduling with WNOPPT Weighted Due-Date Assignment where Earliness, Tardiness and Due-Dates are Penalized

Halil İbrahim Demir*[1], Onur Canpolat[1], Caner Erden[1], Fuat Şimşir[2]

[1] Sakarya University, Faculty of Engineering Industrial Engineering Department, Sakarya, Turkey.
[2] Karabuk University, Faculty of Engineering, Department of Industrial Engineering, Baliklarkayasi Mevkii 78050 Karabük

Abstract

Process planning, scheduling and due date assignment are three important manufacturing functions in production system in which process planning is input to scheduling processes. Because of rigid process plans, alternative plans are not used that may affect global performance improvement in a bad way. Besides, scheduling without considering process plans causes unbalanced machine loadings and leads to several bottlenecks. In the literature, there are numerous works on process planning and scheduling and works on scheduling with due date assignment. These three functions are not integrated much. According to literature, due dates are assigned without considering weights of the customer. In this study, these three functions are integrated and due dates are given according to the importance of the customers. Eight shop floors are studied. Different levels of integration of these three functions are tested and compared with each other. Two search techniques used which are genetic search and random search and results are compared with ordinary solutions. As the level of integration increased solutions became better and search techniques gave a better result than ordinary solutions and the genetic search outperformed random search.

Keywords: Process Planning, Weighted Scheduling, Weighted Due-Date Assignment, Genetic Algorithms, Random Search

Erken Tamamlanma, Gecikme ve Teslim Tarihinin Cezalandırıldığı Durumda Proses Planlama ve Çizelgelemenin WNOPPT Ağırlıklı Teslim Tarihi Belirleme ile Entegrasyonu

Öz

Proses planlama, çizelgeleme ve teslim tarihi belirleme üç önemli imalat fonksiyonudur. Literatüre göre proses planlama ve çizelgelemenin entegrasyonu ve teslim tarihi belirlemeli çizelgeleme üzerine çok sayıda çalışma vardır. Fakat bu üç fonksiyonun entegre edildiği çalışmalar azdır. Literatüre göre teslim tarihleri müşteri ağırlıklarını hesaba katmadan verilmektedir. Bu çalışmada üç fonksiyon entegre edilmiş ve teslim tarihleri müşteri önemi hesaba katılarak verilmiştir. Sekiz atölye çalışılmıştır. Bu üç fonksiyonun farklı entegrasyon seviyeleri test edilmiş, birbirleriyle karşılaştırılmıştır. Genetik arama ve rassal aramadan oluşan iki arama tekniği kullanılmış ve sonuçları sıradan çözümlerle karşılaştırılmıştır. Entegrasyon seviyesi arttıkça sonuçlar daha iyi olmuş, arama teknikleri sıradan çözümlere göre daha iyi sonuçlar vermiş ve genetik arama rassal aramadan üstün çıkmıştır.

Anahtar kelimeler: Proses Planlama, Ağırlıklı Çizelgeleme, Ağırlıklı Teslim Tarihi Belirleme, Genetik Algoritmalar, Rassal Arama

1. Introduction

Process planning, scheduling and due date assignment are three important manufacturing functions and treated separately. These three functions have an effect on each other and it is better if they are treated simultaneously. In the literature, we can see numerous work on scheduling with due date assignment(Adamopoulos and Pappis, 1998; Biskup and Jahnke, 2001; Gordon et al., 2002; Gordon and Kubiak,

* Corresponding Author.
E-mail: hidemir@sakarya.edu.tr

Recieved : 11 June. 2018
Revision : 1 Aug. 2018
Accepted : 3 Aug. 2018

1998; Li et al., 2011; Panwalkar et al., 1982; Ying, 2008) and works on integrated process planning and scheduling (Amin-Naseri and Afshari, 2012; Guo et al., 2009, 2009; Leung et al., 2010; Lim and Zhang, 2004; Moon et al., 2008; Morad and Zalzala, 1999; Zhang and Mallur, 1994). But except authors of this study, there are not many works on integrating these three functions. According to this research, we tested different levels of integration and we observed that higher integration levels give better results because of improved global performance.

Only scheduling sub problem belongs to NP Hard class problems and if we integrate process planning and due date assignment, the problem becomes even more complex and belongs to NP hard problems. That's why exact solutions are only possible for very small problems. As problems get bigger it becomes practically impossible to find the exact solution to the problem. Therefore, heuristic algorithms can and should be used to find a good solution to the problem in a reasonable amount of time. In this study, according to different integration levels, some ordinary solutions are compared with the solutions of genetic search and random search. Always searches are found better than ordinary solutions and genetic search outperformed random search.

If we look at these three functions consecutively; Process planning has been defined by Society of Manufacturing Engineers as the systematic determination of the methods by which a product is to be manufactured economically and competitively. Production scheduling is a resource allocator, which considers timing information while allocating resources to the tasks (Zhang and Mallur, 1994). "The scheduling problems involving due dates are of permanent interest. In a traditional production environment, a job is expected to be completed before its due date. In a just-in-time environment, a job is expected to be completed exactly at its due date" (Gordon et al., 2002).

Because of development in hardware, software and algorithms, it becomes easier to perform some tasks and to solve problems which could not be solved earlier. Recent developments in computer made it possible to prepare process plans. CAPP (Computer Aided Process Planning) is developed and it becomes easy to prepare process plans. The output of process planning is the input of scheduling so poor inputs cause many problems at shop floor. Process planners can select some desired machines repeatedly and may not select some undesired machines at all. This causes unbalanced machine loads and reduces shop floor utilization. In case of some undesired and unexpected occurrences such as machine break down, it is difficult to respond this situation, but if alternative process plans are prepared and if quality process plans are available then it becomes better and easier to schedule at shop floor level. In this case, it becomes possible to react unexpected occurrences and to get balanced machine load and higher shop floor utilization.

Since every customer may not be as important as some other customers we had better schedule important customers first. In this study weighted and unweighted dispatching rules are used. Another very important application of this study is to assign close due dates for the relatively more important customers and far due dates for less important customers. Weighted due date assignment is not treated in the literature much. Findings of this study suggest using weighted due dates assignment. We used WNOPPT (Weighted number of operation plus processing time) as due date assignment method. In this method, due dates are assigned proportionally to processing times plus a proportional amount of number of operations. Motivation in this study is to integrate three functions to improve global performance and use weighted scheduling to schedule important customer first and assign weighted due dates for important customers. Every aspect of this study contributed to overall performance.

As expected weighted tardiness is undesired but in JIT environment weighted earliness is also undesired. We also penalized weighted due dates and far due dates are penalized more. Long due dates may mean customer ill will, customer loss and price reduction. So we should not give far due dates unnecessarily and also we should keep our promises. So it is very important to give close due dates for more important customers and keep our promises. According to performance measure, it is better to give far due dates for less important customers and keep our promises. Jobs should be completed as near as given due dates.

2. Background and Literature Survey

As mentioned earlier there are numerous works on process planning and scheduling and on scheduling with due date assignment. Integration of these three functions is mentioned by ((Demir, H.I. et al., 2004)). In this study integration of process planning and weighted scheduling with WNOPPT due-date assignment was studied. Weighted Earliness, Tardiness and due-dates are punished. Weighted Earliness, Tardiness and due-dates are linearly punished with different proportion and proportional to time and importance of the customer. In case of earliness and tardiness, a fixed cost also added to the performance measure. Higher cost is given for tardiness compared to earliness.

If we look at works on IPPS (Integrated process planning and scheduling) we can see numerous works. If we list earlier works on IPPS, we can see following works. (Khoshnevis and Chen, 1991), (Hutchison et al., 1991), (Chen and Khoshnevis, 1993), (Zhang and Mallur, 1994), (Brandimarte, 1999), (Kim and Egbelu, 1999), (Morad and Zalzala, 1999) worked in this area up to 2000.

If we look at more recent works, we can see following literature. (Tan and Khoshnevis, 2000), (Kim et al., 2003), (Usher, 2003), (Lim and Zhang, 2004), (Tan and Khoshnevis, 2004), (Kumar and Rajotia, 2005), (Moon et al., 2008), (Li et al., 2010), (Leung et al., 2010), (Phanden et al., 2011) .

If we look at the literature we see that it is hard to solve integrated problems. Some solutions are only possible for small problems. For IPPS in the literature, people use genetic algorithms, evolutionary algorithms or agent based approach for integration, or they decompose problems because of the complexity of the problem. They decompose problems into loading and scheduling sub problems. They use mixed integer programming at the loading part and heuristics at the scheduling part, (Demir et al., 2015).

Scheduling with due date assignment is also extensively studied topic. But scheduling with weighted due date assignment is not mentioned much. In this study closer due dates are given to important customers and these customers are scheduled first so we gained from weighted tardiness, due dates and earliness. Relatively far due dates are given for less important customers. A state of the art review on scheduling with due date assignment is given by (Gordon et al., 2002). Conventionally tardiness is penalized and length of due date and earliness are not penalized. Due dates are given independently of the importance of the customer. In this study weighted due date assignment with WNOPPT is integrated with process planning and weighted scheduling. Due dates can be determined internally or externally. If dates are determined externally out of our control we try to meet due dates but if we can determine due dates internally we look for best due dates which are the most profitable and dates with the least cost. According to modern approach earliness and due dates are also penalized as well.

If we look at the literature we can see SMSWDDA (Single machine scheduling with due date assignment) and MMSWDDA (multiple machine scheduling with due date assignment). Most of the works try to find a common due date for the jobs but this research finds different due dates for each customer (Adamopoulos and Pappis, 1998; Biskup and Jahnke, 2001; Cheng et al., 2002; Lauff and Werner, 2004; Nearchou, 2008; Panwalkar et al., 1982).

In the literature, there is not much work done on IPPSDDA (integrated process planning, scheduling and due date assignment). (Demir, H.I. and Taskin, H., 2005) studied IPPSDDA problem in a PhD thesis. Later (Demir, H.I. et al., 2004) studied the benefit of integrating these three functions. Benefits of integrating due date assignment with IPPS is studied by (Ceven, E. and Demir, H.I., 2007) in a Master of Science thesis.

As we mentioned earlier many works are on single machine scheduling with due date assignment. Following works are in this area: (Panwalkar et al., 1982), (Gordon and Kubiak, 1998), (Biskup and Jahnke, 2001), (Cheng et al., 2002), (Ying, 2008), (Nearchou, 2008), (Xia et al., 2008), (Gordon and Strusevich, 2009), and (Li et al., 2011).

There are examples on multiple machine scheduling with due date assignment problems. (Adamopoulos and Pappis, 1998), (Cheng and Kovalyov, 1999), and (Lauff and Werner, 2004) studied multiple machine problems.

In this research, we have multiple customers and each will have their own due date according to the importance of the customers and multiple machine job shop scheduling is integrated with due date assignment and process planning.

3. Problem Studied

With this research, we studied IPPSDDA (Integrated Process Planning, scheduling and due date assignment). We have alternative process plans for each job. For relatively smaller four shop floors, we have five alternative routes for each job and for larger four shop floors in order to find a solution in a reasonable amount of time we have three alternative routes. We integrated process planning with different dispatching rules and with WNOPPT weighted due date assignment rule. For the comparison purpose, we also tested RDM (Random) due date assignment rule. WNOPPT assignment rule is used to represent endogenous due date assignment and RDM rule is used to represent exogenous due date assignment rule.

