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# Identifying and Prioritizing Factors Affecting the Efficiency of Intelligent Energy Management Systems in High-rise Buildings in Mazandaran Using the Fuzzy MABAC Approach

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**Abstract**

This study aimed to identify and prioritize factors influencing the efficiency of smart Energy Management Systems (EMS) in high-rise buildings in Mazandaran using the fuzzy Multi-Attributie Border Approximation area Comparison (MABAC) method. It was an applied, qualitative study utilizing Multi-Criteria Decision-Making (MCDM) techniques. The statistical population included experts in smart construction projects with at least 10 years of experience.

Data were collected via a questionnaire based on theoretical foundations and research literature. Findings ranked the key factors affecting system efficiency, with environmental conditions, the Internet of Things (IoT), and technology acceptance as the top three, followed by home automation, economic factors, employee comfort and health, infrastructure, structural strength, structural size, and construction factors.

The study concluded that smart EMS plays a crucial role in reducing energy consumption, lowering costs, and enhancing efficiency. By leveraging technologies such as IoT and home automation, these systems optimize energy use through intelligent control of heating, cooling, lighting, and ventilation. In addition to energy savings, they provide healthier and more comfortable living conditions, contributing to sustainability and energy resource conservation.

**Keywords:** Smart energy management, Multi-criteria decision making, Fuzzy huff multi-attribute border approximation area comparison, Building.

## 1 | Introduction

The importance of energy and its sources of supply is no secret today and has been and will be one of the main challenges of every country and government in every era. Extensive efforts have been made in various

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fields related to energy, including providing cheap, reliable, more accessible energy sources, increasing energy efficiency, reducing pollution, etc. Technological progress and population growth also increase the need for energy day by day, which adds to the importance of this issue. In this regard, the move towards energy consumption and management programs has attracted the attention of many researchers, managers, and designers in the energy field around the world [1].

In developing countries such as Iran, due to the high share of non-renewable energy sources such as fossil fuels, addressing the issue of energy consumption management and optimization is of particular importance due to its destructive environmental effects [2]. The construction industry, with its share of about 40% of the country's energy consumption, is one of the most influential areas of energy consumption, and paying attention to it can play a significant role in changing the current situation in order to achieve sustainable development. In the construction industry, more than 80% of energy consumption is specific to the operation period, which indicates the importance of paying attention to the management and optimization of energy consumption in this period [3]. Also, according to statistics from recent years, between 1979 and 2004, the amount of energy consumption in Iran increased by 7.8 times. In addition, the amount of energy production has increased by 4.9 times in proportion to this growth in consumption. This increase is while the number of subscribers benefiting from energy has only increased by 5.5 times, which indicates an increasing trend in the energy consumption pattern in Iran [4]. In addition, in Iran, the domestic and administrative sectors account for the largest share of energy consumption, which indicates the importance of addressing methods for optimizing energy consumption during the operational period in the residential and administrative sectors, especially in high-rise buildings [5].

Today, with the ever-expanding use of new technologies in the construction industry, the use of smart technologies has expanded at a faster rate, such that in European countries, the use of smart technologies in commercial construction after 2018 and residential buildings after 2020 has become mandatory [6]. In addition, with regard to the approach to energy conservation in European countries, efforts have been made to achieve a 20% reduction in energy consumption and to replace non-renewable energy sources with renewable energy sources by 2030 [7]. The reason for paying attention to the use of these new technologies can be considered, in addition to its significant effects in reducing energy consumption, in the field of reducing environmental impacts resulting from reducing energy consumption, because in countries such as Iran, the majority of the energy supplied there is supplied from non-renewable energy sources, and this indicates the existence of a direct relationship between the annual energy consumption and the amount of pollutants emitted at the national level. Consequently, given the importance of the environmental impacts of the building life cycle in Iran and its significant share of the total amount of energy consumed and pollutants emitted at the national level, steps have been taken to develop the use of smart building management tools in order to develop the application of these equipment, including the items mentioned in topics 13 and 19 of the National Building Regulations [8].

