International Journal of Applied Research in Management, Economics and Accounting (IJMEA)
ISSN 3023-4964
DOI: 10.63053/ijmea.45

Provide a Mechanism for Pollution Reduction and cost control in the Tehran Steel Plant for Improving Industrial Environmental Management

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ARTICLE INFO

Keywords: *Pollution Reduction, Costs Control, Tehran Steel Plant, Industrial Environmental Management, Optimized Multi-Objective Genetic Algorithm (O-MOGA)*

ABSTRACT

Environmental management in Iran's iron and steel industry must consider multiple targets. The biggest concerns are the realization of environmental goals as well as the smooth development of industry from the government's point of view which is almost inadequate while companies focus most on economic performance metrics such as fixed investment, operating costs, and benefits. Adopting various energy-saving measures and reducing emissions is required to increase costs and at the same time affect innovative performance to varying degrees. Therefore, a multi-objective nonlinear optimization model is presented in this research to solve and cover the problems mentioned so far and also based on the articles reviewed in previous research. As an innovation, this research presents an industrial environmental management mechanism in a steel plant with integrated targets to improve energy consumption, reduce emissions, and reduce costs. The approach of this research is to use the Optimal Multi-Objective Genetic Algorithm (O-MOGA).

Introduction

Since the 20th century, ecological and environmental problems have garnered widespread attention from governments and scholars all over the world. These issues not only affect the quality of people's lives but also have implications for the sustainable development of the global economy and human society (Xian et al., 2024). Today, high pressure is placed on the environment due to the high emission of pollutants and rising costs in industrial workshops which is due to the wrong policies and plans of officials in different countries (Abdelaziz et al., 2011; Cole et al., 2005; Fujii et al., 2013). The growth of pollutants has a negative impact on the environment, so providing management systems to address the problems and challenges of the environment is an important issue. Due to the uncontrolled growth of pollutants and the resulting concerns, different environmental goals are seen in the policies of different countries. For example, reducing sulfur dioxide (SO2), nitrogen oxides (NOx) and particulate emissions (PM) are the most important goals of controlling air pollution while reducing the demand for chemical oxygen (COD) and ammonia nitrogen (NH3-N) are the goals. The main control of water pollution in different regions such as China, the United States, and the European Union(Andersen, 1999; Portney, 1990).

The existence of different goals in the preservation of the environment in the absence of integration, adds more difficulty to the issue of industrial environment management. This is because decision-makers under the constraint of these goals which have a variety of goals, such as saving energy and reducing emissions as much as possible. Integration of goals means that different goals have aggregation and integration with each other and interact with each other in a way that can be considered two important issues of energy saving and reducing emissions. One of the issues that can be referred to as non-integration of goals is the study of energy saving versus the issue of reducing fuel consumption failure to examine these two issues from different perspectives has led to a kind of managerial dispersion and issues such as the use pollutants that require energy consumption which are ignored. In this situation, decision-makers must not only take the necessary steps to achieve each goal but also the complex relationships of cooperation and trade between different goals. Therefore, several energy-saving and emission-reduction goals must be systematically considered to achieve improvements in the overall performance of the environment in the industrial sector. Hence, the decision to save energy and reduce industrial emissions is a multi-objective optimization problem (more than three goals).

The use of private sector models for public sector tasks is limited. For example, if privatization is approved for parts of remedial projects in industrial workshops as considered by environmental management, financial markets may be reluctant to change private sector risk. This could mean that there would be no private-sector volunteers for environmental management to accept the private program, so there would be no cost reduction and no cost increase. In the absence of bidders, smaller tasks - such as design, construction, or operations - should be considered for bids. Some privatization tasks may be fully performed by the government or the guarantor of the loan. In addition, even if the financial markets are willing to fund these commitments, the general public may challenge the solutions of privatized institutions to solve problems and suspend or suspend their implementation.