We have eight shop floors as we mentioned earlier. For instance, first shop floor has 25 jobs and 5 machines. At the relatively smaller shop floors (SF), for example, at the first, second, third and fourth shop floors (SF1, SF2, SF3, SF4), jobs have 5 alternative routes and each route has 10 operations. At the SF1 and SF2 200 iterations are applied. At the larger shop floors (SF), for instance, fifth, sixth, seventh and eighth shop floors (SF5, SF6, SF7, SF8) we have 3 alternative routes and each route has 10 operations. At the SF5 and SF6 100 iterations are applied. In every case, each operation has processing time (PT) according to the formula given in Table 2. We produced processing times randomly and characteristics of each shop floor are given in Table 1.

Table 1. Shop floors

Shop Floor	1	2	3	4	5	6	7	8
# of machines	5	10	15	20	25	30	35	40
# of Jobs	25	50	75	100	125	150	175	200
# of Routes	5	5	5	5	3	3	3	3
# of op. per job	10	10	10	10	10	10	10	10
#of iterations	200	200	150	150	100	100	50	50

Machines are grouped into three and first machine group (MG1) represents new modern machines and requires relatively shorter processing times. MG2 represents average machines and requires average processing times and MG3 represent old machines and requires more processing times. These are all summarized in the Table 2. For smaller shop floors if we select route 1 as the process plan then 80% modern machines are selected and processing times change according to the formula $\lfloor(10 + z * 5)\rfloor$, where processing times assume duration with mean 10 and the standard deviation is 5 minute. 10% average machines are selected and 10% old machines are selected. If route 3 is selected then each group of machines have equal probability to be selected. For route 5 mostly classical old machines are selected. Larger shop floors have only 3 alternative routes.

Table 2. Probability of selecting machine groups and related processing times

SF	MG	PT	Route 1	Route 2	Route 3	Route 4	Route 5
1,2,3,4	1	$\lfloor(10+z*5)\rfloor$	0,8	0,6	0,33	0,2	0,1
	2	$\lfloor(12+z*6)\rfloor$	0,1	0,25	0,33	0,3	0,2
	3	$\lfloor(14+z*7)\rfloor$	0,1	0,15	0,34	0,5	0,7
5,6,7,8	1	$\lfloor(10+z*5)\rfloor$	0,7	0,33	0,2	x	x
	2	$\lfloor(12+z*6)\rfloor$	0,2	0,33	0,2	x	x
	3	$\lfloor(14+z*7)\rfloor$	0,1	0,34	0,6	x	x

We penalized due dates, earliness and tardiness according to the formulas listed below. We assumed one shift per day and total 8*60 = 480 minutes per day.

All terms are punished linearly with different multipliers and constant in earliness and tardiness cases. Tardiness is punished more compared to earliness in terms of fixed and variable cost. All terms are multiplied by the associated weights of the customers to penalize more in case of an important customer. Due dates are punished with proportional to the length of due date times multiplied by 8 and associated weights of the customers. Earliness is punished with fixed cost 5 and proportionally 4 times of the earliness and multiplied by the weights of the customers.

Tardiness is punished with fixed cost 10 and proportionally 12 times of the tardiness and multiplied by the associated weights of the customers. Punishment functions for every job are given below where PD is a penalty for due-date, PE is a penalty for earliness and PT is a penalty for tardiness;

$$P.D = weight\ (j)*8*(Due\text{-}date/480) \tag{1}$$

$$P.E = weight\ (j)*(5+4*(E/480)) \tag{2}$$

$$P.T = weight\ (j)*(10+12*(T/480)) \tag{3}$$

4. Solution Techniques

We used two search techniques and ordinary solutions to compare. As directed search, we used a genetic algorithm and as undirected search, we used random search. Each solution can be explained as follows:

Ordinary Solution: Here we used initial solutions for the comparison purpose. For the genetic algorithm, we defined three population. Main population, crossover population and mutation population. Initially, randomly we produced three populations as big as main population, crossover population and mutation population. If we count best of these three populations as the initial starting main population and as the first iteration then we can say that ordinary solution is the result of the first iteration. Since we just calculated best of initial three populations that's why it took a negligible amount of time to find these results. Defined three populations are required in genetic search during the program run.

Random Search: This is undirected search and used for the comparison purpose. This search always gave better solutions than ordinary solutions. Marginal improvement in performance measure was found good at the very early iterations but sharply reduced as iteration goes on. Here we used three populations as we used in the genetic search. We used the same size of populations to be fair in comparison of random search, genetic search and ordinary solutions. At every iteration, we produced brand new randomly produced populations as big as crossover population and mutation population and selected best of last step main population, newly produced crossover population and mutation population and resulting population is the next step main population.

Genetic Algorithms: In this search, we used three populations at each iteration. Using the last main population with size ten, by applying crossover operator we produced 6 new solutions that constitute crossover population and by applying mutation operator we produced 4 new solutions that make mutation population. For the next step main population, we selected best 10 chromosomes out of 20 chromosomes of three populations.

We represented solutions as chromosomes which have (job size + 2) genes. The first gene is used for due date assignment rules and the second gene is used for dispatching rules. Remaining genes are used to represent each jobs route selected out of 5 or 3 depending on the size of the shop floor. A sample chromosome is given in Figure 1.

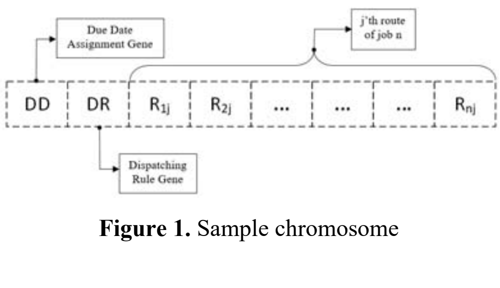


Figure 1. Sample chromosome

Due dates were assigned using mainly two different rules. The first rule is weighted due date assignment rule WNOPPT and represents internal due date assignment and considers weight of each customer. The second rule is random RDM due date assignment rule that assigns due dates randomly which represent external due date assignment. With the multipliers, due date assignment gene takes one of 10 different values. These rules are explained in Table 3.

Table 3. Due-Date Assignment Rules

Method	Multiplier1	Multiplier2	Rule no
WNOPPT	k_x =1,2,3	k_y =1,2,3	1,2,3,4,5,6,7,8,9
RDM			10

In order to dispatch nine different methods were used. Considering weights and different multipliers, the second gene took one of 21 different values. Dispatching rules are given and explained in Table 4.

Table 4. Dispatching Rules

Method	Multiplier	Rule no
WATC	k_x =1,2,3	1,2,3
ATC	k_x =1,2,3	4,5,6
WMS, MS		7,8
WSPT, SPT		9,10
WLPT, LPT		11,12
WSOT, SOT		13,14
WLOT, LOT		15,16
WEDD, EDD		17,18
WERD, ERD		19,20
SIRO		21

5. Compared Solutions

Service in Random Order (SIRO)- Random due assign (RDM), Ordinary Solutions (OS, Random Search (RS), Genetic Algorithms (GA)): In this combination, jobs are scheduled in random order (SIRO) and due dates are determined randomly (RDM). This is the lowest level of integration. In this case, three functions are unintegrated. Ordinary solutions, random search results and genetic search results are compared.

Weighted Scheduling (WSCH)-RDM (OS, RS, GA): Here we integrated WSCH with process plan selection but due dates are still randomly determined.

SIRO- Weighted Number of operations plus

Processing Times (WNOPPT) (OS, RS, GA): With this combination, we integrated due date assignment with process planning and as weighted due date assignment rule WNOPPT is used.

WSCH-WNOPPT (OS, RS, GA): This is the highest level of integration. Here we integrated three functions.

We selected process plans among the list and we dispatched jobs by using 21 dispatching rules and assigned due dates using WNOPPT.

We compared twelve solutions with each other to determine whether the integration of scheduling with process planning or integration of process planning with weighted due date assignment or integrating all three functions are beneficial. We compared search techniques with ordinary solutions and we tested how directed search is well compared to undirected search. Ordinary solutions are found always poor and searches are found well and directed search (GA) outperformed undirected search (RS). We presented results in the experimentation part and made a conclusion in the final part of the paper.

6. Experimentation

We coded problem using C++ which performs genetic or random iterations, assign due dates and schedule jobs according to given 21 dispatching rules.

We tested eight shop floors for twelve types of solutions. We first looked at unintegrated process planning scheduling and due-date assignment as SIRO-RDM (OS, RS, GA). Later we integrated weighted scheduling with process planning and used random due-date assignment. At these solutions, we looked at WSCH-RDM (OS, RS, GA). After that, we tested integration of weighted due date assignment with process planning and tested SIRO-WNOPPT (OS, RS, GA). Finally, we integrated process planning, weighted scheduling and WNOPPT Due-date assignment and looked at the solutions SCH-WNOPPT (OS, RS, GA). Explanations of these solutions are given in section 5.

We tested eight shop floors for twelve types of solutions. The first shop floor is small shop floor and there are 5 machines, 25 jobs with 10 operations each and each job have 5 alternative process plans. We compared twelve solutions and four of them are ordinary solutions for different levels of integration. We used results of initial populations as the ordinary solutions. Because of the limited space only for the fully integrated level, we illustrated ordinary solutions in Table 5. Four of the solutions are genetic search solutions and remaining solutions are the random search solutions.

Results of every shop floor are given in Table 5 and in Figure 2 and Figure 3. According to results, ordinary solutions are the poorest and integration found useful. As integration level increased solutions are found better. Genetic search found better than random search.

Table 5. Comparison of Nine Types of Solutions for Eight Shop Floors

Shop Floor 1	Best	Avg.	Worst
1-1-SIRO-RDM-random	265,0	271,8	276,1
1-1-SIRO-RDM-genetic	241,6	245,4	248,7
1-2-WSCH-RDM-random	212,4	219,4	222,2
1-2-WSCH-RDM-genetic	216,7	218,2	218,8
1-3-SIRO-WNOPPT-random	259,4	265,1	269,0
1-3-SIRO-WNOPPT-genetic	244,8	248,1	250,0
1-4-WSCH-WNOPPT-ordinary	224,6	251,9	318,8
1-4-WSCH-WNOPPT-random	191,0	195,6	197,8
1-4-WSCH-WNOPPT-genetic	184,5	185,2	185,9

Shop Floor 2	Best	Avg.	Worst
1-1-SIRO-RDM-random	601,5	607,2	612,7
1-1-SIRO-RDM-genetic	523,9	534,4	538,5
1-2-WSCH-RDM-random	456,0	474,6	480,4
1-2-WSCH-RDM-genetic	471,6	479,1	482,6
1-3-SIRO-WNOPPT-random	548,2	566,7	573,7
1-3-SIRO-WNOPPT-genetic	515,2	524,2	529,6
1-4-WSCH-WNOPPT-ordinary	485,8	640,2	809,5
1-4-WSCH-WNOPPT-random	448,8	455,9	459,6
1-4-WSCH-WNOPPT-genetic	419,7	425,1	427,1

Shop Floor 3	Best	Avg.	Worst
1-1-SIRO-RDM-random	852,8	894,7	907,9
1-1-SIRO-RDM-genetic	833,5	840,3	843,8
1-2-WSCH-RDM-random	691,2	700,0	707,9
1-2-WSCH-RDM-genetic	648,9	649,1	649,4
1-3-SIRO-WNOPPT-random	838,5	850,7	855,5
1-3-SIRO-WNOPPT-genetic	780,1	783,1	784,8
1-4-WSCH-WNOPPT-ordinary	669,5	866,6	1119,2
1-4-WSCH-WNOPPT-random	622,4	663,2	672,4
1-4-WSCH-WNOPPT-genetic	597,0	601,7	603,2

