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A Review of Metaheuristic Algorithms and Data Envelopment Analysis

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Abstract

Today, many activities from businesses to engineering design, routing on the Internet, and even routing of foodstuff trucks require programming and optimization. Many of these problems have no determinate solution and cannot be solved easily. To solve these problems, algorithms have been developed inspired by nature based on particle intelligence, biological, physical, and chemical systems, and even human communities and have been named after their inspiration source. A metaheuristic optimization algorithm is an innovative way that can be applied to various optimization problems by slight modifications. These algorithms can improve the capability of finding high-quality answers for difficult optimization problems significantly. The present paper reviews the application of various metaheuristic algorithms and data envelopment analysis (DEA) to optimization problems in the literature published in recent years. Descriptions are provided about the application of metaheuristic algorithms in DEA along with their applications, the field of activity, overlaps, and the integration of these two robust methods to find the optimal answer.

Keywords:
data envelopment analysis
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INTRODUCTION

Optimization methods and algorithms are divided into two broad categories – exact algorithms and approximate algorithms. Exact optimization algorithms, e.g. data envelopment analysis (DEA), are an important branch of research in operation. DEA is a non-parametric method of efficiency assessment and/or the calculation of the productivity of a finite number of homogenous decision-making units (DMUs) with multiple inputs and multiple outputs. But, this method is not efficient enough for NP-hard problems. These problems are solved by approximation algorithms, e.g. metaheuristic algorithms, as they can find high-quality answers to hard optimization problems. Various papers have used both optimization methods for problem-solving.

Metaheuristic algorithms

Optimization has always played a significant role in managers' decision processes. So, various branches of science have been developed which can be used in solving optimization problems in some way. A review of the history of optimization methods shows that this branch of science has always been appealing to researchers. The emergence of any phenomenon in the world of computers and calculations has entailed a new wave of growth in optimization. In recent decades, computers have created an inextricable link between artificial intelligence and optimization. The possibility of doing calculations in a very short time and the increase in the calculation capacity of computers have made way for introducing a new class of optimization techniques that came to be called metaheuristic methods (Sadrabadi & Taghavi, 2014).

Metaheuristic methods can be classified by various criteria:

1. Single-solution and population-based: The algorithms based on a single solution change one answer during the search process whereas population-based algorithms consider a population of answers during the search.

2. Nature-inspired and non-nature-inspired: Most metaheuristic algorithms have been inspired by nature, but a few haven't.

3. Memory usage versus memoryless: Some metaheuristic algorithms lack memory. This means that they do not utilize the information that is obtained during the search (e.g. simulated annealing) whilst memory is used in some metaheuristic algorithms such as tabu search. This memory stores information obtained during the search.

4. Deterministic versus stochastic: A deterministic algorithm like tabu search solves a problem by deterministic decisions. But, stochastic metaheuristic algorithms like simulated annealing use a series of stochastic rules during search (Jahanshahlou et al., 2008).

The single-solution based algorithms include simulated annealing, tabu search, GRASP search, variable neighborhood search, guided local search, and iterated local search. The population-based algorithms include genetic algorithm, imperialist competitive algorithm, ant colony optimization algorithm, bee colony algorithm, firefly algorithm, artificial immune system algorithm, harmony search algorithm, and particle swarm optimization algorithm.

Data envelopment analysis

In 1975, Farrell developed an idea to build a function, known as production function, on enveloped data by defining multiple inputs and one output and used the function to calculate the relative efficiency of all units. In 1978, Cooper and colleagues developed Farrell's idea to multiple inputs and outputs and built a technique that could benchmark performance with multiple input and output factors. This technique was called data envelopment analysis (DEA). The method, which is based on mathematical programming to measure the performance of a set of decision-making units (DMUs), has found extensive applications for performance assessment in all organizations including banks, insurance, factories, training institutions, hospitals, highways, etc. in its short life. It should be noted that in this technique, all input and output indices can have any data type. For example, it can be quantitative, qualitative, interval, cardinal, fuzzy, or stochastic. The performance of a DMU can be measured both absolutely and relatively. The absolute performance of a DMU results from its comparison with international standards whereas the relative performance is drawn from the comparison of

DMUs with one another and with a standard obtained from the status quo of this community(Saljougi, 2014).

There are plenty of researches in which metaheuristic algorithms and DEA have been applied to real databases. The models applied are divided into eight groups here including (1) genetic algorithm and DEA, (2) artificial neural networks and DEA, (3) particle swarm optimization algorithm and DEA, (4) Cuckoo optimization algorithm and DEA, (5) bee colony algorithm and DEA, (6) ant colony algorithm and DEA, (7) Tabu search algorithm and DEA, and (8) a composite group of metaheuristic algorithms and DEA.

THE APPLICATION OF GENETIC ALGORITHM AND DATA ENVELOPMENT ANALYSIS

This group encompasses the most number of papers and is itself divided into three sub-groups:

- The application of GA in DEA
- The application of DEA in GA
- The combined application of GA and DEA

The application of GA in DEA

Saradhi and Girish (2015) presented a paper entitled 'Effective parameter tuning of SVMs using radius/margin bound through data envelopment analysis'. The paper provides a method to tune the parameters of multi-class support vector machines (SVM) using radius/margin bound using the improved input-based CCR model of DEA. The relative efficiency of binary SVMs versus one-vs-one multi-class SVM is obtained by the radius as the input and margin as the output using the Charnes, Cooper, and Rhodes (CCR) model. The trend of radius and margin is obtained during the GA run and the objective is to maximize the total relative efficiency of the individual binary SVMs in the one-vs-one multi-class SVM. Empirically, it is observed that the proposed formula outperforms parameter tuning by Keerthi's radius/margin method. Ideally, the radius derived from the proposed method is 1110 times smaller than that derived from Keerthi's method. The margin is also 4.4 times larger and the number of support vectors is fewer by a factor of 5.8 (Saradhi & Girish, 2015) .

Fallahpour et al. (2016) presented an integrated model for green supplier selection in a fuzzy environment by applying DEA and genetic programming (GP) approach. This is the first attempt to integrate the KAM-DEA model and GP for the selection of a green supplier. Since the CCR/BCC DEA models have some drawbacks, the KAM-DEA model is employed to tackle them. The GP technique is applied to cope with the computational complexity and time-consuming of the DEA model (Fallahpour et al., 2016). The following linear programming model is the KAM-VRS model:

$$
\begin{aligned}
&\text{Max} \sum_{j=1}^{m} W_{ij}^{-} S_{ij}^{-} + \sum_{k=1}^{p} W_{ik}^{+} S_{ik}^{+} \\
&\text{s.t.} \\
&\sum_{i=1}^{n} \lambda_i X_{ij} + S_{ij}^{-} = X_{ij} + \varepsilon_{ij}^{-}, \quad \text{for } j = 1,2,\ldots,m \\
&\sum_{i=1}^{n} \lambda_i Y_{ik} - S_{ik}^{+} = Y_{ik} - \varepsilon_{ik}^{+}, \quad \text{for } k = 1,2,\ldots,p \\
&X_{ij} - S_{ij}^{-} \geq 0, \quad \text{for } j = 1,2,\ldots,m \\
&Y_{ik} + S_{ik}^{+} - 2\varepsilon_{ik}^{+} \geq 0, \quad \text{for } k = 1,2,\ldots,p \\
&\sum_{i=1}^{n} \lambda_i = 1 \\
&\lambda_i \geq 0, \quad \text{for } i = 1,2,\ldots,n \\
&S_{ij}^{-} \geq 0, \quad \text{for } j = 1,2,\ldots,m \\
&S_{ik}^{+} \geq 0, \quad \text{for } k = 1,2,\ldots,p
\end{aligned} \tag{1}
$$

González et al. (2015) focused on the use of GA to maximize technical efficiency in DEA. DEA is a non-parametric method to estimate the technical efficiency of a set of DMUs from a database composed of inputs and outputs. The paper explores DEA in terms of maximizing technical efficiency aimed at finding the shortest distance from the evaluated DMU to the production frontier. These models are have usually been solved by non-optimal methods for combinational NP-hard problems. This paper tackles this problem by GA and compares the solutions with the methods based on all frontier elements in DEA. GA provides a solution close to optimum with shorter execution time (González et al., 2015)

Jain et al. (2015) investigated weight restrictions in DEA with an integrated GA-based approach to incorporating value judgments. The article presents a GA-based approach to estimating weight restrictions in DEA. Compared to the conventional methods, the proposed GA-based method has the advantage of dealing with multiple decision-makers and guarantees feasibility at all times (Jain et al., 2015). The basic unrestricted DEA formula with dual role factors is as below:

$$\begin{aligned}
&\text{Max} \sum_{r=1}^{s} u_r y_{ro} + \sum_{f=1}^{F} \gamma_f w_{fo} \\
&\text{s.t} \\
&\sum_{i=1}^{m} v_i x'_{io} = 1 \\
&\sum_{r=1}^{s} u_r y'_{rj} + \sum_{f=1}^{F} \gamma_f w'_{fj} - \sum_{f=1}^{F} \beta_f w'_{fj} - \sum_{i=1}^{m} v_i x'_{ij} \le 0 \\
&v_i \ge \varepsilon \quad \forall i \quad u_r \ge \varepsilon \quad \forall r \quad \gamma_f, \beta_f \ge \forall f
\end{aligned} \tag{2}$$

Martinez-Moreno et al. (2013) used GAs to determine the closest targets in DEA. The paper uses GA to find out the closest efficient targets by the Russell model in DEA. Traditionally, this problem has been solved by unsatisfactory methods in papers since they are related to a combination of NP-hard problems in some way. This paper investigates some algorithms, used in generating, integrating, and mutating chromosomes in a GA, to achieve an efficient metaheuristic that can provide better solutions (Martinez-Moreno et al., 2013).