Energy consumption management using smart tools covers various fields, the most important of which is Demand Response (DR) management. DR management can be referred to as a set of activities carried out by smart devices that ultimately lead to a change in the building consumption curve [9]. The purpose of using energy management tools in the field of DR management is to reduce peak demands and flatten the energy consumption curve, through which peak consumption is reduced. Despite its history, optimizing energy consumption using smart devices has not been widely used in recent years. The idea of smart Building Energy Management Systems (BEMS) first started at the University of Michigan in the United States of America and was implemented in the same country at the University of Arizona in 1995. In the field of energy consumption optimization, the goal is to reduce the final level of energy consumption by reducing or eliminating energy waste by using various tools such as smart energy management tools. As a result, smart devices modify the energy consumption pattern in the building by managing event recording, monitoring and controlling the performance of energy-consuming systems [10].

Alghassab [11] Research results showed that a fuzzy-based smart Energy Management System (EMS) for residential buildings in Saudi Arabia is able to optimize energy consumption, reduce peak demand, and improve energy efficiency.

Anbazhagu et al. [12] Research results showed that a combined neuro-fuzzy approach can help optimize energy consumption in smart homes and provide more accurate decision-making by considering various parameters such as cost and environmental impacts.

Beheshtinia et al. [13] Research results showed that using SWOT analysis and VIKOR-TOPSIS, 18 marketing strategies for BEMS were identified and prioritized, which led to the selection of superior strategies such as online advertising and discounts to consumers.

Research results showed that the scoring model for smart public buildings using various fuzzy analytic hierarchy process methods emphasizes bioclimatic design and renewable energy systems in buildings [13].

Kabir et al. [14] Research results showed that smart energy management technologies in OIC member countries were evaluated using SWOT-AHP and Multi-Criteria Decision-Making (MCDM) analysis, and the importance of smart grids in line with the United Nations Sustainable Development Goals (SDGs) was highlighted.

Kaya et al. [15] Research results showed that smart Integrated Building Management Systems (IBMS) for smart factories using MCDM methods can help improve productivity and reduce costs.

The necessity of conducting the present research is that with the expansion of urbanization and industrialization of cities and the increase in environmental pollution due to the emission of greenhouse gases that occur as a result of excessive use of fossil fuels in vehicles and buildings (which have the largest share of consumption of such fuels), which is accompanied by problems such as environmental destruction in many metropolises. Paying attention to this issue has been of such great importance that since the second half of the last century, and especially since the seventies, climate and environmental protection have been continuously considered, and various environmental groups have been formed in all parts of the world. These groups mainly demand the preservation and restoration of the environment, using technology that is consistent with the natural environment, recycling industrial waste and using clean energy. Our country has about 1% of the world's population and consumes about 2% of the world's energy. Energy consumption in the residential and administrative sectors accounts for 41% of the country's total share, which is actually higher than the total energy consumption in the industrial and agricultural sectors [16]. The importance of this study is that conducting this study can reduce energy consumption in buildings, save energy, reduce costs, increase productivity, reduce environmental pollution, and promote sustainable development.

# 2 | Theoretical Foundations

## 2.1 | Energy Management Systems

As stated in the European Commission's Energy Strategy 2020, energy is the lifeblood of society, and optimization makes energy consumption a major global issue. It has also been argued in the literature that energy sustainability is one of the most urgent social and environmental issues of the contemporary era. In recent decades, preventing energy waste in the residential and building sectors has become a major concern for industrialized and developing countries. According to data published by the European Commission in 2021, buildings account for 40% of energy consumption and 36% of $CO_2$ emissions in Europe, which is more than the energy consumed in the industry and transport sectors such as Heating, Ventilation, and Air Conditioning (HVAC), safety, water, lighting, etc. Such high energy consumption has driven the development of BEMS. BEMS is a tool used to monitor and control the energy needs of a building, and its implementation can be an important step towards reducing energy consumption in buildings. In addition to controlling energy management, BEMS also monitors other aspects of buildings, including HVAC, lighting, intelligent control systems, fire systems, and security systems. According to Yung et al. [17], using BEMS to manage HVAC systems alone can result in energy savings of approximately 14%. A comprehensive review of energy savings opportunities using EMS can be found in the research of Liu and Cheng [18].