Shop Floor 4	Best	Avg.	Worst
1-1-SIRO-RDM-random	1263,6	1278,8	1292,3
1-1-SIRO-RDM-genetic	1208,7	1223,3	1228,0
1-2-WSCH-RDM-random	1002,4	1032,4	1043,3
1-2-WSCH-RDM-genetic	1077,7	1087,8	1098,1
1-3-SIRO-WNOPPT-random	1194,4	1212,7	1220,4
1-3-SIRO-WNOPPT-genetic	1143,2	1158,6	1168,9
1-4-WSCH-WNOPPT-ordinary	943,0	1062,3	1223,7
1-4-WSCH-WNOPPT-random	932,5	936,2	938,7
1-4-WSCH-WNOPPT-genetic	897,2	898,2	899,0

Shop Floor 5	Best	Avg.	Worst
1-1-SIRO-RDM-random	1515,4	1554,5	1568,5
1-1-SIRO-RDM-genetic	1461,7	1476,7	1485,3
1-2-WSCH-RDM-random	1213,5	1225,4	1237,7
1-2-WSCH-RDM-genetic	1227,3	1231,3	1234,1
1-3-SIRO-WNOPPT-random	1463,1	1481,1	1491,4
1-3-SIRO-WNOPPT-genetic	1389,8	1399,3	1404,7
1-4-WSCH-WNOPPT-ordinary	1170,8	1435,1	1689,9
1-4-WSCH-WNOPPT-random	1082,9	1108,4	1116,2
1-4-WSCH-WNOPPT-genetic	1039,3	1041,0	1042,9

Shop Floor 6	Best	Avg.	Worst
1-1-SIRO-RDM-random	1855,4	1882,0	1894,5
1-1-SIRO-RDM-genetic	1790,8	1805,4	1814,1
1-2-WSCH-RDM-random	1458,8	1512,7	1530,4
1-2-WSCH-RDM-genetic	1413,7	1414,4	1415,0
1-3-SIRO-WNOPPT-random	1755,0	1788,4	1800,2
1-3-SIRO-WNOPPT-genetic	1690,2	1698,7	1703,8
1-4-WSCH-WNOPPT-ordinary	1359,3	1542,1	2143,6
1-4-WSCH-WNOPPT-random	1310,4	1348,1	1364,2
1-4-WSCH-WNOPPT-genetic	1262,6	1265,7	1268,1

Shop Floor 7	Best	Avg.	Worst
1-1-SIRO-RDM-random	2112,4	2149,7	2169,2
1-1-SIRO-RDM-genetic	2108,7	2117,2	2121,2
1-2-WSCH-RDM-random	1678,3	1723,0	1756,0
1-2-WSCH-RDM-genetic	1704,2	1709,5	1712,6
1-3-SIRO-WNOPPT-random	2004,9	2034,5	2046,7
1-3-SIRO-WNOPPT-genetic	1977,8	1987,3	1994,1
1-4-WSCH-WNOPPT-ordinary	1576,0	1814,3	2403,3
1-4-WSCH-WNOPPT-random	1519,4	1558,5	1573,2
1-4-WSCH-WNOPPT-genetic	1512,1	1515,5	1517,7

Shop Floor 8	Best	Avg.	Worst
1-1-SIRO-RDM-random	2666,6	2712,8	2730,9
1-1-SIRO-RDM-genetic	2610,3	2622,1	2630,8
1-2-WSCH-RDM-random	2206,9	2227,1	2240,8
1-2-WSCH-RDM-genetic	2016,2	2023,6	2029,1
1-3-SIRO-WNOPPT-random	2519,6	2534,7	2552,0
1-3-SIRO-WNOPPT-genetic	2372,4	2389,8	2400,8
1-4-WSCH-WNOPPT-ordinary	1975,6	2267,8	2708,9
1-4-WSCH-WNOPPT-random	1917,7	1970,7	1999,1
1-4-WSCH-WNOPPT-genetic	1861,9	1870,9	1874,4

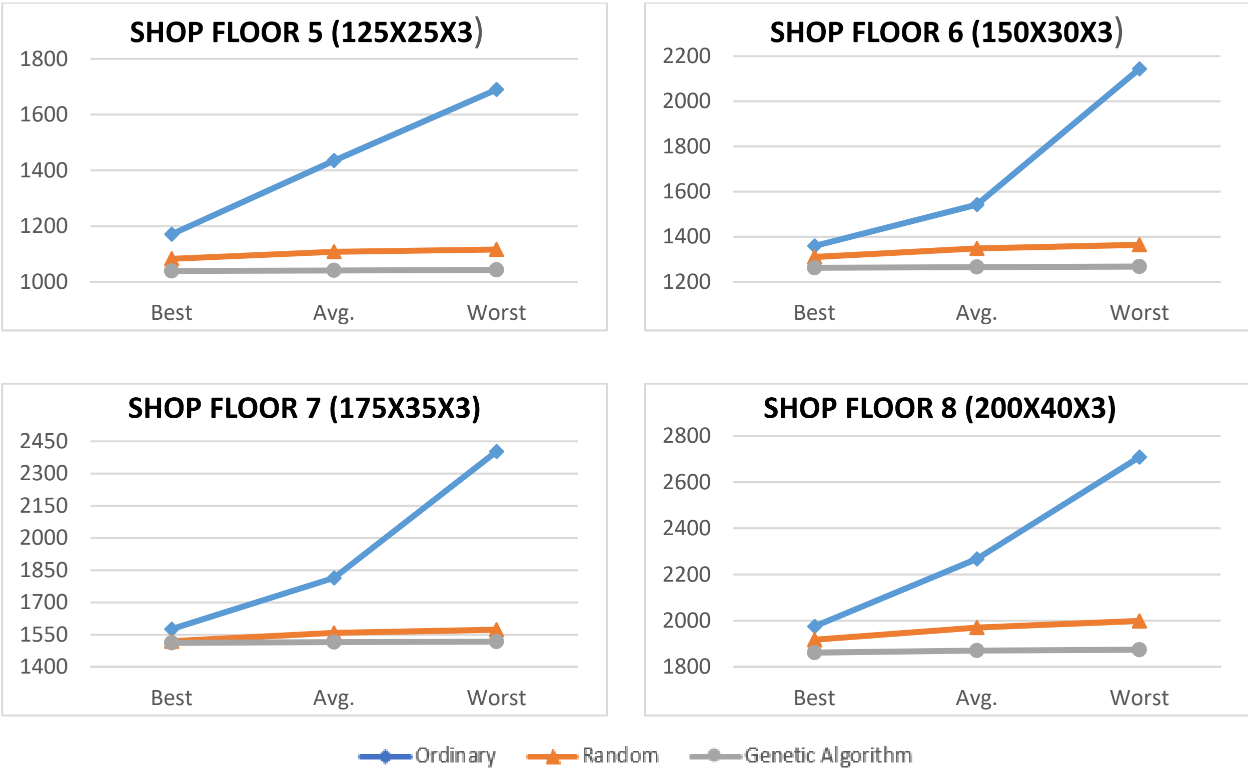


Figure 2. Results of SF5, SF6, SF7 and SF8 (Comparison of Solution techniques OS, RS, GA)

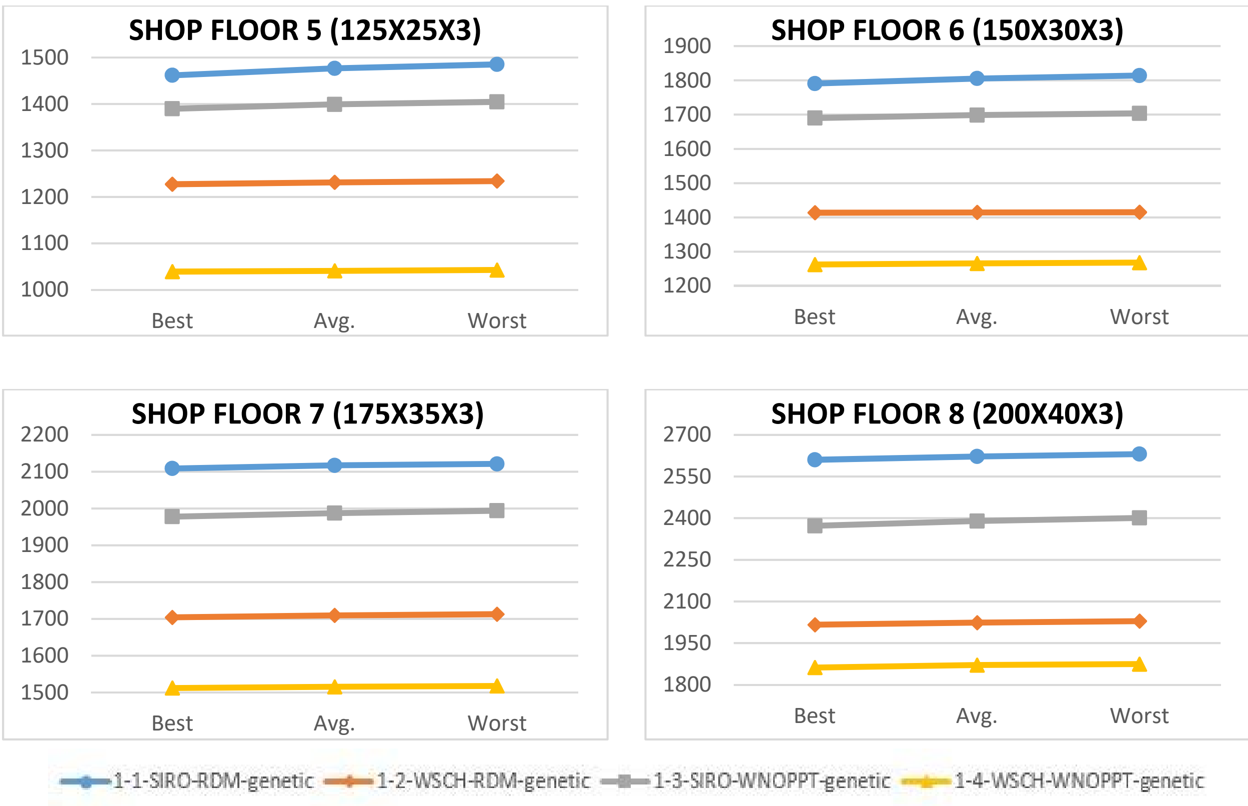


Figure 3. Results of SF5, SF6, SF7 and SF8 (Comparison of integration levels according to GA)

First four figures illustrated and summarized in Figure 2 depict how searches are superior to ordinary solutions. And they also represent directed search (GA) outperforms undirected search (RS). These results are obtained in every eight shop floors and represented for the last four larger shop floors due to limited space.

In Figure 3 again last four larger shop floors are represented and similar results are obtained in any of the eight shop floors. According to Figure 3, it can be seen that WSCH-WNOPPT level that is the fully integrated level gives always the best solution. Second best level is obtained where weighted scheduling is integrated with process planning. This level is represented as WSCH-RDM and at this level, due dates are determined randomly. Third best level is found where due date assignment is integrated with process plan selection but here jobs are scheduled using SIRO rule. This level is SIRO-WNOPPT level. The final level is the totally unintegrated level. In this level, jobs are scheduled using SIRO and due dates are assigned randomly using RDM rule. As it can be seen from Figure 3, lowest level of integration is always found as the worst level and the fully integrated level is found always as the best level of integration.

7. Conclusion

With this study, we tried to integrate process planning, weighted scheduling and WNOPPT weighted due-date assignment. We tested different levels of integration and different search techniques.

At first, we tested unintegrated combination. We solved the problem for SIRO-RDM (OS, RS, GA). Here we assumed that scheduling is unintegrated and we used SIRO (Service in random order) dispatching. We also assumed due-date determination is unintegrated and we used RDM (Random) due-date assignment in place of exogenous, unintegrated due-date determination.