In total, there are three important areas in optimizing environmental management which can be energy management, reducing emissions, and reducing costs. To overcome the limitations mentioned in the articles reviewed in the previous research section, including references (An et al., 2018; Bischi et al., 2014; Chen et al., 2018; Chen et al., 2014; Li et al., 2015; Nguyen et al., 2016; Oda et al., 2009; Park et al., 2017; Park et al., 2016; Sano et al., 2013; L. Wang et al., 2015; X. Wang et al., 2015; Wen et al., 2015; Wen et al., 2014; Winden et al., 2015) in single-objective models, further research has adopted intelligent algorithms. One of the main advantages of these algorithms is that all the goals are considered simultaneously in the optimization process, so the relationships between the goals are present and known. Therefore, references (Eberhart & Kennedy, 1995; Gong et al., 2017; Holland, 1974; Kadambala et al., 2017; Karaboga & Basturk, 2007; Lin et al., 2015; Liu & Li, 2015; Lu et al., 2017; Sweetapple et al., 2014; Tao et al., 2016; Wang et al., 2018; C. Wang et al., 2017; Yu et al., 2016; Yu et al., 2017; Yu et al., 2018) are presented. However, a serious drawback to this research is that the number of targets is less than 4. This is because most of the common algorithms used in previous research are not capable of solving multi-objective optimization problems because achieving the dominant relationship to solve multi-objective problems is difficult which is considered NP-Hard problems. Algorithms usually take the dominant relationship to judge the performance of solutions as well as to motivate the optimization process. However, these methods, make it much easier to consider non-dominant solutions while solving many goal optimization problems. Under these conditions, all solutions, regardless of their distance from the ideal solutions are radically optimal and the motivation for optimization is insufficient.

Therefore, algorithms that can solve many goal optimization problems should be used in the field of industrial environment management.

In this case, the Non-dominated Sorting Genetic Algorithm or NSGA-III proposed by (Wang et al., 2019) is an objective optimization solution method. The NSGA-III innovation is the use of reference point-based selection mechanisms that divide target spaces into different parts, link solution points to a specific part, and distribute the decentralized solution to the next generation. Through this mechanism, the homogeneity of solutions in the solution space increases. So far, through searches, just over 150 articles have covered NSGA-III methods in various fields, including control chart design (Tavana et al., 2016), software improvement (Mkaouer et al., 2015), system planning(Yuan et al., 2015), and algorithm expansion (Yuan et al., 2014; Zhu et al., 2017), but few studies have used this method to manage the industrial environment. In addition, most of these studies solve the problems of unlimited optimization, but usually, the problems of industrial environmental management have limitations to correspond to reality.

Another methodological gap is the development of decision-making programs. For a highly objective optimization problem, the desired results are set (e.g., the front beam in the optimization) and not an individual where there is a large scale of solution points to cover the front beam space. This situation makes it difficult for decision-makers to choose a plan from those diverse solutions. Therefore, it is necessary to adopt a clustering algorithm to search for agents that reflect the characteristics of the whole solution set. The average C-Means fuzzy clustering algorithm (FCM) means a combination of membership and Euclidean distance calculation that clusters the beam segments and finds the final decision schemes (Bezdek et al., 1984). So far, many studies have used the FCM clustering algorithm in the final decision stage (Liu et al., 2018; Wikaisuksakul, 2014). However, in the field of industrial environment management, most research still adopts a simple selection method to determine final decision plans.

The iron and steel industry is the pillar industry in Iran, so this industry has been selected as a case study of this research. This research seeks to provide suggestions that can improve the overall performance of the industrial system, including energy savings, emission reductions for five pollutants, and total cost control. In addition, some decision-making schemes are obtained to support environmental management in the iron and steel industry. The main production process in the iron and steel industry can be divided into two parts: a long process and a short process. In the long process, raw materials, including iron ore and limestone, are used to produce steel by coking, sintering, blast furnaces, base oxygen furnaces, and steel rolling mills, while in the short process, scrap steel or iron is converted to crude steel in an electric arc furnace. Among these processes, the iron-making process of the steel furnace is the main consumer of energy, because a complex redox reaction occurs at high temperatures in the steel furnace. In addition, cooking emits most of the sulfur pollutants, while the iron furnace, base oxygen furnace, and electric arc furnace mainly emit particulate matter and water pollutants such as COD and NH3-N. Five types of pollutants, SO2, NOx, PM, COD, and NH3-N have been considered in this study because they have been addressed in Iran's industrial environmental management policies.

Various types of energy-saving and emission-reduction measures have been applied during the production process. Among these measures, increasing the capacity of equipment and releasing advanced technology is widely accepted. Larger-scale equipment is considered environmentally friendly due to its energy and emission intensity. Since 2005, Iran has pursued a policy of disposing of obsolete equipment and encouraging higher-capacity replacements, emphasizing the importance of these measures in environmental management in the iron and steel industry. Alternatively, the release of advanced technology improves the environmental performance of the industrial system by increasing energy efficiency, reducing final emissions, or recycling by-products. Along with increasing environmental management goals, the correct use of energy-saving measures and emission reductions has become difficult because the goals have complex implications for the environmental and economic performance of industrial systems. For example, many clean generation technologies can simultaneously reduce emissions and achieve energy savings. There are also business relationships, as most end-of-pipe technology systems technologies use energy to reduce pollution. In addition, although it improves environmental performance, increasing the capacity of process equipment is quite costly. Therefore, it is very important that cooperation and trade relations, energy-saving measures, and emission reductions are very important for proper planning of their use in Iran's iron and steel industry.