Mashayekhi and Omrani (2016) present an integrated multi-objective Markowitz-DEA cross-efficiency model with fuzzy returns for portfolio selection problems. The paper discusses a novel multi-objective model for portfolio selection. The proposed model is composed of a DEA cross-efficiency model integrated into the Markowitz mean-variance model and considers portfolio efficiency.

$$\begin{aligned}
&\max \sum_{i=1}^{N} W_i \overline{R}_i \\
&\min \sum_{i=1}^{N} \sum_{j=1}^{N} w_i w_j \operatorname{cov}(R_i, R_j) \\
&\max \sum_{i=1}^{N} W_i \overline{e}_i \\
&\min \sum_{i=1}^{N} \sum_{j=1}^{N} w_i w_j \operatorname{cov}(e_i, e_j) \\
&\text{s.t} \\
&\sum_{i=1}^{n} Z_i \le h \\
&L_i Z_i \le W_i \le u_i Z_i \qquad i = 1,2,\dots,N \\
&\sum_{i=1}^{N} W_i = 1 \\
&W_i \ge 0 \qquad i = 1,2,\dots,N
\end{aligned} \tag{3}$$

In addition, to include uncertainty in the model, the asset return is regarded as fuzzy numbers. Due to the computational complexity of the proposed model, the second version of GA (NSGA-II) is used. To demonstrate the performance of the model, they apply the model to 52 firms listed in Tehran Stock Exchange and report the results. Based on the results, the proposed model outperforms Markowitz and DEA given the return, risk, and efficiency simultaneously (Mashayekhi & Omrani, 2016).

Momeni and Farzipoor (2012) developed a new chance-constrained DEA in the presence of stochastic data. Outsourcing is an important issue in logistics and third-party reverse logistic (PL3) provider evaluation and selection should be realized in a precise way to provide the expected advantages. DEA has successfully been used to select the most efficient source in a supply chain. This paper proposes a new Russell chance-constrained DEA (RCC-DEA) to help decision-makers determine PL3 providers in the presence of various performance metrics, which are indeterminate.

$$\min RE \frac{\frac{1}{m}\sum_{i=1}^{m} \theta_i}{\frac{1}{s}\sum_{r=1}^{s} \varphi_r}$$

$$
\begin{aligned}
\text{s.t} \quad & \varphi_r y_{ro} - \sum_{j=1}^{n} \lambda_j y_{rj} + s_r^{+} - \Phi^{-1}(\alpha)\sigma_r^{o}(\Phi,\lambda) = \\
& s_i^{-} - \theta_i x_{io} + \sum_{j=1}^{n} \lambda_j x_{ij} - \Phi^{-1}(1-\alpha)\sigma_r^{o}(\Phi,\lambda \\
& \varphi_{ro} \geq 1 \qquad r = 1,\dots,s \\
& \lambda_j \geq 0 \qquad j = 1,\dots,n \\
& 0 \leq \theta_{io} \leq 1 \qquad r = 1,\dots,m
\end{aligned}
$$

(4)

in which Φ is the standard normal distribution function and Φ^{-1} is its reverse. Finally,

$$
\begin{aligned}
[\sigma_r^{o}(\varphi,\lambda)]^2 &= \sum_{j\neq o}\sum_{k\neq o} \lambda_j \lambda_k \operatorname{cov}(\tilde{y}_{rj}, \tilde{y}_{rj}) + \\
& 2(\lambda_o - \varphi_r)\sum_{i\neq o} \lambda_j \operatorname{cov}(\tilde{y}_{ri}, \tilde{y}_{ro}) + \\
& (\lambda_o - \varphi_r)^2 \operatorname{VAR}(\tilde{y}_{ro})
\end{aligned}
$$

$$
\begin{aligned}
[\sigma_I^{o}(\theta,\lambda)]^2 &= \sum_{j\neq o}\sum_{k\neq o} \lambda_j \lambda_k \operatorname{cov}(\tilde{x}_{rj}, \tilde{x}_{rj}) + \\
& 2(\theta_i - \lambda_o)\sum_{i\neq o} \lambda_j \operatorname{cov}(\tilde{x}_{rj}, \tilde{x}_{rj}) + \\
& (\theta_i - \lambda_o)^2 \operatorname{VAR}(\tilde{x}_{io})
\end{aligned}
$$

(5)

This model records only variations in outputs and inputs via a variance-covariance matrix and ignores the potential correlation between inputs and outputs. Due to the nonlinear form of $\sigma_r^0(\varphi,\lambda)$ and $\sigma_i^0(\theta,\lambda)$and the fractional form of its objective function, it is clear that this model has been considered nonlinear programming when the number of inputs, outputs, and DMUs increases. So, a GA is suggested to solve this model (Momeni & Farzipoor Saen, 2012).

Qin and Liu (2010) published a paper on DEA modeling by the chance method in hybrid uncertain environments. The paper tries to develop a traditional CCR model and a new class of chance model (C-model) in fuzzy random environments. The paper first provides several formulae for chance distribution for fuzzy random variables and their functions. Then, a new class of chance model is developed in DEA for the fuzzy random environments in which it is assumed that the input and output are specified by the fuzzy random variables with the possibility of known probability distributions. To solve this equivalent random programming, they designed a hybrid algorithm by integrating Monte Carlo (MC) simulation and GA in which MC is used to simulate the calculation of the normal distribution standard functions and GA is used to solve optimization problems. Eventually, a numerical example is presented to demonstrate the proposed model idea and efficiency in the proposed model(Qin & Liu, 2010).

Chuang et al. (2009) used DEA and GA to find an optimal design chain partner combination. The study aimed to develop an integrated decision model to assist firms to create a chain network design and formulate an optimal approach for designing a chain partner combination.

$$
\begin{aligned}
\min TEC &= \sum_{s=1}^{s}(sic_s * sp_s) + \sum_{f=1}^{F}\sum_{j=1}^{J}(fc_{fj} * fp_{fj} * fce_{fjc}) \\
&+ \sum_{f=1}^{F}\sum_{p=1}^{pf}\sum_{k=1}^{kp}(pc_{fpk} * pp_{fpk} * pce_{fpkj}) \\
\min TET &= \sum_{s=1}^{s}(sit_s * sp_s) + \sum_{f=1}^{F}\sum_{j=1}^{J}(ft_{fj} * fp_{fj} * fce_{fjc}) \\
&+ \sum_{f=1}^{F}\sum_{p=1}^{pf}\sum_{k=1}^{kp}(pt_{fpk} * pp_{fpk} * pce_{fpkj}) \\
\text{s.t} & \\
& \sum_{s=1}^{s} sp_s = 1; \\
& \sum_{j=1}^{J} fp_{sf} = 1 \qquad \forall f \in F; \\
& \sum_{K=1}^{KP} pp_{fpk} = 1 \qquad \forall f \in F; \quad \forall_p \in p
\end{aligned}
$$

(6)

To help organizations construct an optimal design of chain partner combination, the research focused on developing a weight-restricted DEA model in which the design of appropriate chain partners is evaluated and selected with respect to the different roles of the partner and a set of appropriate partners is formed. As product development time and costs highly depend on the coordinated productivity of different members in the design of chain partners, the paper considers this factor when developing a multi-objective design chain partner combination selection model. The study uses a multi-objective GA to search for the optimal design chain partner combination in order to achieve the goals of minimum cost and time of new product development with maximum product reliability (Chuang et al., 2009).