After that, we integrated WNOPPT due date assignment with process plan selection. Scheduling is performed randomly and we used SIRO dispatching. We tested here SIRO-WNOPPT (OS, RS, GA).

Finally, we integrated three functions (process planning, weighed scheduling and weighted due-date assignment). In solution (chromosome), at scheduling gene, we used 21 dispatching rules and at due-date assignment gene, we used WNOPPT. Here we solved the problem for WSCH-WNOPPT (OS, RS, GA). At the genetic search, we repeated genetic iterations up to 200, 150, 100 and 50 iterations for eight shop floors. At Random search, we applied these many random iterations for eight different shop floors. Totally these twelve types of solutions and their explanations are given in section 5. In Table 5 only nine types of solutions are summarized because of limited space and similar observation is obtained at every level of integration.

We have shown that integration improves global performance and as integration level increases solutions become better. If we perform each function sequentially and separately then they all try to get local optima and they don't care about the global optima. The output of process planning is an input to the scheduling. If process plans are made independently then process planner may select some machines repeatedly and some machines rarely. This may cause unbalanced machine load at shop floor and poor process plans may not be followed on the shop floor. If due dates are assigned independently from process plans and scheduling, then poor dates can be given that might give an unnecessarily long due date, unnecessarily more earliness or we might be faced with unrealistically close due dates and unnecessarily high tardiness. If we give dates without being aware of the importance of customers then the sum of weighted due date, earliness and tardiness which is performance measure can be much higher than better results that we can find. So it is better to integrate all functions and while assigning due dates and scheduling we should take into account importance of customers.

In short, integration level improves solution performance. So we should use highest integration level. Using weights while determining due dates and scheduling greatly effects weighted overall performance so we should take into account importance of customers. Finally directed search outperforms undirected search and ordinary solutions are the poorest.

References

Adamopoulos, G.I., Pappis, C.P., 1998. Scheduling under a common due-data on parallel unrelated machines. Eur. J. Oper. Res. 105, 494–501. https://doi.org/10.1016/S0377-2217(97)00057-X

Amin-Naseri, M.R., Afshari, A.J., 2012. A hybrid genetic algorithm for integrated process planning and scheduling problem with precedence constraints. Int. J. Adv. Manuf. Technol. 59, 273–287.

Biskup, D., Jahnke, H., 2001. Common due date assignment for scheduling on a single machine with jointly reducible processing times. Int. J. Prod. Econ. 69, 317–322. https://doi.org/10.1016/S0925-5273(00)00040-2

Brandimarte, P., 1999. Exploiting process plan flexibility in production scheduling: A multi-objective approach. Eur. J. Oper. Res. 114, 59–71. https://doi.org/10.1016/S0377-2217(98)00029-0

Ceven, E., Demir, H.I., 2007. Benefits of Integrating Due-Date Assignment with Process Planning and Scheduling (Master of Science Thesis). Sakarya University.

Chen, Q.M., Khoshnevis, B., 1993. Scheduling with flexible process plans. Prod. Plan. Control 4, 333–343. https://doi.org/10.1080/09537289308919455

Cheng, T.C.E., Chen, Z.-L., Shakhlevich, N.V., 2002. Common due date assignment and scheduling with ready times. Comput. Oper. Res. 29, 1957–

1967. https://doi.org/10.1016/S0305-0548(01)00067-3
Cheng, T.C.E., Kovalyov, M.Y., 1999. Complexity of parallel machine scheduling with processing-plus-wait due dates to minimize maximum absolute lateness. Eur. J. Oper. Res. 114, 403–410. https://doi.org/10.1016/S0377-2217(98)00111-8
Demir, H.I., Taskin, H., 2005. Integrated Process Planning, Scheduling and Due-Date Assignment (PhD Thesis). Sakarya University.
Demir, H.I., Taskin, H., Cakar, T., 2004. Integrated process planning, scheduling and due-date assignment. Presented at the International Intelligent Manufacturing Systems, Sakarya, Turkey, pp. 1165–1175.
Demir, H.I., Uygun, O., Cil, I., Ipek, M., Sari, M., 2015. Process Planning and Scheduling with SLK Due-Date Assignment where Earliness, Tardiness and Due-Dates are Punished. J. Ind. Intell. Inf. 3, 173–180. https://doi.org/10.12720/jiii.3.3.173-180
Gordon, V., Kubiak, W., 1998. Single machine scheduling with release and due date assignment to minimize the weighted number of late jobs. Inf. Process. Lett. 68, 153–159. https://doi.org/10.1016/S0020-0190(98)00153-7
Gordon, V., Proth, J.-M., Chu, C., 2002. A survey of the state-of-the-art of common due date assignment and scheduling research. Eur. J. Oper. Res. 139, 1–25. https://doi.org/10.1016/S0377-2217(01)00181-3
Gordon, V.S., Strusevich, V.A., 2009. Single machine scheduling and due date assignment with positionally dependent processing times. Eur. J. Oper. Res. 198, 57–62. https://doi.org/10.1016/j.ejor.2008.07.044
Guo, Y.W., Li, W.D., Mileham, A.R., Owen, G.W., 2009. Optimisation of integrated process planning and scheduling using a particle swarm optimisation approach. Int. J. Prod. Res. 47, 3775–3796.
Hutchison, J., Leong, K., Snyder, D., Ward, P., 1991. Scheduling approaches for random job shop flexible manufacturing systems. Int. J. Prod. Res. 29, 1053–1067. https://doi.org/10.1080/00207549108930119
Khoshnevis, B., Chen, Q.M., 1991. Integration of process planning and scheduling functions. J. Intell. Manuf. 2, 165–175. https://doi.org/10.1007/BF01471363
Kim, K.-H., Egbelu, P.J., 1999. Scheduling in a production environment with multiple process plans per job. Int. J. Prod. Res. 37, 2725–2753. https://doi.org/10.1080/002075499190491
Kim, Y.K., Park, K., Ko, J., 2003. A symbiotic evolutionary algorithm for the integration of process planning and job shop scheduling. Comput. Oper. Res. 30, 1151–1171. https://doi.org/10.1016/S0305-0548(02)00063-1
Kumar, M., Rajotia, S., 2005. Integration of process planning and scheduling in a job shop environment. Int. J. Adv. Manuf. Technol. 28, 109–116. https://doi.org/10.1007/s00170-004-2317-y
Lauff, V., Werner, F., 2004. Scheduling with common due date, earliness and tardiness penalties for multimachine problems: A survey. Math. Comput. Model. 40, 637–655. https://doi.org/10.1016/j.mcm.2003.05.019
Leung, C.W., Wong, T.N., Mak, K.L., Fung, R.Y.K., 2010. Integrated process planning and scheduling by an agent-based ant colony optimization. Comput. Ind. Eng. 59, 166–180. https://doi.org/10.1016/j.cie.2009.09.003
Li, J., Yuan, X., Lee, E.S., Xu, D., 2011. Setting due dates to minimize the total weighted possibilistic mean value of the weighted earliness–tardiness costs on a single machine. Comput. Math. Appl. 62, 4126–4139. https://doi.org/10.1016/j.camwa.2011.09.063
Li, X., Gao, L., Zhang, C., Shao, X., 2010. A review on Integrated Process Planning and Scheduling. Int. J. Manuf. Res. 5, 161–180. https://doi.org/10.1504/IJMR.2010.03163
Lim, M.K., Zhang, D.Z., 2004. An integrated agent-based approach for responsive control of manufacturing resources. Comput. Ind. Eng., Special Issue on Selected Papers from the 27th. International Conference on Computers and Industrial Engineering, Part 1. 46, 221–232. https://doi.org/10.1016/j.cie.2003.12.006
Moon, C., Lee, Y.H., Jeong, C.S., Yun, Y., 2008. Integrated process planning and scheduling in a supply chain. Comput. Ind. Eng. 54, 1048–1061. https://doi.org/10.1016/j.cie.2007.06.018
Morad, N., Zalzala, A., 1999. Genetic algorithms in integrated process planning and scheduling. J. Intell. Manuf. 10, 169–179. https://doi.org/10.1023/A:1008976720878
Nearchou, A.C., 2008. A differential evolution approach for the common due date early/tardy job scheduling problem. Comput. Oper. Res. 35, 1329–1343. https://doi.org/10.1016/j.cor.2006.08.013
Panwalkar, S.S., Smith, M.L., Seidmann, A., 1982. Common Due Date Assignment to Minimize Total Penalty for the One Machine Scheduling Problem. Oper. Res. 30, 391–399. https://doi.org/10.1287/opre.30.2.391
Phanden, R.K., Jain, A., Verma, R., 2011. Integration of process planning and scheduling: a state-of-the-art review. Int. J. Comput. Integr. Manuf. 24, 517–534. https://doi.org/10.1080/0951192X.2011.562543
Tan, W., Khoshnevis, B., 2004. A linearized polynomial mixed integer programming model for the integration of process planning and scheduling. J. Intell. Manuf. 15, 593–605.

https://doi.org/10.1023/B:JIMS.0000037710.80847.b6
Tan, W., Khoshnevis, B., 2000. Integration of process planning and scheduling— a review. J. Intell. Manuf. 11, 51–63. https://doi.org/10.1023/A:1008952024606
Usher, J.M., 2003. Evaluating the impact of alternative plans on manufacturing performance. Comput. Ind. Eng. 45, 585–596. https://doi.org/10.1016/S0360-8352(03)00076-7
Xia, Y., Chen, B., Yue, J., 2008. Job sequencing and due date assignment in a single machine shop with uncertain processing times. Eur. J. Oper. Res. 184, 63–75. https://doi.org/10.1016/j.ejor.2006.10.058
Ying, K.-C., 2008. Minimizing earliness–tardiness penalties for common due date single-machine scheduling problems by a recovering beam search algorithm. Comput. Ind. Eng. 55, 494–502. https://doi.org/10.1016/j.cie.2008.01.008
Zhang, H.-C., Mallur, S., 1994. An integrated model of process planning and production scheduling. Int. J. Comput. Integr. Manuf. 7, 356–364. https://doi.org/10.1080/09511929408944623

Zeki Sistemler Teori ve Uygulamaları Dergisi 1(1) 2018, 26-30

Determining Amounts of Energy Saver Devices in an Electronic Industry Using Fuzzy Linear Programming

Çağatay Teke[1,*] and Alper Kiraz[2]

[1] *Industrial Engineering Department, Bayburt University Bayburt, Turkey, cagatayteke@bayburt.edu.tr*
[2] *Industrial Engineering Department, Sakarya University Esentepe Campus Serdivan/Sakarya, Turkey, kiraz@sakarya.edu.tr*

Abstract
Rapid and accurate decision making is not only important for people but also for organizations. However, uncertainty makes decision making difficult. Fuzzy logic approach is deal with uncertainty situations. Namely, fuzzy logic is a precise logic of uncertainty and approximate reasoning. Besides, Fuzzy Linear Programming (FLP) is also known as a strategy that can take into consideration to fuzziness. Determining amounts of production is one of the most important factors effecting the profitability level of enterprises. The aim of this study which is prepared since classical mathematical programming models are inadequate to examine situations that consist of uncertainty; is to bring up how FLP model for providing the best decision making under fuzzy environments can be used at determining amounts of energy saver devices. Required data is obtained and the problem is figured out via Zimmerman approach which is one of the approaches for FLP. In this way, problems that may occur such as cost, waste of time, overstock and customer loss will be prevented. As a result, the solution gives the amount of production for each energy saver device in order to get optimal solution for profit maximizing. This study makes a contribution to practicality of FLP, by supplying a wider moving area than classical set theory to decision makers.