1. Literature Review

2.1Management Vision

The purpose of resource flow life cycle management is to achieve sustainable resources by using traditional linear flow changes in a circular mode. Considering the UNEP framework of coexistence-based life cycle management and resource flow life cycle in the previous section, this study proposes a coexistence-based life cycle management framework for industrial resource flow management in terms of the five aspects. The framework manages the life cycle system of resource flows which consists of five subsystems, including exploration, production, consumption, logistics and delivery and disposal, recycling, and disposal, all of which are integrated with a set of management strategies. This can help decision-makers to achieve sustainable resources, which are targeted by the flow of circular resources in the life cycle system. The evaluation system is used to evaluate resources in the life cycle system in terms of two categories of indicators, namely environmental impacts and sustainable use. The evaluation system also has a sub-feedback system that gives evaluation results to decision-makers to gradually adjust the relevant strategies to achieve the goal.

The proposed life cycle management approach of this research presents a systematic management solution based on a specific coexistence system and a comprehensive life cycle assessment with the aim of sustainable management for the flow of resources in the industrial ecosystem. The coexistence system is designed to solve environmental problems and use resources. Comprehensive assessment focuses on the impact of management and the identification of problems at each stage of the life cycle. The results show that coexistence-based life cycle management can minimize environmental impacts and facilitate sustainable use of resources. Meanwhile, the use of mineral resources is known as the main problem of the life cycle during which the stage of wastewater disposal is the main source of the effects of the use of mineral resources due to the exploitation of a particular production of some chemical reagents is characterized. Based on these observations, decision-makers can take action by encouraging companies to use alternative reagents that have minimal impact. Given that the results provided in the following work provide information that includes the degree of improvement and the main problems of each stage of the life cycle, decision-makers can not only be aware of the impact of management but can take targeted actions. To solve the problems of using unsustainable resources. Therefore, coexistence-based life cycle management on resource resources is efficient and feasible.

2.2 Recent Researches

To date, many studies have examined industrial environmental management through optimization methods, one of which is bottom-up models. For example, (Li et al., 2015) used the integrated model of the MARKAL EFOM SYSEM system (TIMES) and in (Wen et al., 2015; Wen et al., 2014) respectively the integrated model of the Asian-Pacific Integrated (ACM) to plan energy-saving measures and reduce emissions in China used iron and steel and cement industry. Many other studies of various types such as DNE21 in(Oda et al., 2009) (Sano et al., 2013), Energy Flow Optimization Model (EFOM) in(X. Wang et al., 2015) (Bischi et al., 2014), TIMES model in(Chen et al., 2014; Park et al., 2017; Park et al., 2016)[and National Energy Technology model in(An et al., 2018; Chen et al., 2018; Tang et al., 2018), In these models, industrial systems are optimized based on minimizing system costs, including fixed investments in energy-saving measures and reducing emissions and economic benefits (for example, avoiding fuel purchases and paying pollution taxes). However, as these models are widely used, their drawbacks are also evident. First, energy savings, emission reductions, and cost control cannot be fully accounted for by net income generation. Second, it is difficult to make accurate decisions on environmental factors due to subjective cognitive biases, because the monetary benefits of energy savings and emission reductions vary significantly in different studies (Nguyen et al., 2016; L. Wang et al., 2015; Winden et al., 2015). Therefore, these methods are not suitable for the current industrial environment management.

Many intelligent algorithms such as the Non-dominated Sorting Genetic Algorithm II or NSGA-II (Holland, 1974), the Particle Swarm Optimization or PSO (Eberhart & Kennedy, 1995), and the Artificial Bee Colony algorithm or ABC (Karaboga & Basturk, 2007) have been used in the industrial environment. For example, (Yu et al., 2017) combine the two NSGA-II algorithms and the PSO to examine optimal investment plans in the coal mining industry with three objectives: minimizing energy consumption, emissions, and total cost. In (Liu & Li, 2015) focused on the smart grid and built a two-stage energy-saving model through NSGA-II to minimize energy consumption as well as total cost. In (Yu et al., 2016) NSGA-II was used as a multi-objective input and output optimization model with three objectives to examine whether countries can achieve their energy-saving goals by adjusting the industrial structure. Many other studies have been conducted using similar methods in industrial energy and environmental management. NSGA-II has been applied in the planning of energy-efficient stores (Lu et al., 2017), reducing emissions in the wastewater treatment industry (Sweetapple et al., 2014), and saving energy and reducing emissions in Chinese coal. The electrical industry and steel (C. Wang et al., 2017) have been adopted with the help of the PSO algorithm and in energy planning in petrochemical industries (Gong et al., 2017) and closed-loop sustainable supply chain networks (Kadambala et al., 2017) [35] and industrial structure planning (Yu et al., 2018). The ABC algorithm has been used in energy management for microgrids (Lin et al., 2015) and green matter selection (Tao et al., 2016). Most research has solved two or three objective problems.