Wittaker et al. (2017) presented a paper on spatial targeting of environmental policy using two-level evolutionary optimization. The paper takes the optimal design of environmental policy as a two-level optimization problem and proposes an integrated approach using a hybrid GA. They use the hybrid GA to simulate full awareness of all policies in two-level optimization. The proposed hybrid GA integrates a biophysical model (soil and water assessment tool – SWAT) with an economic model (maximum profit; DEA) (Whittaker et al., 2017).

$$\begin{aligned} \max\ & \sum_{m=1}^{M} p_m y_m - \sum_{\nu=1}^{p} w_\nu x_\nu \\ \text{s.t.}\quad & \sum_{k=1}^{k} z^k y_m^k \geq y_m \quad , \qquad m = 1,\dots,M, \\ & \sum_{k=1}^{k} z^k y_\nu^k \leq x_\nu \quad , \qquad \nu = \text{Fertilizer} \\ & \sum_{k=1}^{k} z^k x_f^k \leq x_f^{k'} \quad , \qquad f = 1,\dots,N, \\ & z^k \geq 0, \qquad k = 1,\dots,K \end{aligned} \tag{7}$$

SWAT is used to show environmental goals and DEA is used to model producer behavior in response to the environmental policy.

Application of DEA in GA

Lu (2015) presented a robust DEA approach for the assessment of algorithmic performance. The paper suggests two robust BCC models based on the robust collaborative optimization (RCO) methods with a focus on evaluating the relative efficiency of metaheuristic algorithms and improving decisions for determining an effective combination of algorithmic operators. These models consider not only mean but also variations in the algorithm output values due to the design of probability operators in different metaheuristic algorithms. The paper, then, uses three DEA models including BCC, BCC-BN, and BCC-BS to assess various combinations of GA operators to solve PDVRPSTW (pickup and delivery vehicle routing problem with soft time windows) and a set of parameter adjustments of an SA metaheuristic algorithm to solve VRPTW (vehicle routing problem with time windows). The recommended models are applied to assess a set of distinct configurations for a GA and a set of parameter adjustments for a simulated annealing metaheuristic algorithm. Although the paper demonstrates the viable application of robust DEA models for the evaluation of GA operator combinations and SA parameter adjustment, the robust DEA models can also be used to assess the relative efficiency of multiple metaheuristic algorithms (Lu, 2015).

Canessa-Terrazas et al. (2016) published a paper on the use of DEA and Pareto GA (PGA) to robust design in multi-response systems. The paper uses a DEA BCC input-oriented model to rank and select approaches for obtaining PGA for robust design problems in multi-response systems with multiple control and noise variables. The efficiency analysis of the approaches by DEA shows that PGA finds a good approximation with an effective frontier. In addition, DEA is used to determine a combination of a certain level of mean adjustment and variance in the responses of a system to minimize the economic cost of achieving these two objectives. With respect to single-response systems, by estimating cm (cost or penalty of reaching a certain amount of mean adjustment) and cs (cost or penalty of a standard deviation), the suggested approach can clearly show the exchange between mean adjustment and the reduction in variations in the production/service process and the management can select an option that matches a certain quality level. The same holds for multi-response systems, but pm and pv prices are used. If for any reason, an approach is selected that does not rely on the effective frontier, the recommended approach can be used to compare technical efficiency and the penalty of the applied approach to allow the management to clearly assess the relative downgrading of these values (Canessa-Terrazas et al., 2016).

Azadeh et al. (2012) presented a new hybrid fuzzy logic-GA-DEA method to optimize the simulation of problems pertaining to the design of pressure vessels. They proposed a combination of fuzzy logic and GA to optimize nonlinear problems of pressure vessel design. The obtained fuzzy nonlinear program is solved by GA and its initial population is generated by simulation. The paper compares the efficiency of some design optimization algorithms and the proposed method based on the Anderson-Peterson output-oriented DEA. Based on the DEA results, the proposed method is superior. The authors have integrated GA and fuzzy logic for optimizing pressure vessel design problems for the first time. The proposed method can be used to solve NP-hard problems too. It can be applied to most engineering design problems that deal with ambiguous data. The model can be improved and reinforced by the use of a quadratic constraint membership function in the fuzzification method (Azadeh et al., 2016).

Mobin et al. (2015) presented a multi-purpose X-bar control chart designed by integrating NSGA-II and DEA. The paper provides a two-stage multi-objective optimization. At the first stage, an NSGA-II algorithm is used to obtain Pareto frontier solutions, which are placed without considering one another. Then, a DEA-CCR method is employed to discover equally acceptable optimal Pareto solutions out of efficient solutions (Mobin et al., 2015).

Razavyan and Tohidi (2011) presented a full ranking method using integrated DEA models and used it to change GA to find an optimal solution for Pareto multi-objective programming problems. The paper employs integrated DEA models to rank all efficient DMUs. Then, the researchers utilize the integrated DEA ranking method to change GA in order to find efficient solutions for the MOP Pareto problem. The modified GA can reduce computational efforts and can be used to produce effective Pareto frontiers from convex and non-convex MOP problems. It can also be used to solve MOP problems with two or more objective functions. In other words, the authors use a short-cut to reduce repetitions for finding efficient solutions to MOP Pareto problems (Razavyan & Tohidi, 2011).

$$
\begin{aligned}
&\min \quad M \\
&\text{s.t.} \\
&M - d \geq o, \qquad j \in E_p \\
&\sum_{i=1}^{m} \qquad \leq 1, \qquad j \in E_p \\
&\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} w_i x_{ij} + d_j = o \quad , \quad j \in E_p \\
&\sum_{j \in E_p}^{m} \theta_j = \left|E_p\right| - 1 \quad , \\
&\theta_j - d_j \beta_j = o \quad , j \in E_p \\
&\beta_j \geq 1, \quad d_j \geq o \quad , \theta_j \in \{o,1\} \quad j \in E_{p1} \\
&w_i \geq \varepsilon^* \quad , i = 1, \ldots, m \\
&u_r \geq {}^* \quad , r = 1, \ldots, s
\end{aligned}
\tag{8}
$$

Li et al. (2016) proposed multi-objective multi-stage reliability growth planning at the early product development stage. Multi-stage reliability growth planning is common in practice and is oriented with the various growth and development steps of a new product such as designing a concept, details, a prototype, and the final production version. A multi-objective formula reflects the requirements of multiple objectives of product development including program cost, planning, and reliability. The optimal solutions of Pareto multi-stage multi-objective formula are searched for reliability growth planning by using a genetic algorithm (NSGA-II). To reduce a high volume of Pareto optimal solutions to an executable size of efficiency solutions for implementing the plan, both constant and variable returns-to-scale DEA are used to determine the efficient solutions. Based on tradeoff and analysis of sensitivities, insights and procedures are presented to select appropriate reliability growth programs in terms of optimal allocation of testing time and unit and the time of introducing new technologies. The paper also discusses the growth rate at various product development stages and its impact on development costs, plans, and reliability (Li et al., 2016).

Lin et al. (2013) published a paper entitled ‘Multi-objective simulation optimization using data envelopment analysis and genetic algorithm: Specific application to determining optimal resource levels in surgical services'. They aimed to simulate a robust tool to model complicated systems with complicated relationships between different individuals and resources. Simulation optimization implies methods that search for a design space to find a system configuration with the best performance. Since simulation is often time-consuming, sampling from the feasible design space is intended. However, concerning multiple objectives, traditional simulation optimization methods fail to discover an efficient frontier. The authors present a framework for multi-objective simulation optimization that combines the robustness of GA, which can effectively be used to search gigantic design spaces, with CCR-DEA to assess simulation results and guide search process (Lin et al., 2013).

Lu and Vincent (2012) used DEA to assess the efficiency of a GA in solving the vehicle routing problem with soft time windows. The paper proposes an alternative for conventional empirical analysis for assessing the relative efficiency of various combinations of algorithmic operators and/or parameter values of GA in solving the problem of vehicle routing and delivery with a soft time window. The proposed approach regards each combination of a DMU and uses the CCR model of DEA to determine the relative and cross efficiency of each combination of GA operators and parameter values in solving vehicle routing and delivery problem with a soft time window. To demonstrate the applications and benefits of the proposed method, the paper runs several combinations of three main algorithmic operators of GA, i.e. selection, crossover, and mutation, and uses DEA to assess and rank their relative efficiencies. The numerical results reveal that DEA performs well in finding the optimal combination of GA operators (Lu & Vincent, 2012)

Park et al. (2014) dealt with operator allocation in cellular manufacturing systems (CMS) by integrating GA and fuzzy DEA. Operator allocation is the foremost parameter dictating the performance of a CMS. This paper presents a novel integration of GA, simulation, and DEA for the selection of the best operator allocation scenario. The present method first uses GA to generate a full set of feasible operator allocation cases. Then, the efficiency of the cases is assessed by a multi-objective DEA-CCR model derived from a simulation. The proposed approach has two advantages over the other methods based on DEA for the selection of the best operator allocation in a content management system – first, it is not necessary for the decision-maker to redefine all available cases and second, not only the number of operators but also the extra knowledge on who is allocated to each machine are provided(Park et al., 2014).