Keywords: Fuzzy linear programming, production planning, electronic industry

Bulanık Doğrusal Programlama ile Elektronik Endüstrisindeki Enerji Tasarrufu Cihazlarının Miktarlarının Belirlenmesi

Özet
Hızlı ve doğru karar verme, sadece insanlar için değil, aynı zamanda organizasyonlar için de önemlidir. Ancak belirsizlik karar vermeyi zorlaştırmaktadır. Bulanık mantık yaklaşımı belirsizlik durumları ile ilgilidir. Yani, bulanık mantık kesin bir belirsizlik ve yaklaşık anlam çıkarma mantığıdır. Ayrıca, Bulanık Doğrusal Programlama (BDP), aynı zamanda, bulanıklığı dikkate alabilecek bir strateji olarak da bilinir. Üretim miktarlarının belirlenmesi, işletmelerin karlılık düzeyini etkileyen en önemli faktörlerden biridir. Klasik matematiksel programlama modellerinin, belirsizlikten kaynaklanan durumları incelemek için yetersiz olması nedeniyle hazırlanan bu çalışmanın amacı; bulanık ortamlarda en iyi karar vermeyi sağlayan BDP modelinin, enerji tasarrufu cihazlarının miktarlarını belirlemede nasıl kullanılabileceğini ortaya koymaktır. Gerekli veriler elde edildikten sonra problem, bulanık doğrusal programlama yaklaşımlarından biri olan Zimmerman yaklaşımıyla çözülmüştür. Bu sayede maliyet, zaman kaybı, stok fazlası ve müşteri kaybı gibi problemler önlenecektir. Sonuç olarak, çözüm, kar maksimizasyonu için en uygun çözümü elde etmek amacıyla her bir enerji tasarrufu cihazı için üretim miktarını vermektedir. Bu çalışma, karar vericilere klasik küme teorisinden daha geniş bir hareket alanı sağlayarak, BDP'nın pratikliğine katkı sağlamaktadır.

Anahtar kelimeler: Bulanık doğrusal programlama, üretim planlama, elektronik endüstrisi.

1. Introduction

Decision making generally depends on decision support system tools. Selecting and applying of decision making method which is the most appropriate with structure of the problem provide a useful insight to executives for giving rational decision. Structure of the problem must be understood in order to select the appropriate decision support method. If there is any imprecision, uncertainty or incompleteness situation in the problem, decision support tools integrated fuzzy logic should be used for getting better solution. In this study, fuzzy linear programming (FLP) method is preferred because expected profit and the demand of the energy saver devices are uncertain.

Zadeh and Bellman propounded the notion of maximizing the decision for decision making problems. A fuzzy approach concerning multi-objective Linear Programming (LP) problems was introduced by Zimmermann. Studies in recent years suggest new

* Corresponding Author

Recieved : 3 Aug. 2018
Accepted : 28 Sep. 2018

techniques with the purpose of ranking fuzzy numbers and coming to an optimal solution (Gani et al., 2009).

Many authors proposed several approaches and solved their own problems with FLP model. For example; Abdullah and Abidin are used FLP with single objective function for getting optimal solutions and profits of red meat production problem. They successfully obtained to the profit of red meat production with the variability of fuzzy memberships in FLP (Abdullah et al., 2014). Kalaf et al. have developed a fuzzy multi-objective model for solving aggregate production planning problems that contain multiple both periods and products in fuzzy environments. They adopted a new method that utilizes a Zimmermans approach. This proposed model attempts to minimize total production costs and labor costs synchronically (Kalaf et al., 2015). Elamvazuthi et al. were solved a FLP problem in which the parameters involved are fuzzy quantities with logistic membership functions. They determined monthly profit and production planning quotas via numerical example of home-textile group to explore the applicability of the method (Elamvazuthi et al., 2009). Demiral used FLP model for production planning problem of a dairy industry because of the uncertain supply of milk and demand of dairy products. Results of his study was shown that FLP is more realistic than LP (Demiral, 2013). Herath and Samarathunga are presented a fuzzy multi-criteria mathematical programming model. This study was undertaken to find out the optimal allocation for profit maximizing and cost minimizing subjected to the utilizing of 'water and demand' constraint. They achieved to get optimal production plan with this model (Herath and Samarathunga, 2015).

In this study, FLP method is used for determining amounts of 6 different energy saver devices under uncertainty environment. The objective of this paper is to determine amounts of these devices for obtaining maximum profit and minimum deviation of demand by taking capacities of labour and production into consideration.

This paper is organized as follows. Section 2 and 3 respectively describes FLP and types of FLP. Zimmerman Method is described in Section 4. A case study and its results presented in Section 5. Finally, conclusions are given in Section 6.

2. Fuzzy Linear Programming

2.1. Linear programming

Programming problem. From an analytical perspective, a mathematical program attempts to identify a minimum or maximum point of a function, which furthermore satisfies a set of constraints. Objective function and problem constraints are linear in LP (Dervişoğlu, 2005).

A classical model of LP, also called a crisp LP model, may have the following formulation:

$$\begin{aligned} &Max \quad Cx \\ &s.t. \\ &A_i x \leq b_i \qquad i=1, \ldots, m \end{aligned} \tag{1}$$

in which x is an n × 1 alternative set, C is a 1 × n coefficients of an objective function, Ai is an m × n matrix of coefficients of constraints and bi is an m × 1 right-hand sides.

The traditional problems of LP are solved with LINDO optimization software and obtain the optimal solution in a precise way. If coefficients of constraints, objective function or the right-hand sides are imprecise, in other words, being fuzzy numbers, traditional algorithms of LP are unsuitable to solve the fuzzy problem and to obtain the optimization.

In the real world, the coefficients are typically imprecise numbers because of insufficient information, for instance, technological coefficients. Many researchers formed FLP of various types, invented approaches to convert them into crisp LP, and finally solved the problems with available software (Lee and Wen, 1996).

2.2. Fuzzy linear programming

FLP follows from the fact that classical LP is often insufficient in practical situations. In reality, certain coefficients that appear in classical LP problems may not be well-defined, either because their values depend on other parameters or because they cannot be precisely assessed and only qualitative estimates of these coefficients are available. FLP is an extension of classical LP and deals with imprecise coefficients by using fuzzy variables (Ren and Sheridan, 1994).

We consider the FLP Problem

$$\begin{aligned} &Max\, \tilde{Z} = \tilde{C}^T x \\ &s.t. \\ &\tilde{A}\, x \leq \tilde{b} \\ &x \geq 0 \end{aligned} \tag{2}$$

The solution of this problem is to find the possibility distribution of the optional objective function Z. Many researchers had handled this problem by converting the fuzzy objective function and the fuzzy constraints into crisp ones (Gasimov and Yenilmez, 2002).

3. Types of Fuzzy Linear Programming

FLP model divides into parts in terms of fuzzy coefficients. For instance, while objective function is fuzzy, constraints cannot be fuzzy. Combinations of possible situations are briefly introduced as below:

- Objective Function is Fuzzy

In a real life, there are many situations that parameters of objective function (profit and cost) are imprecise. FLP model of this was propounded by Verdegay.

- Right-Hand Sides are Fuzzy

There are two approach for this type of problem. While first approach concerning asymmetric models belongs to Verdegay, second approach concerning symmetric model belongs to Werners.

- Right-Hand Sides and Coefficients of Constrains are Fuzzy

Negoita and Sularia developed an approach for this type of FLP model.

- Objective Function and Constrains are Fuzzy

As it is understood the title, in this model, both objective function and constrains involve fuzziness. Zimmermann and Chanas have different approaches about it.

- All Coefficients are Fuzzy

Sometimes, all coefficients can be fuzzy in the problem. Carlsson and Korhonen developed the approach for this.

4. Zimmermann Method

LP with a fuzzy objective function and fuzzy inequalities shown by Zimmermann is indicated as follows (Lee and Wen, 1996):

$$\begin{aligned} &C^T x \tilde{\geq} b_0 \\ &(Ax)_i \tilde{\leq} b_i \\ &x \geq 0 \quad i = 1,\ 2,\ \dots,\ m \end{aligned} \tag{3}$$

Inequality is a symmetrical model of which the objective function becomes one constraint. To write a general formulation, inequality is converted to a matrix form as (Lee and Wen, 1996):

$$-C^T x \tilde{\leq} -b_0 \tag{4}$$

In which

$$B = \begin{bmatrix} -C \\ A_i \end{bmatrix} \quad b = \begin{bmatrix} -b_0 \\ b_i \end{bmatrix} \tag{5}$$

The inequalities of constraint signify "be as small as possible or equal" that can be allowed to violate the right-hand side b by extending some value. The degree of violation is represented by membership function as (Lee and Wen, 1996):

$$\mu_0(x) = \begin{Bmatrix} 0 & ,if\ Cx \leq b_0 - d_0 \\ 1 - \dfrac{b_0 - Cx}{d_0} & ,if\ b_0 - d_0 \leq Cx \leq b_0 \\ 1 & ,if\ Cx \leq b_0 \end{Bmatrix} \tag{6}$$

$$\mu_i(x) = \begin{Bmatrix} 0 & ,if\ (Ax_i) \geq b_i + d_i \\ 1 - \dfrac{(Ax)_i - b_i}{d_i} & ,if\ b_i \leq (Ax)_i \leq b_i + d_i \\ 1 & ,if\ (Ax)_i \leq b_i \end{Bmatrix} \tag{7}$$

In which d is a matrix of admissible violation.

This problem can be transformed by introducing the auxiliary variable λ as follows:

$$\begin{aligned} &\mu_0(x) \geq \lambda \\ &\mu_i(x) \geq \lambda \\ &\lambda \in [0,1] \end{aligned} \tag{8}$$

This problem can be stated as LP as follows:

$$\begin{aligned} &Max\ \lambda \\ &s.t. \\ &\mu_0(x) \geq \lambda \\ &\mu_i(x) \geq \lambda \\ &\lambda \in [0,1] \end{aligned} \tag{9}$$

This problem was shown with membership functions of fuzzy objective function and fuzzy constrains as follows:

$$\begin{aligned} &Max\ \lambda \\ &s.t. \\ &1 - \frac{b_0 - Cx}{d_0} \geq \lambda \\ &1 - \frac{(Ax)_i - b_i}{d_i} \geq \lambda,\ \forall i \\ &\lambda \in [0,1] \\ &x \geq 0 \end{aligned} \tag{10}$$

After some simplification, FLP model obtains as follows:

$$\begin{aligned} &Max\ \lambda \\ &s.t. \\ &C^T x - \lambda d_0 \geq b_0 - d_0 \\ &(Ax)_i + \lambda d_i \leq b_i + d_i,\ \forall i \\ &\lambda \in [0,1] \\ &x \geq 0 \end{aligned} \tag{11}$$

Table 1. Data for FLP model

Variables						
Variable name	X_1	X_2	X_3	X_4	X_5	X_6
Unit profits (TRY per item)	0.55	0.41	0.32	0.38	0.1	2.51
Expected demands (item per month)	16204	16220	17110	5935	7021	3436
Tolerances for demands (item per month)	242	208	167	150	140	138
Labour usage (minute per item)	0.427	0.468	0.315	0.63	0.35	0.99
Expected profit (TRY)	35000					
Tolerance for profit (TRY)	3000					
Monthly production capacity (item)	70,000					
Monthly labour capacity (minute)	208,000					

5. Application

5.1. Problem definition

Data used for the application was obtained a factory in an electronic industry. It produces 6 different energy saver devices. Since the expected profit and the demand of the product types are uncertain the problem is built as

FLP model in order to determine production amounts per month for each product type for maximizing the profit. Data about the production and its constraints are given in Table 1.