Studies like Li et al. (2020) have combined the NSGA-II algorithm with a Grey Wolf Optimization (GWO) algorithm to optimize energy consumption, emissions, and cost in a steel production process. This hybrid approach provides a more robust and efficient search for optimal solutions compared to using a single algorithm. Similarly, Wang et al. (2023) used a Support Vector Regression (SVR) model to predict energy consumption and then integrated it with an NSGA-II algorithm for multi-objective optimization in the textile dyeing industry. This data-driven and dynamic optimization approach allows for continuous improvement and adaptation to changing conditions. In another study, Zhang et al. (2024) explored the use of a Deep Q-network (DQN) to manage energy consumption and emissions in a power plant. Their research achieved significant improvements compared to traditional methods, demonstrating the effectiveness of using DQN in optimizing energy consumption and emissions.

Chen et al. (2023) proposed a cloud-based multi-objective optimization framework that utilizes real-time sensor data from an industrial facility to optimize energy consumption and emissions. This approach allows for continuous improvement and adaptation to changing conditions, making it a valuable tool in industrial environmental management. Sun et al. (2024) focused on optimizing water resource management and wastewater treatment in the papermaking industry using a multi-objective evolutionary algorithm. Their targeted approach provides solutions tailored to the unique challenges of each industry.

In (Wang et al., 2019), presented the optimization of several industrial environment management objectives using the NSGA-III algorithm with a case study of the Chinese iron and steel industry. Under the constraint of several industrial environmental goals, the difficulty of managing the industrial environment as a multi-objective optimization problem has increased significantly. Because traditional optimization methods, such as bottom-up models and intelligent algorithms, usually have problems solving multi-objective optimization problems, this research is the third version of the NSGA-III which introduces the issue of environmental management in China's steel and iron industry. This research creates a multi-objective optimization model for application planning of four types of decision variables: process equipment, clean production technologies, pipe result improvement technologies, and synergy technologies. In total, 7 goals are included, including minimizing energy consumption, 5 types of pollution reduction, and economic costs. In addition, the FCM clustering algorithm for clustering optimal beam solutions is adopted to formulate the final decision plans. The results show that NSGA-III has good performance at center distance, distance measurement, and computational efficiency. Optimal beam solutions indicate that the goal of reducing SO2 is too strict while other factors, such as energy savings and reduced PM emissions are too lax. In addition, four final decision schemes have been obtained based on different target preferences. Overall, it has been proven that the proposed method can solve many optimization problems and help make decisions in industrial environmental management.

3 Proposed Method and Results

The subject of this study is a steel plant in Tehran for industrial environmental management based on a multi-objective genetic algorithm by examining three interrelated goals including improving energy consumption, improving pollution emissions, and improving cost reduction. Four different areas for industrial environmental management in a steel plant are considered by examining the stated objectives which include "circular economy", "MILP model", "factor-based model", and "multi-criteria analysis". There are three managerial issues, including "scenario analysis", "sustainable decision making", and "integrated evaluation model" which should also be considered analysis of the decision-making management system process is useful, but they do not take into account the strategic behavior of the actors involved in the negotiation. In contrast, the MILP model provides a valuable perspective on how actors 'preferences and decisions influence their opponents' choices which offers its next and final results of strategic interaction. For example, if one of the participants dramatically as a way offers something to persuade competitors to submit more bids, the price at which it is sold may be different from if two or more bidders gradually volunteer until one reaches the maximum perceived value. Another advantage of the MILP model is that it considers the behavior of individuals based on their interests in practice and seeks to achieve optimal system outcomes of individual selfish behaviors.