Yun et al. (2001) published a paper on the generation of efficient frontiers in multi-objective optimization problems by generalized DEA. Extensive efforts have been made on using GA in generating efficient frontiers in multi-objective optimization problems. This approach is effectively applicable when one is dealing with problems with two or three objective functions. Nonetheless, these methods usually fail to provide a good approximation of precise efficient frontiers within a few generations despite time constraints. This paper describes a generalized DEA (GDEA), composed of the current DEA models such as CCR, BCC, and FDH in which the value of the parameter α is changed, and GA for generating efficient frontiers in multi-objective optimization problems.

$$
\begin{aligned}
&\text{Maximize } \Delta \\
&\text{s.t.} \\
&\Delta \le \tilde{d}_j + \alpha\left(\sum_{k=1}^{n} u_k (y_{ko} - y_{kj}) + \sum_{i=1}^{m} \nu_i (-x_{io} + x_{ij}\right), \\
&\qquad J=1,\dots,p \\
&\sum_{k=1}^{n} u_k + \sum_{i=1}^{m} \nu_i = 1, \\
&u_k \ge \varepsilon, \\
&\text{where} \\
&\tilde{d}_j = \max_{\substack{k=1,\dots,n \\ i=1,\dots,m}} \left\{ \nu_k (y_{ko} - y_{kj}), u_i (-x_{io} + x_{ij}) \right\},
\end{aligned}
\tag{9}
$$

DMU is FDH efficient, is α-efficient if and only if α is small enough α > 0

DMU is BCC efficient, is α-efficient if and only if α is large enough α > 0

In the GDEA problem, the equation

$\sum_{k=1}^{s}\mu_k y_{ko} = \sum_{i=1}^{m}\nu_i x_{io}$ is added to the constraint.

So, DMU is CCR-efficient, is α-efficient if and only if α is large enough (α > 0).

GDEA removes the dominant design choice faster than the GA-based method. The proposed method can generate optimal frontiers even in non-convex problems as well as in convex problems (Yun et al., 2001).

Yun et al. (2005) used GA for multi-objective optimization by GDEA. Recently, many GAs have been proposed as an approximation method to generate Pareto frontier (a set of optimal Pareto solutions) for multi-objective optimization problems. Multi-objective GAs have two main problems: how to assign fitness to each individual and how to obtain diverse individuals. To cope with these problems, the paper suggests a novel multi-objective GA using GDEA. By numerical examples, the paper demonstrates that the proposed method can use the following GDEA equation to generate Pareto frontiers with good distribution and approximation but by fewer performance assessments (Yun et al., 2005).

$$
\begin{aligned}
&\text{Maximize } \Delta \\
&\text{s.t. } \Delta \le \tilde{d}_j - \alpha \sum_{i=1}^{m} \nu_i \left(f_i(x^o) - f_i(x^j)\right), \quad j = 1,\dots,p \\
&\sum_{i=1}^{m} \nu_i = 1, \\
&\nu_i \ge \varepsilon, \quad i = 1,\dots,m
\end{aligned} \tag{10}
$$

Mousavi et al. (2012) compared bi-objective genetic algorithms for hybrid flow shop scheduling with sequence-dependent setup times. The paper addresses the problems of hybrid flow shop scheduling with two objectives of minimizing makespan and total tardiness. Since the problem is NP-hard, GA-based evolutionary algorithms are presented to search for the optimal Pareto frontier. These algorithms generate a part of next-generation solutions by using a neighborhood search structure on the best individual in each generation. The selection trend chooses the best chromosome based on an evaluation mechanism employed in the algorithm (i.e. total weight, crowding distance, TOPSIS, and single-objective). The paper aims to specify if the intended characteristic is efficiency and improves the efficiency of the algorithms. So, the authors compared the recommended algorithms to find out the best alternative. The FDE-EDA model is used to evaluate the performance of the approximate methods (Mousavi et al., 2012).

Hybrid application of GA and DEA

Kuah et al. (2012) used Monte Carlo DEA with a GA to measure knowledge management performance. The authors provide a framework for the assessment of knowledge performance in a stochastic setting. The paper aims to devise an actual knowledge management performance measurement model in a stochastic setting by building on DEA, Monte Carlo simulation, and GA as below:

$$
\begin{aligned}
&\text{Max} E^{o}_{KM} = \frac{\sum_{r=1}^{s} u_r Y_{ro}}{\sum_{i=1}^{m} \nu_i x_{io}} \\
&\text{s.t.} \\
&\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} \nu_i x_{ij} \le 0, \quad \forall j \\
&u_1 Y^1_{1j} + b^1_2 u_2 Y^1_{2j} + b^1_9 u_9 Y^1_{9j} - (a^1_1 \nu_1 x^1_{1j} + a^1_2 \nu_2 x^1_{2j} + \\
&\nu_3 x^1_{3j} + a^1_4 \nu_4 x^1_{4j} + \nu_5 x^1_{5j}) \le 0, \forall j \\
&b^2_3 u_3 Y^2_{3j} + u_4 Y^2_{4j} + u_5 Y^2_{5j} - \\
&(\alpha^2_1 \nu_1 x^2_{1j} + \alpha^2_2 \nu_2 x^2_{2j} + \nu_6 x^2_{6j}) \le 0, \forall j \\
&b^3_3 u_3 Y^3_{3j} + u_6 Y^3_{6j} + u_7 Y^3_{7j} - \\
&(\alpha^3_1 \nu_1 x^3_{1j} + \alpha^3_2 \nu_2 x^3_{2j} + \alpha^3_4 \nu_4 x^3_{4j} + \nu_7 x^3_{7j}) \le 0, \forall j \\
&b^4_3 u_3 Y^4_{3j} + u_8 Y^4_{8j} + b^4_9 u_9 Y^4_{9j} - \\
&(a^4_1 \nu_1 x^4_{1j} + a^4_2 \nu_2 x^4_{2j} + \nu_8 x^4_{8j}) \le 0, \forall j \\
&u_r, \nu_i > 0, \forall r, i \\
&0.15 \le a^1_1, a^2_1, a^3_1, a^4_1, a^1_2, a^2_2, a^3_2, a^4_2 \le 0.37 \\
&0.3 \le a^1_4, a^3_4, b^1_2, b^2_3, b^3_3, b^4_3, b^1_9, b^4_9 \le 0.7 \\
&\sum_{p=1}^{4} b^p_r = 1, \forall r \\
&\sum_{p=1}^{4} a^p_i = 1, \forall i
\end{aligned} \tag{11}
$$

The proposed model assesses knowledge management by using a set of activities related to the main processes. Data collection budget allocation specifies the maximum accuracy of the model by GA. The redundant data are produced and analyzed by an advanced Monte Carlo DEA model to estimate overall knowledge productivity and the efficiency of knowledge management processes (Kuah et al., 2012).

Nabavi-Pelesaraei et al. (2016) published a paper on the use of optimization techniques to improve energy efficiency and greenhouse gases (GHG) emissions in wheat production. The paper employs CCR (DEA) and a multi-objective genetic algorithm to estimate energy efficiency and GHG emission reduction by wheat farmers in Ahvaz County, Iran. Data were collected from 39 farmers with a questionnaire by face-to-face interviews. The results showed that based on the model of constant return to scale, 41.02% of the wheat farms were efficient. However, this was 53.23% based on the model of variable return to scale. Mean technical, pure technical, and scale efficiencies were estimated at 0.94, 0.95, and 0.98, respectively (Nabavi-Pelesaraei., 2016).

Parthiban et al. (2009) presented a hybrid model for sourcing selection with order quantity allocation with multiple objectives in a fuzzy setting. Faced with severe global competition, sourcing selection with order quantity allocation is a crucial issue for organizations that seek the viability of their business so that it is growing as a stable competitive advantage. Sourcing selection is a complicated multi-objective decision-making problem that becomes more complicated with the increase in the interdependence of the selection criteria. They used the fuzzy theory to model the uncertainty in sourcing selection and integrated order allocation. A hybrid method is proposed by the paper by integrating DEA and GA (Parthiban et al., 2009). The hybrid model for sourcing selection with order quantity allocation is composed of three steps:

• Initially screening suppliers by CCR

• Developing a fuzzy multi-objective supplier selection model

• Finding an optimal solution for the fuzzy multi-objective supplier selection model using GA

Verma et al. (2016) presented a green space distribution network expansion strategy with hierarchical GA (HGA) and multi-criteria DEA (MCDEA) under uncertainty. Distribution network expansion programming is complicating in nature. Additionally, the increase in new load centers due to the increasing conversion of green spaces to habitats needs more severe and organized planning strategies. Since practical distribution networks are very huge, there will exist more candidates (load centers), so there is a considerable number of variables. By optimizing a big system, the accuracy may decrease and the time may increase considerably. To unveil this issue, a segmentation method was implemented for which a sensitivity analysis was applied to find the dependent variables. Clearly, a correct segmentation can reduce calculation time while reducing accuracy very slightly. This paper proposes a scheme to link three green load centers with an available initial distribution system using an HGA. To this end, two new load centers were first used in the existing system with GA and HGA approaches. At the next step, the third load center is included by HGA and MDEA. The contribution of the paper is the optimization of the best selection for linking the new load centers to the existing systems by AHP and GA. The results are confirmed by the following advanced MCDEA:

$$
\begin{aligned}
&\text{Min } d_o \\
&\min \sum_{j=1}^{n} d_j \\
&\text{Min } \quad M \\
&\text{s.t.} \\
&\sum_{j=1}^{m} v_i x_{ij} = 1 \\
&\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} = o; \quad \forall j \\
&m - d_j \geq o; \quad \forall j \\
&u_r, v_i, d_j \geq o; \quad \forall j
\end{aligned}
\tag{12}
$$

Xu et al. (2016) published a paper entitled ‘Capacity-oriented passenger flow control under uncertain demand: Algorithm development and real-world case study’. The paper addresses the problem of organizing passenger flow in subway stations under uncertain demand. The existing concepts of station service capacity are developed and it is categorized within three different demand scenarios. To increase the calculation speed, the authors integrate the SBM DEA model and GA with the proposed algorithm to study the results of simulation and find an optimal solution. Mathematical models are designed to measure the proposed three capacities and an algorithm based on integrated simulation for their solution (Xu et al., 2016).