5.2. FLP model

Problem was modelled as monthly basis. The FLP model of the problem is given below:

$$
\begin{aligned}
&C^T x = 0.55x_1 + 0.41x_2 + 0.32x_3 + 0.38x_4 + \\
&0.1x_5 + 2.51x_6 \\
&b_0 = 35{,}000 \qquad d_0 = 3000 \\
&b_1 = 16204 \qquad d_1 = 242 \\
&b_2 = 16220 \qquad d_2 = 208 \\
&b_3 = 17110 \qquad d_3 = 167 \\
&b_4 = 5935 \qquad d_4 = 150 \\
&b_5 = 7021 \qquad d_5 = 140 \\
&b_6 = 3436 \qquad d_6 = 138
\end{aligned} \tag{12}
$$

$$
\begin{aligned}
&Max\ \lambda \\
&s.t. \\
&0.55x_1 + 0.41x_2 + 0.32x_3 + 0.38x_4 + \\
&0.1x_5 + 2.51x_6 - 3000\lambda \geq 32{,}000 \\
&x_1 + 242\lambda \leq 16446 \\
&x_2 + 208\lambda \leq 16428 \\
&x_3 + 167\lambda \leq 17277 \\
&x_4 + 150\lambda \leq 6085 \\
&x_5 + 140\lambda \leq 7161 \\
&x_6 + 138\lambda \leq 3574 \\
&x_1 + x_2 + x_3 + x_4 + x_5 + x_6 \leq 70{,}000 \\
&0.427x_1 + 0.468x_2 + 0.315x_3 + 0.63x_4 + \\
&0.35x_5 + 0.99x_6 \leq 208{,}000 \\
&\lambda \in [0,1] \\
&x_i \geq 0 \\
&i = 1,2,\dots,6 \\
&\forall x_i \in Z^+
\end{aligned} \tag{13}
$$

5.3. Problem solution

FLP model of the problem has been solved using Lindo optimization software. Results of the solution are given in Table 2 and Table 3.

As can be seen from the solution, the factory should produce 16360 x1, 16354 x2, 17217 x3, 6031 x4, 7111 x5, 3525 x6.

Table 2. Results of the solution

Variable	Value	Reduced Cost
λ	0.354	0
X_1	16360	-0.000183
X_2	16354	-0.000137
X_3	17217	-0.000107
X_4	6031	-0.000127
X_5	7111	-0.000033
X_6	3525	-0.000837

Table 3. Results of the solution

Row	Slack or Surplus	Dual Price
2	0.000000	-0.000333
3	0.234396	0.000000
4	0.284109	0.000000
5	0.814645	0.000000
6	0.839502	0.000000
7	0.383535	0.000000
8	0.092342	0.000000
9	3402	0.000000
10	178159.125	0.000000

Total profit of the factory can be calculated as follows:

$$
\begin{aligned}
&(0.55\times 16360) + (0.41\times 16354) + (0.32\times 17217) + (0.38\times 6031) + \\
&(0.1\times 7111) + (2.51\times 3525) = 3306321\ TRY
\end{aligned} \tag{14}
$$

6. Conclusion

This paper has discussed the use of FLP for solving a production planning problem in an electronic industry. It can be concluded that this method introduced is a promising method for solving such problems. This problem was solved by using Zimmerman approach which is one of the approaches for FLP, because the model has fuzziness in both objective function and constraints. Amounts of 6 different energy saver devices are determined for obtaining maximum profit and minimum deviation of demand by taking capacities of labour and production into consideration. The example illustrates how particular problems of real production systems can be treated by the theory on fuzzy sets.

References

Abdullah L., Abidin N. H., 2014. A Fuzzy Linear Programming in Optimizing Meat Production. International Journal of Engineering and Technology, 6(1):436-444, 2014.

Demiral M. F., 2013. A Case Study at Dairy Industry with Fuzzy Linear Programming. The Journal of Faculty of Economics and Administrative Sciences, Suleyman Demirel University, 18(2):373-397.

Dervişoğlu E., 2005, Fuzzy Linear Programming: Review and Implementation, Sabanci University, İstanbul.

Elamvazuthi I., Ganesan T., Vasant P., Webb J. F., 2009. Application of a Fuzzy Programming Technique to Production Planning in the Textile Industry, International Journal of Computer Science and Information Security. 6(3): 238-243.

Gani A. N., Duraisamy C., Veeramani C., 2009. A note on fuzzy linear programming problem using L-R fuzzy number. International Journal of Algorithms, Computing and Mathematics, 3:93-106.

Gasimov R. N., Yenilmez K., 2002. Solving Fuzzy Linear Programming Problems with Linear Membership Functions. Turk J Math, 26:375-396.

Herath H.M.I.U., Samarathunga D.M., 2015. Multi-Objective Fuzzy Linear Programming In Agricultural Production Planning. International Journal of Scientific and Technology Research, 4(10):242-250.

Kalaf B. A., Bakar R. A., Soon L. L., Monsi M. B., Bakheet A. J. K., Abbas I. T., 2015. A Modified Fuzzy Multi-Objective Linear Programming to Solve Aggregate Production Planning. International Journal of Pure and Applied Mathematics, 104(3):339-352.

Lee C. S., Wen C. G., 1996. River assimilative capacity analysis via fuzzy linear programming. Fuzzy Sets and Systems, 79:191-201.

Ren J., Sheridan T. B., 1994. Optimization with fuzzy linear programming and fuzzy knowledge base, IEEE, 0-7803-1896-X/94.

Zeki Sistemler Teori ve Uygulamaları Dergisi 1(1) (2018) 31-35

Gri İlişkisel Analiz Yöntemiyle Optimum Lastik Seçimi

Abdullah Hulusi Kökçam*[1], Özer Uygun[2], Emre Kılıçaslan[3]

Öz

Çok sayıda performans kriterini hesaba katarak birçok alternatif arasından en iyisini seçme problemi günlük hayatımızda sürekli karşılaştığımız önemli bir konudur. Gri ilişkisel analiz yöntemi yetersiz, eksik veya kesinlik içermeyen verilerin bulunduğu durumlarda derecelendirme, sınıflandırma ve karar verme tekniği olarak kullanılmaktadır. Bu çalışmada, ortalama 4-8 yılda bir yapılan ve maliyetli bir alışveriş olan lastik alımında göz önünde bulundurulması gereken kriterler belirlenerek gri ilişkisel analiz metodu ile lastik seçimi konusu ele alınmıştır. Çalışma kapsamında 6 farklı kriter belirlenmiş ve 10 farklı lastik alternatifi değerlendirilmiştir. Gri ilişkisel analiz gibi uygulaması kolay tekniklerin hızlı bir şekilde doğru karar vermemize katkı sağladığı gösterilmiştir.

Anahtar kelimeler: Gri ilişkisel analiz, lastik seçimi, çok kriterli karar verme.

Optimum Tire Selection with Grey Relational Analysis

Abstract

The problem of choosing the best among the many alternatives by considering many performance criteria is an important issue that we are constantly facing in our daily lives. Grey relational analysis is used as a rating, classification and decision-making technique when there is insufficient, incomplete or uncertain data. In this study, the criteria that should be taken into consideration in the purchase of tires, which is a costly shopping made in an average of 4-8 years, is determined and selection of tires with grey relational analysis method is discussed. Six different criteria were identified, and 10 different tire alternatives were evaluated. It is shown that easy-to-apply techniques, such as the grey relational analysis, contribute to making the right decision quickly.

Keywords: Grey relational analysis, tire selection, multi-criteria decision making.

1. Giriş (Introduction)

Günlük hayatta birçok defa çok sayıda kriteri göz önünde bulundurarak karar verme durumuyla karşılaşılmaktadır. Mevcut alternatifleri çoğunlukla birbiriyle çelişen birçok kritere göre değerlendirerek aralarından en iyi olanını bulma Çok Kriterli Karar Verme (ÇKKV) problemi olarak ortaya çıkmaktadır.

Araçların sürüş güvenliğini ve konforunu birinci derecede etkileyen bileşenlerden biri lastiktir. Lastiğin virajda yol tutuşu, bir yüzeyde ne kadar kolay döndüğü, frenleme, hızlanma, yol tutuşu ve çekiş özellikleri, direksiyon hakimiyeti, suda kızaklama direnci, lastik delindiğinde veya söndüğünde bir müddet daha sürüşe izin vermesi, ıslak zeminde yol tutuşu, kuru zeminde yol tutuşu, tümsek veya diğer düzensizliklerden kaynaklanan şoku emme kabiliyeti, gürültü, frenleme mesafesi, kullanım ömrü gibi çok sayıda özelliği bulunmaktadır (Goodyear, 2018). Son kullanıcı açısından bütün bu özellikleri göz önünde bulundurarak karar vermek pek de kolay değildir. Bu işi sistematik bir şekilde çözmek ve doğru karar vermek için ÇKKV çözüm yöntemleri kullanılabilir.

Literatürde araç lastikleriyle ilgili çeşitli alanlarda çalışmalar bulunmaktadır. Harned vd. (1969) lastiklerin frenleme gücü özelliklerini çeşitli lastik ve yollarda farklı hızlara göre ölçmüşlerdir. Miano vd. (2004) lastiklerin yol tutuş davranışları üzerinden mekanik özelliklerini lineer ve lineer olmayan modellerle

* Sorumlu yazar / Corresponding Author
[1] Sakarya Üniversitesi, Mühendislik Fakültesi, Endüstri Mühendisliği Bölümü, Sakarya, akokcam@sakarya.edu.tr
[2] Sakarya Üniversitesi, Mühendislik Fakültesi, Endüstri Mühendisliği Bölümü, Sakarya, ouygun@sakarya.edu.tr
[3] Sakarya Üniversitesi, Mühendislik Fakültesi, Endüstri Mühendisliği Bölümü, emre_kilicaslan@goodyear.com

Alındı : 13 Aug 2018
Revizyon : 3 Oct 2018
Kabul : 4 Oct 2018

optimize etmişlerdir. Benedetti vd. (2006) diferansiyel denklemler, yapay sinir ağları, modelleme, deney tasarımı, çok amaçlı optimizasyon ve bulanık en iyi tabanlı karar vermenin entegrasyonuyla endüstriyel olarak en iyi lastik tasarım stratejisinin bulunması konusunda çalışmışlardır. Sandberg vd. (2016) lastiklerin gürültü ve yuvarlanma direncine göre kış lastiklerini yazlık ve dört mevsimlik lastiklerle karşılaştırmışlardır. Chitra ve Malarvizhi (2018) lastik seçiminde müşteri memnuniyetini literatürde yer alan bilgiler ile anket ve mülakat tekniklerini kullanarak araştırmışlardır.

Nedělková vd. (2017) kamyon ve yolcu taşıyan araçlar için enerji kaybını minimize edecek lastik seçimi konusunda çalışmışlardır. Literatürde son kullanıcılar için alternatifler arasından belirli kriterlere göre lastik seçimi yapan bir çalışmaya rastlanmamıştır.

Gri sistem teorisi ve bunun altında yer alan Gri ilişkisel analizle ile ilgili olarak literatürde çok sayıda çalışma bulunmaktadır. Lin vd. (2002) çok cevaplı bir sürecin optimizasyonu için ortagonal dizi ve bulanık Taguchi yöntemine dayanan Gri ilişkisel analiz yöntemini kullanmışlardır. Tosun (2006) iş parçası yüzey pürüzlülüğü ve çapak yüksekliği için delme işlemi parametrelerinin optimize edilmesi için gri ilişkisel analiz yöntemini kullanmıştır. Satolo vd. (2018) Gri sistem teorisiyle yalın üretim sisteminin araçlarını sıralamış ve bu araçların organizasyonların dünya standartlarında üretimine nasıl yardımcı olduklarını belirlemişlerdir. Sridharan vd. (2019) sürdürülebilir tedarik zinciri yönetiminde karşılaşılan engelleri sezgisel bulanık bir ortamda gri ilişkisel analiz yöntemiyle sıralayarak değerlendirmişlerdir.