The reference (Zechman, 2011) has provided detailed studies based on the issue of factor-based modeling in environmental management, on which there are weaknesses, including not raising the issue of multi-objective at all, and its multi-objective structural model is clear. It has not been done and only the MILP model and the circular economy and their factors have been studied. Therefore, considering that this research also works in the same field, the reference (Zechman, 2011) has recently done similar work but with many weaknesses, which

then, to its weaknesses and covered it with the approach presented in this Research is covered.
Agent-based modeling simulates the interaction between several independent factors and evaluates the impact of their actions on a system (Gatti & Grazzini, 2020). Agent-based modeling is used to observe the effects of the system and the interactions between agents and their behaviors. This technique is used to simulate group dynamics resulting from the interactions of individual factors in societies. Factor-based modeling is a useful technique that deals with a significant number of factors in a system and the interaction between and the behavior of factors is complex and can be considered when people are different from each other. The main characteristics of a factor in factor-based modeling are 1) trying to achieve a set of goals, 2) interacting with the environment and other factors are guided by a specific set of social rules, and 3) they can be through the system. Predetermined communications affect the behavior of other factors. Factor-based modeling, rather than being defined by a definition, involves the interaction between factors and the interaction between the environment and factors that create complex system behavior. Agents can learn from the environment and will be able to adapt to different situations and new data.
When studying an economic system, agent-based modeling can easily model an evolving macro space resulting from the interaction between multiple factors that are governed by simple determined actions (D. Wang et al., 2017). Instead of trying to predict the future, factor-based modeling examines the different futures of alternative conditions (Lange et al., 2017). This technique can understand the relationship between publishing processes and customer purchasing decisions from their derivatives. Agent-based modeling has also been used to study collaboration in industrial areas and in-house supply chains. In factor-based modeling, the definition of rules is very important and a simple change in rules can have a fundamental impact on the behavior of factors and model results.
Multi-criteria decision analysis intends to organize alternative options hierarchically, thereby effectively prioritizing the criteria. This is an operational assessment that is useful for studying topics with high uncertainty, multiple interests, and conflicting goals. Multi-criteria decision analysis can rank policy options using stakeholder perspectives and cost/benefit information. Multi-criteria decision analysis may be used to solve complex obscure and highly uncertain problems. In multi-criteria decision analysis, the complementary weight determination method is used to rank the options. Multi-criteria decision analysis is used when several parameters affect the performance of a task. The most well-known application of multi-criteria decision analysis is to address decision management problems that are affected by conflicting criteria.
Study scenario analysis studies how to achieve a set (normative) goal in the future that occurs in an unspecified (exploratory) way or how to move from an exploration to a stimulus (normative) scenario as a transition scenario (Hunt et al., 2013). This analysis is used to test a range of development strategies and select the best application using optimization methods. The analysis was performed with the aim of identifying excellent scenarios by considering technical, social, economic, environmental, and political criteria. Uncertainty in scenario analysis is interpreted as a set of possible future outcomes, in other words, problem analysis creates models in which the uncertain future is the basis for the decision management system (Pallottino et al., 2005). Scenario analysis should not be confused with prediction. Instead, scenario analysis is an acceptable way in which the future may develop. Valuable insights are provided for policymakers when assessing the future implications of current and planned procedures(Islam, 2017), for example for analyzing the implications of increasing or decreasing recycling rates. Scenario analysis to reduce the risk of a wrong decision management system, consider your internal scenario analysis with factor-based systems to temporarily evolve statistically independent scenarios to provide a robust choice. This analysis has created the best options considering the short-term and long-term costs and benefits of different expected results (Geng et al., 2010).
To show the complementary potential of the MILP model to its key points in the decision management system in industrial environmental management, an example of how to use the MILP model in advancing the principles of circular economics using the programs (Ghafourian et al., 2021) is presented. The program uses three decision management methods such as cost-benefit analysis (CBA), life cycle, and multi-criteria decision analysis, and combines them with the principles of the MILP model to be the best solution to a bargaining or Nash Equilibrium problem. This example assumes that there is a negotiation between a city council member representing the citizens and the manager of a steel company to agree on the cost of services. With the cost-benefit analysis tool, it is calculated that the operating cost of the industrial environmental management plan is assumed to be 3 million Tomans per ton and through multi-criteria decision analysis weighting methods, citizens are willing to pay 10,000 Tomans per service for this service which tons are estimated. Both representatives of the organization know that the cost is less than 10,000 Tomans per ton and the value paid is more than 3 million Tomans per ton. There is a cost surplus per ton that must be shared between them, i.e. an