Yuan et al. (2015) focused on China's regional vulnerability to drought and its mitigation strategies under climate change using DEA and AHP integrated approach. Climate change may entail frequent severe droughts with heavy economic losses in China. So, the paper aims to assess China's regional vulnerability to drought and suggest appropriate mitigation approaches for these drought-prone regions. The authors develop an integrated index composed of exposure, sensitivity, and adaptability to measure regional vulnerability to drought which is measured by an integrated approach in which slack-based measure in DEA is combined with an AHP-based GA (Yuan et al., 2015)

Chai et al. (2013) suggested a DEA-GA multi-objective scheduling algorithm for chip-multi-processors. The proposed design adopts a modified GA as a tool to discover the solution space, and the fitness of each individual (program) is assessed by the DEA-BCC method. Building on the comparison with the multi-objective scheduling algorithm in simulation, the proposed algorithm always produces more efficient solutions (Chai et al., 2013).

THE APPLICATION OF ARTIFICIAL NEURAL NETWORK AND DATA ENVELOPMENT ANALYSIS

This group is composed of two categories:

- The application of ANN in DEA
- The application of DEA in ANN

Application of ANN in DEA

Azadeh and Zarrin (2016) presented an intelligent framework to assess productivity and analyze human resources in terms of resilience engineering, motivational factors, HSE, and ergonomics. Human resource management aims to maximize organizational productivity by optimizing personnel efficiency and effectiveness. The paper provides an intelligent framework for productivity assessment and human resource analysis in a large-sized petrochemical power plant. The efficiency and effectiveness of the human resource were measured against three concepts of resilience engineering (RE), motivational factors in the workplace (WMF), and health, safety, environment, and ergonomics (HSEE). The framework has four primary steps. In the first step, data are collected with a valid and reliable questionnaire. In the second step, the efficiency scores of the people are calculated by an output-oriented DEA-BCC model. The rationale for the selection of DEA as a tool to calculate efficiency scores is its advantages over other similar models, e.g. regression models. For example, DEA is a linear mathematical model that can address different inputs and outputs. In the third step, an intelligent algorithm based on ANN, ANFIS and two other well-known metaheuristic algorithms, i.e. GA and PSO, is proposed to determine the efficiency scores of DMUs. Eventually, the impact of RE, HSEE, and workspace motivational factors (WMF) is statistically analyzed on performance measures (efficiency and effectiveness). The results show that from the perspective of efficiency, top management commitment from RE, ergonomics from HSEE, and work stress and overall workload from WMFs have significant positive impacts on productivity. Effectiveness is also influenced significantly and positively by top management commitment, flexibility, reporting culture, awareness, and teamwork from RE, safety from HSEE, and job satisfaction, work stress, and overall workload from WMF (Azadeh and Zarrin , 2016).

Application of DEA in ANN

Gutiérrez and Lozano (2010) published a paper about DEA for multiple response experiments. The Taguchi method is the strategy commonly used in robust designs. It is composed of experiments by using orthogonal arrays and estimation of the combination of factor levels that optimizes a certain performance measure. The problem becomes much more complicated for numerous responses because the factor level combinations that optimize various responses are usually different. The paper uses an ANN trained by the results of experiments to estimate responses for all factor level combinations. Then, DEA is applied to select the effective factor level combinations and then to select the level that has the most severe punishment for quality loss. A VRS DEA with fixed units, non-radial and pure input is used to assess relative efficiency. Finally, a second DEA is used to select the effective factor combinations that allow overall punishment more than quality loss with respect to different properties (Gutiérrez & Lozano, 2010).

Silva et al. (2014) worked on measuring the efficiency of fitness function by DEA. A very popular approach for the problem of time series prediction with the expert system is to use an evolutionary algorithm for the fit of a predictor model's parameters. Thereby, a critical point in the design of the evolutionary algorithm is defining the fitness function. However, studies on the properties of the fitness function have been rare and these rare studies have usually used only one performance measure, mainly MSE, as a statistical measure to guide the evolutionary algorithm. This paper uses a CCR/BCC-IO IO DEA process to evolve the most effective fitness function used in the evolutionary algorithm with a fixed number of iterations of an ANN as a predicting model. The model is idealized by using 20 different functions. Each individual function is a combination of three performance measures. The results show that irrespective of time-series attributes, DEA can find the best fitness function based on the concept of efficiency (Silva et al., 2014).

Azadeh et al. (2011) explored an integrated ANN-GA-rough set algorithm to assess the efficiency of personnel. Personnel characteristics have the strongest impact on total efficiency. These characteristics can help us design workspace and enhance total efficiency. The method proposed in this paper introduces a six-step analysis to assist managers in developing an effective decision-making process to display critical characteristics that influence people's efficiency and total efficiency. This process aims to alert the managers to critical characteristics that they should consider if they expect the decision to increase total efficiency. Determining the critical characteristics of personnel is an effective process to cope with the problems arising from the multiplicity of inputs and outputs. The suggested algorithm measures the effect of people's characteristics on total efficiency by DEA, ANN, and rough set theory (RST).

- Step 1. Calculate the efficiency of DMUs by DEA/BCC-OO (efficiency scores of branches)
- Step 2. Develop a decision system (people's characteristics)
- Step 3. Determine reduction via RS (reduction list)
- Step 4. Estimate the implementation of ANN for each reduction by validity test (input variables of DEA)
- Step 5. Select the best reduction with ANN results via DEA (reduction ranking)
- Step 6. Predicting the efficiency of DMUs by the reduction selection through ANN

The proposed algorithm is advantageous versus conventional and existing models and algorithms. The integrated method is successfully applied to 102 branches of a private-sector bank and assesses the characteristics of the people that influence the total efficiency of the branches. The results indicate that four subsets of conditional characteristics with a total of 9 characteristics out of 28 critical characteristics influence the accuracy of the optimal solution. This reduction of the number of characteristics reduces the time required by the decision process, thereby making saving on the cost of efficiency assessment (Azadeh et al., 2011).

Kheirkhah et al. (2013) used ANN, principal component analysis (PCA), and DEA to improve the estimation of electricity demand. Since electricity consumption is subject to seasonal and monthly variations and its modeling with conventional methods is difficult, the paper proposes a novel algorithm in which ANN, PCA, DEA (constant return to scale), and analysis of variance (ANOVA) are employed to estimate and predict electricity demand considering the seasonal and monthly variations in its consumption. The study uses the pre-processing and post-processing techniques in the context of data mining and analyzes the effect of data pre-processing and post-processing on the performance of ANN by building an ANN-MLP. The built ANN models are compared by DEA whose inputs include mean, minimum, maximum, and standard deviation of mean absolute percentage error (MAPE) of each built ANN. DEA helps the user utilize an appropriate ANN model as an acceptable prediction tool. In other words, various error estimation methods are used to find out a robust ANN learning algorithm. Besides, PCA is used as an input selection method. It chooses a preferred time-series model from the linear (ARIMA) and nonlinear models. As soon as the condition of nonlinearity is satisfied, the preferred nonlinear model is selected and compared with the preferred ARIMA model (linear time series) and the best time series is chosen too. Then, a new algorithm is developed to estimate the time series. For each case, an ANN or conventional time series is selected for estimation and prediction. To demonstrate the applicability and superiority of the suggested ANN-PCA-DEA-ANOVA algorithm, data for electricity consumption of Iran from April 1992 to February 2004 are used. The results show that the suggested algorithm provides a precise approach to tackle the problem of electricity consumption estimation. The results of DEA reveal the positive impact of data preprocessing on the ANN performance and the performance of ANN learning algorithms. Based on the results of the Granger test, ANN outperforms ARIMA. The following features of the suggested algorithm have not been considered in preceding studies:

1. The impact of data pre-processing on ANN
2. The use of PCA for input selection versus the trial and error method used in previous studies
3. The use of McLeod-Li test to consider both linear and nonlinear conditions of time series modeling
4. The use of the Granger test to compare the time series models
5. The use of DEA to compare ANN learning algorithms

Finally, future research may focus on the complexity and time-consuming issues of the suggested algorithm (Kheirkhah et al., 2013).