Bu çalışmada mevcut bilgilerin eksik, yetersiz veya belirsiz olduğu durumlarda karar vermek amacıyla kullanılabilen Gri sistem teorisinden yararlanılmıştır.

2. Problemin Tanımı (Problem Definition)

Lastik ömrü, kullanıma ve şartlara göre değişebilmekle beraber belirlenen koşullarda kullanılması ve herhangi bir darbe almaması durumunda ortalama olarak 4-8 yıl veya 50.000-80.000 km civarındadır (Otodetay, 2016). Ayrıca lastik diş derinliğinin yasal sınır olan 1,6 mm'ye düşmesi de lastiğin değişim zamanının geldiğini göstermektedir. Lastik; güvenlik ve konfor açısından önemli ve aynı zamanda da pahalı bir ekipman olduğu için uygun lastik seçimi; araç sahipleri açısından karar vermesi her zaman zorlu bir süreç olmuştur.

3. Yöntem (Method)

Gri sistem teorisi Julong Deng tarafından belirsizliğin sayısallaştırılması amacıyla 1982 yılında geliştirilmiş ve birçok disiplinde uygulama alanı bulmuş matematiksel bir yöntemdir (Deng, 1982). Gri ilişkisel analiz yöntemi yetersiz, eksik veya kesinlik içermeyen verilerin bulunduğu durumlarda derecelendirme, sınıflandırma ve karar verme tekniği olarak anlamlı sonuçlar verdiği kanıtlanmış bir yöntemdir. Bu yöntem sistem davranışını ilişkilendirme analizi yaparak ve model kurarak keşfeder (Kuo vd., 2008).

Gri ilişkisel analizin karmaşık formüllerle ve hesaplamalarla uğraşmadan birçok farklı alandaki probleme kolaylıkla uygulanabilmesi bu yöntemi ön plana çıkmaktadır (Kose vd., 2011). Bu yöntemde siyah bilinmeyen bilgi, beyaz bilinen bilgi, gri ise kısmen bilinen ve kısmen bilinmeyen bilgiyi ifade etmektedir.

4. Uygulama (Application)

Bu çalışmada Gri Sistem Teorisinin önemli bir alt başlığı olan "Gri İlişkisel Analiz" metodu kullanılmıştır. Uygulama için 10 farklı lastik alternatifi 6 farklı kriter göz önünde bulundurularak incelenmiştir. Lastik seçimi için belirlenen kriterler Tablo 1'de verilmiştir. Belirlenen lastik alternatiflerinin özellikleri Tablo 2'de sunulmuştur. Islak zeminde fren mesafesi (K1) ve yakıt tüketimi (K2) kriterleriyle ilgili detaylar Tablo 3'te, hız indeksi (K3) kriteriyle ilgili detaylar ise Tablo 4'te verilmiştir.

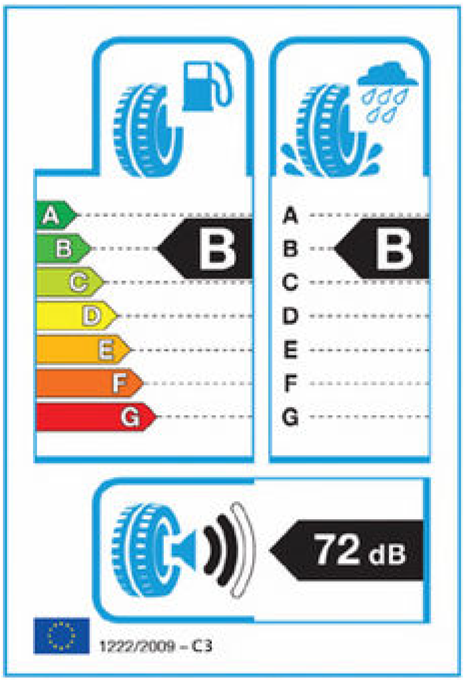
Tablo 1. Lastik seçimi için belirlenen kriterler (Determined criteria for tire selection)

Kriter	Açıklama
K1	Islak zeminde fren mesafesi
K2	Yakıt tüketimi
K3	Hız indeksi
K4	Gürültü (db)
K5	Üretim zamanı üzerinden geçen süre (hafta)
K6	Fiyat (TL)

Tablo 2. Seçilen lastiklerin özellikleri (Specs of chosen tires)

Lastik	K1	K2	K3	K4	K5	K6
1	B	C	V	72	4	300
2	A	D	W	68	52	280
3	D	A	T	76	32	250
4	C	C	T	80	12	260
5	E	B	H	72	8	240
6	A	F	S	66	44	270
7	C	C	Q	80	16	200
8	D	B	H	64	12	250
9	F	D	T	72	8	220
10	B	B	H	74	26	320

Lastik etiketleme Avrupa Birliği tarafından uygulanmaya başlandı ve ülkemizde de 2012 yılından itibaren "Lastiklerin Yakıt Verimliliği ve Diğer Esas Parametreler Gözetilerek Etiketlenmesi Hakkında Yönetmelik" hükümleri uyarınca zorunlu olarak uygulanmaktadır. Bu yönetmelik ile nihai kullanıcıların lastik satın alırken yakıt tasarrufu, ıslak zeminde yol tutuş ve dış yuvarlanma gürültüsü hakkında standardize edilmiş bilgilere göre seçim yapmalarına olanak sağlanması amaçlanmaktadır (Resmî Gazete, 2012). Şekil 1'de örnek bir lastik etiketi verilmiştir. Etiket üzerindeki değerler bağımsız değerlendirme kuruluşları tarafından yapılan testler sonucu belirlenmektedir.



Şekil 1. Lastik etiketi (Tire label) (Lastik Sanayicileri ve İthalatçıları Derneği, 2018)

Etiket üzerindeki kodlara karşılık gelen değerler Tablo 3'te verilmiştir. Ayrıca lastik üzerinde bulunan hız indeksine karşılık gelen değerler Tablo 4'te verilmiştir (Goodyear, 2018).

Tablo 3. Lastiklerin yakıt tüketimi ve ıslak zeminde fren mesafeleri (Tires fuel consumption and braking distance on wet grip)

Kod	Yakıt tüketimi (lt/ay)	Islak zeminde fren mesafesi (m)
A	92,5	10,5
B	93	11,3
C	94	12,0
D	95,5	12,8
E	97	13,5
F	98,5	14,3
G	100	15,0

Tablo 4. Lastiklerin hız indeksi (Tires speed ratings)

Kod	Hız indeksi (km/h)
Q	160
R	170
S	180
T	190
U	200
H	210
V	240
W	270
Y	300

4.1. Karar Matrisinin Oluşturulması (Preparing the Decision Matrix)

Öncelikle Tablo 2'de verilen kodların rakamsal değerleri Tablo 3 ve Tablo 4 yardımıyla belirlenerek Tablo 5 oluşturulmuştur.

K1, K2, K4, K5 ve K6 kriterleri En Küçük En İyi (EKEİ); K3 kriteri ise En Büyük En İyi (EBEİ) prensibine göre değerlendirilecektir.

Tablo 5. Seçilen lastik alternatifleri (Chosen tire alternatives)

	K1	K2	K3	K4	K5	K6
1	11,25	94	240	72	4	300
2	10,5	95,5	270	68	52	280
3	12,75	92,5	190	76	32	250
4	12	94	190	80	12	260
5	13,5	93	210	72	8	240
6	10,5	98,5	180	66	44	270
7	12	94	160	80	16	200
8	12,75	93	210	64	12	250
9	14,25	95,5	190	72	8	220
10	11,25	93	210	74	26	320

4.2. Referans Serilerinin eklenmesi (Adding Up Reference Series)

Referans serisi tüm kriterler için hedeflenen değer şeklinde düşünülebilir. Referans serisi; EBEİ olan kriterler için serinin en büyük değeri; EKEİ olan kriterler için ise serinin en küçük değeri alınarak Tablo 6'da verildiği gibi oluşturulmuştur.

Tablo 6. Referans serisi (Reference serial)

	K1	K2	K3	K4	K5	K6
RS	10,5	92,5	270	64	4	200

4.3. Karşılaştırma Serisinin Oluşturulması ve Verilerin Normalize Edilmesi (Preparing Comparison Series and Normalizing Data)

Her biri farklı değer aralıklarında yer alan kriterler standartlaştırılarak aynı aralığa getirilmesiyle değerlendirme işlemi kolaylaştırılmaktadır. Bu işlemde değerler EBEİ kriterler için Denklem 1, EKEİ kriterler için ise Denklem 2 kullanılarak normalize edilmektedir. Bu formülasyonlara göre normalize edilmiş değerler Tablo 7'de verilmiştir.

$$X_i(k) = \frac{x_i(k) - min(x_i(k))}{maks(x_i(k)) - min(x_i(k))} \quad (1)$$

$$X_i(k) = \frac{maks(x_i(k)) - x_i(k)}{maks(x_i(k)) - min(x_i(k))} \quad (2)$$

Tablo 7. Normalize edilmiş veriler (Normalized data)

	K1	K2	K3	K4	K5	K6
RS	1	1	1	1	1	1
1	0,80	0,75	0,73	0,50	1,00	0,17
2	1,00	0,50	1,00	0,75	0,00	0,33
3	0,40	1,00	0,27	0,25	0,42	0,58
4	0,60	0,75	0,27	0,00	0,83	0,50
5	0,20	0,92	0,45	0,50	0,92	0,67
6	1,00	0,00	0,18	0,88	0,17	0,42
7	0,60	0,75	0,00	0,00	0,75	1,00
8	0,40	0,92	0,45	1,00	0,83	0,58
9	0,00	0,50	0,27	0,50	0,92	0,83
10	0,80	0,92	0,45	0,38	0,54	0,00

4.4. Uzaklıkların Alınması ve Mutlak Değer Tablolarının Oluşturulması (Calculating Distance and Preparing Absolute Value Tables)

Alternatiflerin her bir kriterden aldıkları değerlerin referans değere olan uzaklıkları farklarının alınmasıyla belirlenmektedir. Hesaplanan mutlak değerler Tablo 8'de verilmiştir.

Tablo 8. Mutlak değer tablosu (Absolute value table)

	K1	K2	K3	K4	K5	K6
RS	1	1	1	1	1	1
1	0,20	0,25	0,27	0,50	0,00	0,83
2	0,00	0,50	0,00	0,25	1,00	0,67
3	0,60	0,00	0,73	0,75	0,58	0,42
4	0,40	0,25	0,73	1,00	0,17	0,50
5	0,80	0,08	0,55	0,50	0,08	0,33
6	0,00	1,00	0,82	0,13	0,83	0,58
7	0,40	0,25	1,00	1,00	0,25	0,00
8	0,60	0,08	0,55	0,00	0,17	0,42
9	1,00	0,50	0,73	0,50	0,08	0,17
10	0,20	0,08	0,55	0,63	0,46	1,00

4.5. Gri İlişkisel Katsayı Matrisinin Oluşturulması (Calculating Grey Relational Coefficient Matrix)

Farklı veri dizilerine ait gri ilişkisel katsayı matrisi hesaplanırken Δenb ve Δenk değerleri hesaplanmaktadır.