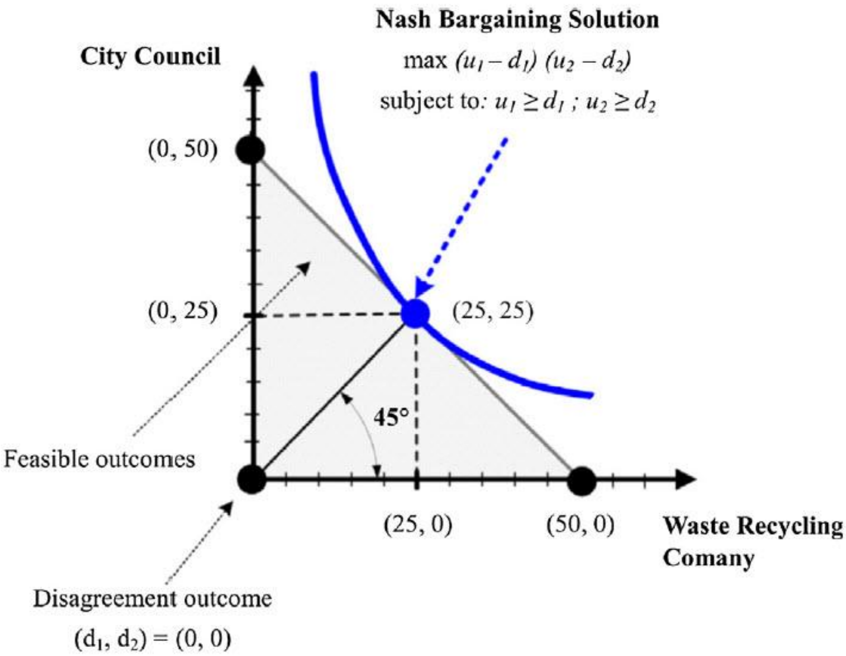
agreement on the cost of subsequent services is required. It is assumed that people of both players are rational and always try to maximize their desired value. Likewise, they are both supposed to be intelligent - they have the same information, they understand the situation, and they can make inferences about it. Table (1) shows the repayment of the decisions made by their peers. The value on the left is the refund of the recycling company and the value on the right is the refund of the steel company. These surplus values share the tonnage for shareholders. If both people agree to divide the surplus, they will each receive a refund of 7,500 Tomans. If one agrees and the other disagrees, the player receives 5,000 Tomans of consent, while the other receives no share. On the other hand, if both stakeholders disagree, the result will be zero (i.e. (d1, d2) = (0,0)). Stability in this area means no change of government due to a lack of incentive to deviate from strategies to receive better repayments. If the situation of the game is (d1, d2), the council of the steel company has incentives to deviate from the strategy, because it has a preferential surplus (10,000 Tomans per ton), in the same way the recycling company motivates users to change their strategy. If both modes (d1, u2) and (d2, u1) are considered unstable for the steel company for industrial environmental management, respectively, as if they deviate from their strategies, in case of transition to mode (u1 , u2),. Hence, it is observed that the condition (u1, u2) is stable for both players because the deviation means getting a less preferential refund for the steel company (u1, d2) = (5000, 0) or the waste recycling company (d1, u2) = (0.10000) is known as the Nash equilibrium. This is a solution concept in the MILP model that says participants have no incentive to keep working.

Table (1), Negotiated cost model of industrial environmental management services

Company Council			
agree on u2	Oppose d2		
10000 and 0	0 and 0	Oppose d1	Tehran Steel Production Company
0 and 10000	5000 and 5000	agree on u1	

As shown in Figure (1), both stakeholders have symmetric tool functions, then for negotiation of surplus (u1, d2) = (5000, 5000) is Nash bargaining solution, i.e. 7500 Tomans service cost and it should be and it has been agreed to be paid. It is clear that the example of the MILP model shows the potential for improving partnerships in industrial environmental management and the circular economy, as it helps to distribute benefits and costs fairly among stakeholders, and in this case, a steel company council representing Citizens and an industrial environmental management company, this model can be implemented and results similar to the approach of this research can be obtained.

Figure (1), model solution for negotiating the cost of industrial environmental management services with the MILP model



However, there are weaknesses in this proposed MILP solution. First, industrial environmental management, based on the studies in the introduction and previous studies, requires an industrial ecosystem and a multi-objective structure for optimization. Therefore, the use of genetic algorithms in the continuation of this method will be discussed. Here are some key goals that should be optimized with a multi-objective genetic algorithm that MILP did not allow. It is necessary to answer the main research questions here, which are the following two:

How can optimal energy saving and emission reduction decisions be achieved under multiple environmental and economic goals?

To what extent can taking these measures improve objective performance (e.g. energy savings and emission reductions)?