Han et al. (2016) studied energy optimization and prediction of complex petrochemical industries using an improved ANN integrated with DEA. Since complex petrochemical data are characterized by multi-dimensionality, uncertainty, and noise, energy consumption of petrochemical systems can hardly be optimized and predicted correctly. The paper proposes an ANN integrated with DEA (DEA-ANN) in which the DEACCWH (Charns, Cooper, Wei, Huang) model with slack variables is used for sensitivity analysis to identify effective DMUs and show optimized direction for ineffective DMUs (Eq. 13-16) (Han et al., 2016).

$$\begin{cases} \max y^T y_o \\ \alpha^T x_j - \beta^T y_j \in k,\ j1,\dots,n \\ \alpha \in A - \{o\} \\ \beta \in B - \{o\} \end{cases} \tag{13}$$

$$\begin{cases} \max y^T y_o = \alpha^o \\ \alpha^T x_j - \beta^T y_j \geq k,\ j = 1,\dots,n \\ \alpha^T x_o = 1, \\ \alpha \geq 0,\quad \beta \geq 0 \end{cases} \tag{14}$$

$$\begin{cases} \min \lambda \\ \sum_{j=1}^{n} x_j w_j \leq \lambda x_o, \\ \sum_{j=1}^{n} y_j w_j \geq y_o \\ w_j \geq o,\ j = 1,2,\dots,n \quad \lambda \in O_1 \end{cases} \tag{15}$$

$$\begin{cases} \min \lambda \left[\lambda - \varepsilon (e_1^T \tau^- + e_2^T \tau^+) \right] \\ \sum_{j=1}^{n} w_j x_{ij} + \tau^- = \theta x_{jN},\ j = 1,2,\dots,m \\ \sum_{j=1}^{n} w_i y_{rj} - \tau^+ = y_{rN},\ r = 1,2,\dots,s \\ w_i \geq o,\ j = 1,2,\dots,n \\ \tau^- \geq o, \tau^+ \geq o,\ N = 1,2,\dots,n \end{cases} \tag{16}$$

Finally, the proposed model (Eq. (13-16) is confirmed by a program in the complicated ethylene production system of the petrochemical industry in China. The energy efficiency is improved. The proposed method can determine reasonable rations of crude oil, steam, fuel, water, and power use. It can also provide optimal production conditions and improve the energy efficiency ratio by about 2% under different input-output configurations. At the same time, the method successfully supplies data on energy use indicates to help decision-makers effectively enhance energy efficiency. This data can guide the ethylene production process at a reasonable price (Han et al., 2016).

THE APPLICATION OF PARTICLE SWARM OPTIMIZATION ALGORITHM AND DATA ENVELOPMENT ANALYSIS

This group is divided into two categories:

- The application of PSO algorithm in DEA
- The application of DEA in PSO algorithm

The application of PSO algorithm in DEA

Meng (2014) proposed a hybrid PSO algorithm for satisfactory DEA under fuzzy chance constraints. The paper presents a satisfactory DEA under a fuzzy system (Eq. 17).

$$\max_{u_i v_j} \theta = Cr\left\{\frac{\sum_{j=1}^{r} v_j \tilde{y}_{jo}}{\sum_{i=1}^{m} u_i \tilde{x}_{io}}\right\} \geq \beta_o$$

$$\text{s.t.}$$

$$cr\left\{\frac{\sum_{j=1}^{r} v_j \tilde{y}_{jk}}{\sum_{i=1}^{m} u_i \tilde{x}_{ik}}\right\} \geq 1-\alpha_k, \quad k = 1, 2, \ldots, n$$

$$u_i \geq o, \quad v_j \geq o, \quad \forall i, j$$

(17)

When inputs and outputs of the trapezoidal fuzzy variables are mutually independent, the satisfactory DEA model is converted to a deterministic equivalent programming problem. The authors designed a PSO algorithm for the general fuzzy input and output variables by integrating the approximation method, neural network, and PSO algorithm to use it to solve the proposed DEA model. The approximation method is used to calculate the credibility functions, the neural network is used to approximate the credibility functions, and the PSO algorithm is applied to find the optimal solution for the proposed DEA problem. The paper discusses the sensitivity analysis of the proposed model too. Finally, they perform some numerical experiments to demonstrate the effectiveness of the hybrid PSO algorithm. The results indicate that the hybrid PSO algorithm outperforms the hybrid GA in terms of execution time and solution quality (Meng, 2014).

The application of DEA in PSO algorithm

Yun et al. (2016) used generalized DEA (GDEA) and PSO to produce Pareto optimal solutions. Metaheuristic methods, e.g. PSO and GAs, are used to solve multi-objective optimization problems and are also effective in producing good approximations of Pareto optimal solutions. This paper proposes a multi-objective PSO (MOPSO) using GDEA (Eq. 18) to determine the MOPSO parameters and improve convergence and diversity in searching for approaches. In addition, some numerical examples are employed to check the effectiveness of the proposed method by GDEA in comparison with conventional methods. For practical problems, it is confirmed that the proposed method can provide better results than other MOPSO's or MOGA's (Yun et al. (2016).

$$\text{minimixe} \quad \theta^i - \varepsilon I^T s^i$$

$$\text{s.t.}$$

$$\{\alpha(-F_i + F) + D\}\lambda^i - \theta^i I + s^i = o$$

$$I^T \lambda^i = 1.$$

$$\lambda^i \geq o, s^i \geq o,$$

$$\lambda^i \in R^N, s^i \in R^m,$$

wherN: the number of particles

$$F = [f(x_1) \ldots f(x_N)] \in R^m \times R^N$$

$$F_i = [f(x_i) \ldots f(x_i)] \in R^m \times R^N$$

D: matrix replace by o exept for the maximal component in each colum of the matrix $(-F+F)$

$$I = (1, \ldots, 1)^T$$

(18)

Pouya et al. (2016) used invasive weed optimization (IWO) to solve a multi-objective portfolio optimization problem. Portfolio optimization is one of the most important problems in effective and economic investment and it has been subject to extensive research. Most studies have tried to make Markowitz's primary portfolio selection model more realistic or solve it to achieve optimal portfolios. This paper adds P/E criterion and expert advice for market sectors to Markowitz's mean-variance model. There are various methods to solve portfolio optimization, but almost none have considered the IWO algorithm. This research converts the suggested multi-objective portfolio selection model into a single-objective programming model using fuzzy normalization and uniform design method. Then, the model is applied to monthly data of 50 firms listed in Tehran Stock Exchange in 2013. Then, the model is solved in three ways: (i) the proposed IWO algorithm, (ii) the PSO algorithm, and (iii) the reduced gradient method. The approaches of these algorithms are compared with one another using the cumulative model and constant return to scale (non-radial) DEA. It is concluded from the comparisons that the IWO and PSO algorithms perform similarly in terms of most important criteria, but the IWO algorithm is less time-consuming than the PSO algorithm and outperforms it in dominant effective approaches too. In addition, the PSO algorithm outperforms in total violation of the constraints (Pouya et al., 2016).

THE APPLICATION OF CUCKOO OPTIMIZATION ALGORITHM AND DATA ENVELOPMENT ANALYSIS

This can be classified into two groups:

- The application of COA in DEA
- The application of DEA in COA

The application of COA in DEA

Shadkam and Bijari (2015) published a paper on multi-objective simulation optimization for selection and determination of order quantity in supplier selection problem under uncertainty and quality criteria. Simulation optimization aims to provide approaches for practical stochastic problems. Supplier selection is one of the most critical decisions for the survival of an organization. The paper proposes a novel multi-objective simulation optimization method for making decisions on supplier selection and order quantity determination. Since a multi-objective real supplier chain has indeterminate parameters and includes quantitative and qualitative variables, the proposed method considers these issues and is applicable to real-world problems. Also, the method considers supplier selection and order quantity allocation to each supplier, which are interconnected as an integrated model. The proposed method has four primary modules: COA, discrete event simulation, supplier chain model, and GDEA.

$$
\begin{aligned}
&\max \Delta \\
&\text{s.t.} \\
&\qquad \Delta \le \overline{d}_j - \alpha \sum_{i=1}^{m} v_i (F_i(x^{o}) - F_i(x^{j})), \\
&j = 1,\ldots,n \\
&\qquad \sum_{i=1}^{m} v_i = 1 \\
&\qquad v_i \ge \varepsilon, \quad i = 1,\ldots,m
\end{aligned}
\tag{19}
$$

Unlike most multi-objective methods, the proposed method is not confined to the number of objective functions and this is a major advantage for it. This method also pays attention to organizational efficiency and finding inputs that can lead to the best output values. Besides convergence, the method considers Pareto frontier dispersion as the second metric for the selection of a good approach. To implement the proposed method, numerical results are discussed for the problem of supplier selection in the conditions of multi-product, multi-customer, and unknown and quantitative variables and Pareto frontiers are presented. The performance of each supplier configuration is measured by three main performance measures including costs, service level, and delivery time, which are specified by simulation. Then, based on the simulation results as output and cuckoo inhabitant as input, the efficiency of the GDEA model is calculated for each system configuration. In the proposed method, the GDEA model evaluates the relative efficiency of the existing approaches and all efficient approaches specified in previous iterations and it does not limit itself to the comparison of the efficiency of just the present iteration approaches. This enhances the robustness of GDEA and contributes to the correct identification of efficient approaches from inefficient ones. Also, the dispersion of approaches is studied as the second criterion. The performance of the proposed method in finding Pareto optimal approaches and Pareto frontier in each iteration is evaluated by two indices, i.e. mean efficiency score and percentage of efficient approaches. The Pareto frontier of the proposed method approached the real efficient frontier by specifying the order of the approaches (Shadkam & Bijari, 2015).