$\Delta enb = dizi\ içindeki\ en\ büyük\ değişim\ değeri$

$\Delta enk = dizi\ içindeki\ en\ küçük\ değişim\ değeri$

$$K(j) = \frac{(\Delta enk + \delta \Delta enb)}{(\Delta i(j) + \delta \Delta enb)} \qquad (3)$$

Denklem 3'te $\Delta i(j)$, Δi fark veri dizisindeki j. değeri göstermektedir. δ katsayısı Δenb veri dizindeki en uç değeri küçültmek amacıyla kullanılmakta ve genellikle 0,5 olarak alınmaktadır. Hesaplanan gri ilişkisel katsayılar Tablo 9'da verilmiştir.

Tablo 9. Gri ilişkisel katsayı matrisi (Grey relational coefficient matrix)

	K1	K2	K3	K4	K5	K6
1	0,71	0,67	0,65	0,5	1	0,375
2	1,00	0,50	1,00	0,67	0,33	0,43
3	0,45	1,00	0,41	0,40	0,46	0,55
4	0,56	0,67	0,41	0,33	0,75	0,50
5	0,38	0,86	0,48	0,50	0,86	0,60
6	1,00	0,33	0,38	0,80	0,38	0,46
7	0,56	0,67	0,33	0,33	0,67	1,00
8	0,45	0,86	0,48	1,00	0,75	0,55
9	0,33	0,50	0,41	0,50	0,86	0,75
10	0,71	0,86	0,48	0,44	0,52	0,33

4.6. Gri İlişkisel Derecenin Hesaplanması (Calculating Grey Relational Degree)

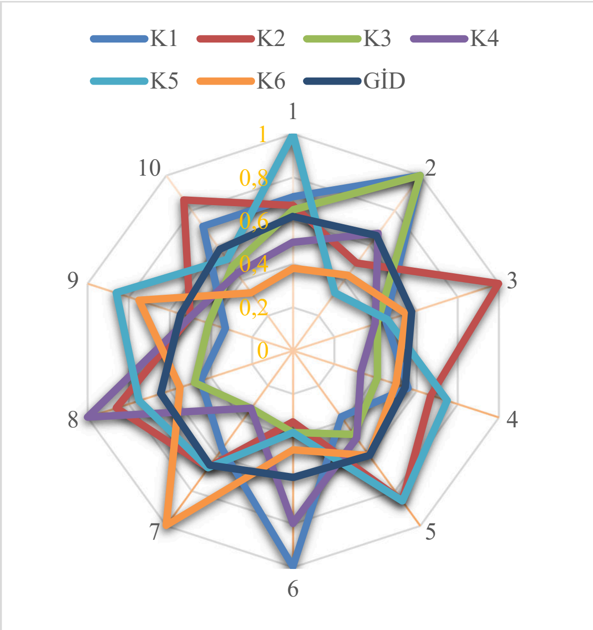
Gri İlişkisel Derece (GİD), her bir kriterin önemine göre verilen ağırlıklar (W) ile gri ilişkisel katsayılar çarpılarak Denklem 4'teki formülde verildiği gibi hesaplanmaktadır.

$$\gamma_i = \sum\big(\omega(k)\xi(k)\big) \qquad (4)$$

Sektörde çalışan alanında uzman bir kişiyle yapılan mülakat ile belirlenen kriter ağırlıkları (tablonun ilk satırında) ve bu ağırlıklarla çarpılarak elde edilen GİD değerleri Tablo 10'da verilmiştir. Ayrıca elde edilen gri ilişkisel dereceler Şekil 2'de radar grafiği üzerinde de gösterilmiştir. Radar grafiğinin çevresinde 1'den 10'a kadar alternatifler yer almaktadır. Her bir alternatifin her bir kriterden aldığı değerler ve GİD değerleri ilgili alternatifin bulunduğu noktadan görülebilmektedir. GİD değeri karşılaştırılan alternatif ile referans serisi arasındaki benzerliği ortaya koymaktadır. Eğer referans serisiyle aynı değere sahip bir alternatif varsa bunun değeri 1 olacaktır. Referans serisinden uzaklaştıkça bu değer de düşecektir.

Tablo 10. Gri ilişkisel dereceler (Grey relational degrees)

	K1	K2	K3	K4	K5	K6	GİD
W	0,25	0,2	0,1	0,1	0,1	0,25	
1	0,71	0,67	0,65	0,50	1,00	0,38	0,620
2	1,00	0,50	1,00	0,67	0,33	0,43	0,657
3	0,45	1,00	0,41	0,40	0,46	0,55	0,577
4	0,56	0,67	0,41	0,33	0,75	0,50	0,546
5	0,38	0,86	0,48	0,50	0,86	0,60	0,601
6	1,00	0,33	0,38	0,80	0,38	0,46	0,587
7	0,56	0,67	0,33	0,33	0,67	1,00	0,656
8	0,45	0,86	0,48	1,00	0,75	0,55	0,644
9	0,33	0,50	0,41	0,50	0,86	0,75	0,547
10	0,71	0,86	0,48	0,44	0,52	0,33	0,578

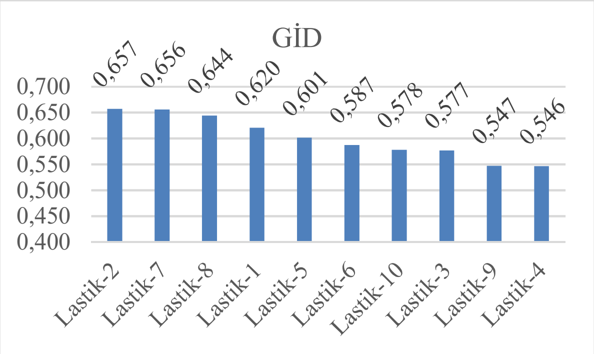


Şekil 2. Gri ilişkisel derecelerin radar grafiği (Radar graph of grey relational degrees)

5. Sonuç (Conclusion)

Lastik, araçların en temel parçalarından biri olup sürüş güvenliğini ve konforunu doğrudan etkileyen bir bileşenidir. Birçok farklı kritere göre doğru lastik seçim kararını vermek çok kriterli bir karar verme problemi olarak ortaya çıkmaktadır.

Bu çalışmada lastik seçimi probleminin çözümü için gri ilişkisel analiz yöntemi kullanılarak en iyi alternatif belirlenmiştir. Uygulama sonucunda lastiklerin gri ilişkisel değerlerinin karşılaştırılması Şekil 3'te sunulmuştur. GİD değeri en büyük olan lastik alternatifler arasında seçilmesi en uygun olan yani optimum lastiktir. Belirlenen kriterlere göre alternatifler arasından en uygun alternatifin Lastik-2 olduğu ancak hemen ardından gelen Lastik-7'nin de çok yakın bir değere sahip olduğunun göz önünde bulundurulması gerektiği görülmektedir.



Şekil 3. Lastiklerin gri ilişkisel değerlerinin karşılaştırılması (Comparison of tires grey relational degrees)

Çok sayıda performans kriterini hesaba katarak birçok alternatif arasından en iyisini seçme problemi günlük hayatımızda sürekli karşılaştığımız önemli bir konudur. Bu çalışmada gösterilen gri ilişkisel analiz gibi uygulaması kolay teknikler, hızlı bir şekilde doğru karar vermemize katkı sağlamaktadır.

Kaynaklar (References)

Benedetti, A., Farina, M., Gobbi, M., 2006. Evolutionary multiobjective industrial design: the case of a racing car tire-suspension system. IEEE Trans. Evol. Comput. 10, 230–244. https://doi.org/10.1109/TEVC.2005.860763

Chitra, S., Malarvizhi, M., 2018. A study on Consumer Reaction on Passenger Car Tyre Selection in Theni. Int. Res. J. Manag. IT Soc. Sci. 5, 64. https://doi.org/10.21744/irjmis.v5i2.608

Deng, J.L., 1982. Grey system fundamental method. Huazhong Univ. Sci. Technol. Wuhan China.

Goodyear, 2018. Lastik Sözlüğü [WWW Document]. URL https://www.goodyear.eu/tr_tr/consumer/learn/tire-glossary.html (accessed 6.10.18).

Harned, J.L., Johnston, L.E., Scharpf, G., 1969. Measurement of Tire Brake Force Characteristics as Related to Wheel Slip (Antilock) Control System Design. https://doi.org/10.4271/690214

Kose, W., Temiz, İ., Erol, S., 2011. Grey system approach for economic order quantity models under uncertainty. J. Grey Syst. 23, 71–82.

Kuo, Y., Yang, T., Huang, G.-W., 2008. The use of grey relational analysis in solving multiple attribute decision-making problems. Comput. Ind. Eng. 55, 80–93. https://doi.org/10.1016/j.cie.2007.12.002

Lastik Sanayicileri ve İthalatçıları Derneği, 2018. AB Lastik Etiketi Nedir? [WWW Document]. URL http://lasid.com.tr/lastik/lastik-ve-guvenlik/lastigin-teknik-ozellikleri/lastik-etiketi (accessed 6.11.18).

Lin, C.L., Lin, J.L., Ko, T.C., 2002. Optimisation of the EDM Process Based on the Orthogonal Array with Fuzzy Logic and Grey Relational Analysis Method. Int. J. Adv. Manuf. Technol. 19, 271–277. https://doi.org/10.1007/s001700200034

Miano, C., Gobbi, M., Mastinu, G., 2004. Multi-Objective Optimization of the Handling Performances of a Road Vehicle: A Fundamental Study on Tire Selection. J. Mech. Des. 126, 687. https://doi.org/10.1115/1.1759359

Nedělková, Z., Lindroth, P., Jacobson, B., 2017. Modelling of optimal tyre selection for a certain truck and transport application. Int. J. Veh. Syst. Model. Test. 12, 284–303. https://doi.org/10.1504/IJVSMT.2017.089998

Otodetay, 2016. Oto Lastik Ömrü Ne Kadardır? Oto Lastik Ömrü Kaç Km'dir? Oto Lastik Raf Ömrü Ne Kadar? [WWW Document]. URL http://otodetay.net/yaz%C4%B1lar/oto-lastik-%C3%B6mr%C3%BC-ne-kadard%C4%B1r-oto-lastik-%C3%B6mr%C3%BC-ka%C3%A7-kmdir-oto-lastik-raf-%C3%B6mr%C3%BC-ne-kadar.html (accessed 7.20.18).

Resmî Gazete, 2012. Lastiklerin Yakıt Verimliliği ve Diğer Esas Parametreler Gözetilerek Etiketlenmesi Hakkında Yönetmelik.

Sandberg, U., Ejsmont, J., Vieira, T., 2016. Noise and Rolling Resistance Properties of Various Types of Winter Tyres Compared to Normal Car Tyres. INTER-NOISE NOISE-CON Congr. Conf. Proc. 253, 5886–5897.

Satolo, E.G., Leite, C., Calado, R.D., Goes, G.A., Salgado, D.D., 2018. Ranking lean tools for world class reach through grey relational analysis. Grey Syst. Theory Appl. 8, 399–423. https://doi.org/10.1108/GS-06-2018-0031

Sridharan, R., Anilkumar, E.N., Vishnu, C.R., 2019. Strategic Barriers and Operational Risks in Sustainable Supply Chain Management in the Indian Context: A Grey Relational Analysis Approach. Emerg. Appl. Supply Chains Sustain. Bus. Dev. 238–259. https://doi.org/10.4018/978-1-5225-5424-0.ch014

Tosun, N., 2006. Determination of optimum parameters for multi-performance characteristics in drilling by using grey relational analysis. Int. J. Adv. Manuf. Technol. 28, 450–455. https://doi.org/10.1007/s00170-004-2386-y