It can be seen that it is not possible to answer these two questions with MILP, so modeling of the multi-objective genetic algorithm should be done to optimize or near-optimal goals such as energy saving, emission reduction, objective performance improvement. Consideration of two important criteria, emissions least cost (ELC) and ambient least cost (ALC) are considered in this research to provide a structure close to optimal. In formulating the lowest emission cost, optimization is used to identify the minimum set of controls needed to achieve the emission reduction goal. The transport and chemical contaminants are not explicitly shown in the formulation of the lowest emission costs and, as a result, the effects of the control site are not considered. In contrast, the lowest-cost models of the environment include a representation of the relationship between source emissions and the concentration of the environment at the receiver site. A simple formula is the lowest environmental cost in equation (1).

$$\min \sum_{i=1}^{N} c(e_i, u_i) \quad , \ \Psi(u,e,r) \le T \quad , \quad 0 \le e_i \le 1 \forall i \qquad (1)$$

In this equation, N is the total number of inventory sources, i is the source, and u is the emission rate from source i. Also, e_i is the efficiency of reducing emissions at source i and c is a function that determines the cost of control in i as a function of u_i and e_i, Ψ is the maximum concentration of environmental pollutants at each receiver site. T is the maximum allowable concentration of environmental pollutants and u, e and r are vectors that determine the amount of emission, emission reduction, and location of each source. In this formulation, an air quality management strategy is defined by a set of emission reductions at each source, represented by the vector e. Optimization is used to identify the lowest cost of reduction so that the cost is minimized and the maximum concentration of environmental pollutants resulting from it does not exceed a specific goal. The relationship between diffusion and concentration at the receiver site is the relationship between source and receiver [S-R] and the function Ψ shown in $\Psi(u,e,r) \le T$. The lowest environmental cost formulas can be classified with the function form Ψ. For contaminants that are non-reactive or linearly reactive, the S-R relationship is linear. As a result, reducing each unit of source emission reduces the concentration of the medium at a particular receiver by a constant amount, although it can be associated with the MILP model and the circular economy in steel mills, but for multi-objective optimization has a development that will be examined later. In addition, the effects of reducing greenhouse gas emissions from different sources are independent of each other and therefore additive. The linear relationship S-R can be shown in an air quality model as a matrix of fixed and linear transfer coefficients that allow Equation (2) to be as follows:

$$\sum_{i=1}^{N} a_{ij} \times (1 - e_i) \times u_i \le T_j \quad , \ \forall j \qquad (2)$$

In this regard, j is the receiver index, a_{ij} is the transfer coefficient related to the emission in i i with the receiver concentration j, and T_j is the maximum pollutant concentration of the permissible medium in the receiver j. The lowest-cost environmental problems with transfer coefficients are often easily solved using traditional mathematical optimization methods such as linear and correct programming. Previous studies have presented a multi-objective structure in which some weaknesses have already been examined. If the nonlinear contaminant is reactive, the extent to which the source affects the receiver depends on the extent to which it is emitted from other sources. As a result, the S-R equation is nonlinear and may not be sufficiently represented as a matrix of transfer coefficients. Demonstrating this nonlinear behavior in the context of mathematical programming may be impossible for realistic problems. Therefore, it is considered in this research to cover the lowest emission cost and the lowest environmental cost as two internal goals in reducing pollution, along with two other goals including cost reduction (based on the structure of the circular economy) and energy consumption, intelligent multi-objective genetic algorithm optimized.

The iron and steel industry as a high-consumption industry needs to take integrated action to achieve the energy-saving goal set by the Iranian government. Therefore, reducing energy consumption is a major goal. In this model, energy consumption can be affected by two methods. The first is the difference in energy consumption due to changes in the scale structure of process equipment and the second is energy saving through the spread of technologies. This goal is defined as equation (3).

$$minEnergy = \sum_{p \epsilon P}^{n=I} [PR_{p,eq,t+\Delta t} - PR_{p,eq,t}) \times E_{p,eq} + (PR_{p,eq,t+\Delta t} - PR_{p,eq,t}) \times E_{p,i}] \times SR_p +$$