The application of DEA in COA

Gorjestani et al. (2015) proposed a hybrid COA-DEA method for multi-objective problems. COA has been developed to solve single-objective problems, so it cannot be used to solve multi-objective problems per se. This paper proposed a multi-objective COA based on DEA which can obtain Pareto effective frontiers. The algorithm has been developed by the output-oriented DEA CCR model. The selection criterion is the higher efficiency for the next iteration of the proposed hybrid method. Thus, the profit function of COA is replaced with the efficiency value obtained by DEA. The paper compares this algorithm with other methods using several test problems. The results show that the use of COA and DEA for multi-objective problem-solving increases the speed and precision of the constructed approaches. The researchers conclude that the proposed method not only provides the most optimal and efficient responses, but its processing time is also much shorter than the other algorithms. Pareto frontiers obtained by this method are compared with the solutions obtained by other similar algorithms, e.g. GA-DEA, ranking method, GA-GDEA, etc. The proposed algorithm exhibits profound convergence towards the solution. It is, therefore, a suitable and reliable way to solve optimization problems (Gorjestani et al., 2015).

THE APPLICATION OF BEE COLONY ALGORITHM AND DATA ENVELOPMENT ANALYSIS

The application of bee colony algorithm in DEA

Chang and Lee (2012) focused on an integrated fuzzy DEA and knapsack formulation model for project selection. Project selection is of crucial importance in science and engineering. The paper discusses the problem of selecting a set of projects so that organizational goals can be accomplished without violating the limited capital resources, especially when the projects have ambiguous input and output data for selection. The researchers propose a combination of DEA-CCR, knapsack formulation, and fuzzy set theory to tackle this issue and demonstrate its performance by a case study in the engineering-procurement-manufacturing industry. Furthermore, the paper uses three techniques to cope with constraints: factor-free penalty function based, the conversion of a constrained optimization problem into an unconstrained one, and the use of artificial bee colony (ABC) algorithm to search for approaches for the first time. The performance of these three constraint-coping techniques is compared against the ABC algorithm in this work for the first time (Chang & Lee, 2012).

Hsu (2014) explored an integrated portfolio optimization process based on DEA, ABC algorithm, and genetic programming. Portfolio optimization is an important problem in investment/financial decision-making so that it has provoked interest in researchers. However, in addition to portfolio optimization, a complete investment process should include the selection of profitable investment and the determination of an optimal timeframe for the buying/selling of the investment goals. This paper proposes an integrated process based on the DEA CCR-IO model, ABC algorithm, and genetic programming to solve portfolio optimization problems. The proposed process was assessed by a case study on investment in the stock of semi-conductor subsectors in the Taiwan Stock Market for four years. The mean six-month investment return of 9.31% from November 1, 2007 to October 31, 2011 shows that the proposed process can be a feasible and effective way of building outstanding investment programs to gain profit in the Taiwan Stock Market. Also, it is a strategy to help investors reach profits when the whole stock market incurs a loss (Hsu, 2014).

• Step 1: Stock selection

o Assessing candidate firms by DEA

o Ranking candidate firms by efficiency score (first priority) and dividend (second priority)

o Determining stock for portfolio investment based on the ranks of the candidate firms

• Step 2: Portfolio optimization

o Describing the portfolio optimization problem by Markowitz mean-variance model

o Optimizing investment share of each selected stock by ABC algorithm

• Step 3: A prediction model construction

o Constructing stock price prediction models with genetic programming

• Step 4: Stock selling/buying

o Developing three rules of transaction

o Selling or buying stock based on these three rules

o Assessing portfolio investment profit

THE APPLICATION OF ANT COLONY ALGORITHM AND DATA ENVELOPMENT ANALYSIS

The application of ant colony algorithm in DEA

Kuah et al. (2013) proposed an ant colony system (ACS) based on DEA for the assessment of knowledge sharing. Knowledge sharing is a key process in knowledge management and happens in a dynamic environment. The authors did not find a specific tool to assess the performance of knowledge sharing in this environment in the relevant literature. The paper they published aims to fill this gap by proposing a hybrid model based on the DEA CCR model. The Monte Carlo simulation is added to the model to handle stochastic data. In addition, an ACS metaheuristic algorithm is integrated with the Monte Carlo simulation and DEA to improve the model accuracy. The new model is named ACS-DEA and can increase the precision and reliability of the results. Although the model aims to evaluate the performance of knowledge sharing, it can also be applied in other dynamic settings. The process of knowledge sharing has a stochastic nature per se and its data are indeterminate. So, MC-DEA is proposed as it can address stochastic data. Stochastic models are preferred due to their capability in dealing with stochastic data and producing more reliable results. However, analytical reliability capability that uses limited datasets is a major concern because the results may be highly uncertain and unreliable. Furthermore, organizations usually have a certain limit or budget for data collection. So, ACS-DEA is proposed for designing an effective data collection program that can optimize the accuracy of the results. Based on the real-world applications, it is observed that ACS-DEA outperforms MC-DEA because it produces more accurate results. The proposed ACS-DEA can be used as an internal assessment tool to evaluate knowledge sharing in different sections of an organization (Kuah et al., 2013).

Fathian et al.(2015) used new clustering algorithms for a vehicular ad-hoc network (VANET) in a highway communication setting. A VANET is a network in which vehicles are interconnected as dynamic nodes. VANETs are a good infrastructure for the development of intelligent transportation systems. Stable communication within a VANET ensures the safety of drivers and better traffic management. Clustering techniques that organize similar vehicles in similar groups are a plausible way to continuously improve communication inside a VANET. This paper proposes the following two new clustering algorithms that are appropriate for the dynamic setting of a VANET (Fathian et al., 2015).

* The multi-objective DEA clustering algorithm as a mathematical clustering model

$$
\begin{aligned}
&\min \theta \\
&\text{s.t.} \\
&\sum_k x^{jk} \times \lambda_k \le x^{jk^*}\theta \qquad j = 1, \dots, m_1 \\
&\sum_k y^{ik} \times \lambda_k \ge y^{ik^*} \qquad i = 1, \dots, m_2 \\
&\lambda_k \ge o \\
&\max \varphi \\
&\sum_k x^{jk} \times \lambda_k \le x^{jk^*}\theta \qquad j = 1, \dots, m_1 \\
&\sum_k y^{ik} \times \lambda_k \ge y^{ik^*} \qquad i = 1, \dots, m_2 \\
&\lambda_k \ge o
\end{aligned}
\tag{20}
$$

* The ACS-based clustering algorithm as a metaheuristic clustering model

$$\begin{cases} \arg \max \{\tau(r,u)\eta(r,u)^{\beta}\} & \text{if } q \le q_0 \\ s & \text{otherwise} \end{cases} \tag{21}$$

The authors conduct a comparative simulation study in a highway environment to assess the proposed methods and compare them with the most common VANET clustering algorithms. The results imply that the proposed algorithms are more stable and less time-consuming and outperform the existing algorithms. Also, it is observed that in the VANET environment, the proposed mathematical clustering model provides better results than the metaheuristic algorithm.

THE APPLICATION OF TABU SEARCH ALGORITHM AND DATA ENVELOPMENT ANALYSIS

The application of TS algorithm in DEA

Van den Bergh et al. (2013) proposed a three-stage approach for aircraft line maintenance personnel rostering using MIP, discrete event simulation, and DEA. Personnel planning problems should deal with the priorities of the people, coverage constraints, legal limitations, and so on. The authors present a three-stage method for personnel roster selection. First, various rosters of personnel are produced by a mathematical programming model. Then, the performance of the rosters is assessed by discrete event simulation in terms of several service criteria. At the third stage, they are ranked by the DEA CCR model. The method is tested on a aircraft line maintenance personal rostering problem. The DEA model enables the maintenance company to select a roster that is the best based on objective inputs and outputs of MILP, tabu search, simulation model, and assignment of specific weights to these input and output parameters. This method prevents the selection of rosters merely with a view on costs and a random change sequence as decision parameters (Van den Bergh et al., 2013).

Bozorgi et al. (2014) used a tabu search metaheuristic algorithm for the efficiency of a dynamic facility layout problem. The facility layout affects the efficiency of products inside the production system. To ensure the optimal performance of a production system, the facility layout should keep pace with changes over time. Demand for products invariably changes over time. The problem of dynamic facility layout aims to find the most effective layout with respect to three criteria – cost, adjacency, and required distance. The paper uses DEA and TS to find the most optimal layout; the former to measure the efficiency of the layouts in terms of the three criteria and the latter with diverse strategies to avoid rotation and acceptance of non-improving movements to escape from a local optimal value and search for a global optimal value (Eq. 22) (] Bozorgi et al., 2015).

* The DEA formula

$$\begin{aligned} &\text{Max } w_r = \frac{\sum_{j=1}^{J} u_j O_{jr}}{\sum_{i=1}^{I} v_i I_{ir}} \\ &\text{s.t.} \\ &\frac{\sum_{j=1}^{J} u_j O_{jk}}{\sum_{i=1}^{I} v_i I_{ik}} \le 1 \quad k = 1,\dots,n \qquad u_j, v_i \ge 0 \end{aligned} \tag{22}$$

* Minmax model

$$\begin{aligned} &\min z = M \\ &\text{s.t.} \\ &\sum_{i=1}^{I} v_i x_{io} = 1 \\ &\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} + d_j = 0 \quad M - d_j \ge 0 \\ &(j = 1,\dots,n) \quad u_r, v_i, d_j \ge 0 \end{aligned} \tag{23}$$

The datasets obtained from the literature are used to assess the proposed metaheuristic algorithm. The calculations show that the metaheuristic algorithm performs better than the other algorithms and yields the most optimal layout.

A HYBRID GROUP OF VARIOUS METAHEURISTIC ALGORITHMS AND DATA ENVELOPMENT ANALYSIS

Azadeh et al. (2015) proposed a flexible ANN-GA-multivariate algorithm for the assessment and optimization of machinery productivity in complex production units (CPUs). The flexible algorithm, which is based on ANNs, GAs, and multivariate analysis, assesses and optimizes the performance of CPUs against machinery productivity indices. Multivariate techniques include DEA-AP-OO model, principal component analysis (PCA), and numerical taxonomy (NT). The proposed method is applied to two case studies. In the first case, the machinery productivity indices are divided into four standard groups including availability, machinery stoppage, random failure, and value added and production value. In the second case, the productivity of the production units is assessed by the indices of health, safety, environment, and ergonomics. The flexible algorithm can deal with the linearity and complexity of both datasets. The algorithm is applied to a large set of production units to demonstrate its superiority over conventional methods. The results indicate that ANN outperforms GA and conventional methods with respect to nonlinear data. The flexible algorithm proposed in this paper can readily be generalized for the assessment and optimization of CPUs by machinery indices in other units (] Azadeh et al., 2015).

Azadeh et al. (2011) studied the use of an integration of ANN and GA-based clustering ensemble (GACE) to assess DMU performance. The paper proposes a nonparametric effective frontier analysis method based on ANN and GACE to assess efficiency as a supplementary instrument for the techniques used in previous studies on efficiency. The ANN-GA algorithm can find the stochastic frontier based on input-output observational datasets and it does not need straightforward hypotheses as to the function structure of stochastic frontier. The CCR-DEA model is employed as a criterion to demonstrate the advantages of the proposed algorithm (Azadeh et al., 2011).

López-Espín et al. (2014) published a paper on benchmarking and DEA as an approach based on metaheuristics. DEA is a non-parametric technique to estimate the technical efficiency of units. It also provides information on benchmarking. The authors study the Russell DEA model based on the closest efficient targets that are linked to the minimum distance and allow inefficient units to find the easiest way to reach the efficient frontier. The literature has solved these models by unsatisfying methods related to NP-hard problems. This paper is an attempt to solve the problem with metaheuristic techniques. Since the problem is subject to many constraints, it is very difficult to find approaches for the use of metaheuristic algorithms. So, the paper analyzes and compares some metaheuristic algorithms to find approaches to the problem. Each constraint plays a decisive role in determining the design of these algorithms. As such, the problem is considered by adding the constraint one by one (López-Espín et al., 2014).

CONCLUSIONS

In this review paper, metaheuristic algorithms and DEA were studied in eight groups. The first group, which was composed of three subgroups, had the most number of papers. GAs have a lot of applications in solving optimization problems. The most number of DEA models used in the papers are the base models of DEA (AP, CCR, BCC, and Russell) and non-classic models. The second group, which included ANN and DEA, had less application than the first group. The papers in this group have mostly been in the fields of human resource management, quality engineering, and prediction. The DEA models used in this group mostly include the base DEA models such as CCR and BCC. The third group was composed of the PSO algorithm and DEA. The papers using them deal with portfolio optimization and multi-objective optimization and mostly employ non-classic DEA models. The fourth group included COA and DEA in which supply chain management and multi-objective problems have been explored. They have used non-classic and base models of DEA. Ant colony algorithm and DEA were classified in the fifth group. The papers reviewed within this group were in the fields of knowledge management and transportation (ad-hoc network). They have used the base CCR models. The sixth group included the bee colony algorithm and DEA. The papers address the engineering-construction industry and portfolio optimization. They have used CCR and non-classic models of DEA. TS algorithm and DEA can be found within the seventh group in which the papers have focused on factory management such as facility layout and human resource planning. They have mainly used the base CCR and non-classic models. Finally, the last group was a combination of metaheuristic algorithms and DEA. The papers reviewed in this section deal with machinery productivity in complex production units and efficiency estimation. They have used the CCR, Anderson Peterson, and Russell models.

Based on Figure 1 and Table 1, to answer the question as to which DEA model and metaheuristic algorithm has been most frequently applied in optimization problems, it is concluded that the CCR models, which are among the base and radial models of DEA, have been most common and among metaheuristic algorithms, GA has been most abundantly used when compared to all other algorithms. Due to the gigantic amount of calculations, it is not possible to precisely check the feasibility of optimal scheduling. Instead, metaheuristics can be used. GAs are a viable way to produce satisfying solutions for many programming problems. When these two optimization methods are combined, they tackle the constraints of one another by overlapping and allow finding a better answer than when either one is applied alone. This research can be extended in the future by exploring more papers and their strengths, weaknesses, and recommendations and making different classifications.

Table 1: Type and number of models

	CCR	BCC	Russell	AP	SBM	FDH	Non-classic model
GA Algorithm	10	2	2	1	2	1	10
ANN Algorithm	2	3	-	-	0	0	1
PSO Algorithm	-	-	-	-	1	-	2
CO Algorithm	1	-	-	-	-	-	1
AC Algorithm	2	-	-	-	-	-	-
BC Algorithm	1	-	-	-	-	-	1
TS Algorithm	1	-	-	-	-	-	1
Hybrid	1	-	1	1	-	-	-
Total	18	5	3	2	3	1	16

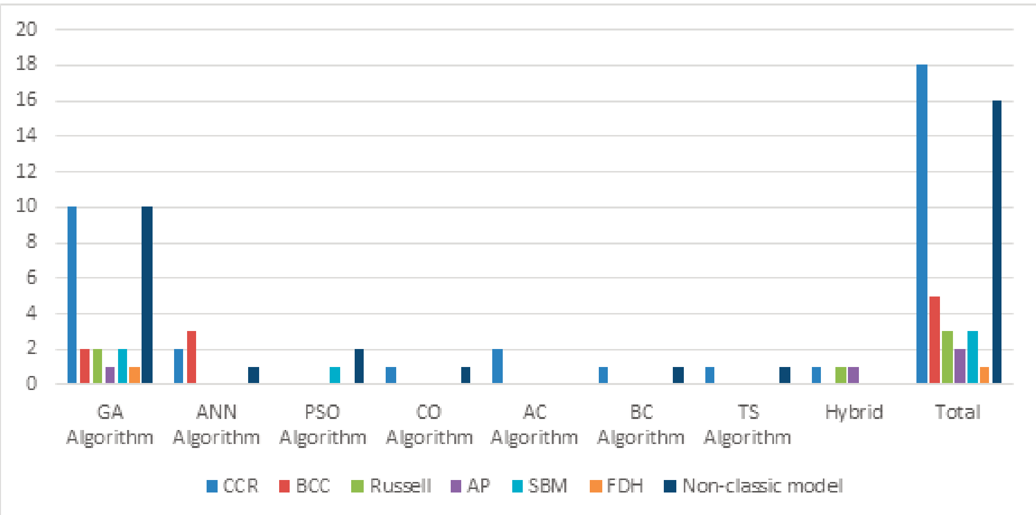

Fig. 1. The extent of the application of models and algorithms

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