$$InitialChromosome\ \sum_{t=1}^{n=1} MOGA\ Operator \tag{3}$$

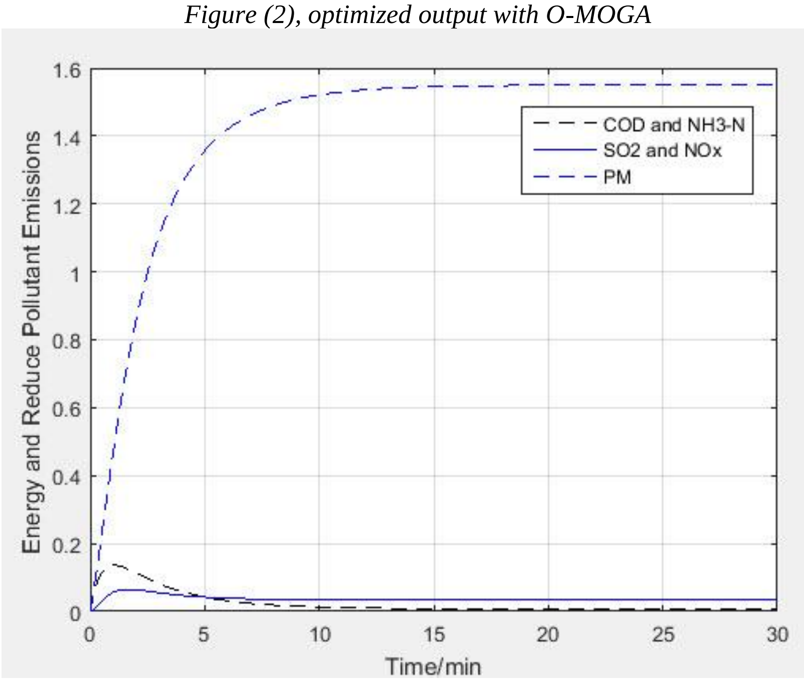
Another major goal of industrial environment management is to reduce emissions which means reducing emissions. Here, according to the introduction part, the policies of different countries, including Iran are mentioned and five types of climate pollutants are set as targets: SO2, NOx, PM, COD, and NH3-N. Emissions can be reduced in various ways. The expansion of equipment and the release of cleaner production technology will reduce greenhouse gas emissions, the release of end-of-pipe treatment technology will reduce pollutants, and the release of synergistic technology will reduce Excess emissions that become industrial waste. These goals are defined as equation (4).

$$minPollution = \sum_{p\epsilon P}^{n}\left[PR_{p,eq,t+\Delta t} - PR_{p,eq,t}\right) \times SR_p] + \sum_{t=1}^{n=1} PE - MOGA\ Operator_{Pollution=(SO_2,NO_X,PM,COD,NH_3-N)} \tag{4}$$

In these two relations, P is a set of processes, eq is a set of equipment processes, I is a set of technologies, SR is a set of steel ratios, p is a set of processes, i is a technology, t is the year index as the base year, t+Δt is the index years as the year of optimization, PR penetration rate, E energy intensity equipment or technology, PE pollution emission reduction rate.

Then, based on the proposed approach, a simulation is performed in MATLAB environment. Initial quantification of MOGA factors includes the initial population of chromosomes with 100 chromosomes with 5 elite genes in 100 iteration cycles with a crossover rate of 0.2 and a mutation rate of 0.02 and a random selection method and the Niching and Pareto approach. The output of the simulation is shown in Figure (2).

Figure (2), optimized output with O-MOGA



It is clear that the reduction of energy and pollution was done in 30 minutes with MOGA, and for each of the futures, it is illustrative. The optimized numerical results for Pipe, COD, NH3-N, SO2, NOx, and PM are shown in Figure (3).

Figure (3), numerical results of O-MOGA

Pipe	COD	NH3-N	SO2	NOx	PM
0.0001	0.0020	0.0089	0.4419	0.1318	0.4152
0.0008	0.0081	0.0207	0.0920	0.0789	0.7996

4 Conclusion

Advances in environmental management have been made by steel industrial companies around the world in recent years. Some steel industry companies now compare their processes to environmental goals with industry goals, for example, using benchmarking. To determine "best practices" and define "business behavior", several industrial models in industrial workshops with integrated models and objectives should be considered. The Environmental Management Program identifies areas where the effectiveness of efforts can be enhanced using management practices developed and used in the private sector. The iron and steel industry has long been a global pillar industry supplying raw materials for infrastructure construction. However, behind this huge capacity is a lot of energy consumption and emissions, because the iron and steel industry is a high-energy, high-emission industry. This problem is extremely severe in Iran. In 1397, Iran's crude steel production was more than 27 million tons, which accounted for 6% of world production. According to the statistical yearbook, the iron and steel industry accounted for 15.4% of China's industrial energy consumption, SO2 for 14%, NoX for 24%, PM for 29%, COD for 3.8%, and 13.8% of NH3-N emissions in 2016. Is. Therefore, providing energy-saving methods and reducing emissions in the iron and steel industry in Tehran Steel Plant is essential and can be an example of a complete model of environmental management of the entire industrial sector.

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