## 2.2 | Importance of Energy Management Systems

The use of Energy Management Systems (EMS) is common in the context of smart grids, which enable the management of electrical loads and resources using centralized or decentralized techniques. Depending on the context, it is possible to control resources with these systems implemented in smart homes efficiently. One of the great advantages of these systems is that they can include artificial intelligence models, the most common of which are learning models that learn with the user and the context and, at the same time, can provide intelligent control [19].

With the use of EMS, demand-side management (DSM) becomes possible as end users can control their energy consumption. End users can participate in DR programs and energy transactions. However, there is a problem because usually the end-user data needs to be shared and therefore, the end-users need to agree to the data sharing, which raises privacy issues.

## 2.3 | Challenge of Energy Consumption in the Building Sector

Due to the challenges posed by global warming and climate change, many countries have committed to achieving carbon neutrality by 2050 or 2060. Considering that the building sector is responsible for approximately 40% of carbon emissions worldwide, decarbonization of the building sector becomes crucial in the pursuit of carbon neutrality. Highly efficient energy systems such as ground source heat pumps, Photovoltaics (PV), and energy storage systems have been widely used in the past few years to improve building energy efficiency and reduce operating costs. However, many buildings are currently not operating optimally, leading to increased energy waste. For example, a study by Vandenbogaerde et al. [20] estimated that a significant portion of 15% to 30% of the energy consumed by commercial buildings is lost due to inadequate maintenance, equipment degradation, and waste. Inadequate system control and management Proper assessment and optimization of Building Energy Systems (BESs) is crucial to achieving increased energy savings and reduced carbon emissions. However, achieving optimal Building Energy Management (BEM) requires consideration of many interrelated factors, such as occupant patterns, weather conditions, and system interactions. Conventional techniques such as statistical analysis or expert knowledge-based strategies may not be able to capture the complex dynamics and nonlinear relationships inherent in BESs; therefore, more advanced strategies are needed to identify building operational problems, analyze building energy consumption patterns, and provide solutions to optimize building operations [21].

Energy is a necessity in every aspect of life. With the increasing population, the demand for energy is also increasing. In the conventional energy system, energy is generated only from fossil fuels. Since fossil fuels are depleting and also cause carbon emissions, environmentally friendly energy generation is required. In a smart power system, microgrid plays a very important role due to the integration of renewable energy sources. Microgrids can be operated in both grid-connected and off-grid scenarios. Large grid-connected buildings are also very effective once in a while in the power system network. Smart grids have evolved as a solution to many problems within the current electrical system as a result of the global increase in electricity needs. Using sustainable energy bases, power storage, and empowering the user to make decisions about energy consumption are all innovative components of smart grids [22].

## 2.4 | Performance of Energy Management Systems in the Building Sector

Proper assessment, diagnosis and optimization of building operations are essential building blocks for increasing building energy efficiency. To facilitate these complex processes, BEM systems have been widely used to monitor and manage various BES such as HVAC, lighting and other power systems. These systems can implement advanced strategies to achieve various BEM objectives, such as building performance assessment, energy consumption forecasting and DSM to improve building energy performance and save costs [19].

Building energy performance assessment is a critical process that plays a critical role in ensuring efficient building performance. This process involves identifying inefficiencies in building operations and determining the root causes of these inefficiencies.

The conventional methods available for assessing building energy performance mainly include engineering calculations, statistical modeling and model-based metrics. Engineering calculations involve the use of physical laws and principles to derive the energy performance of a building, while statistical modeling often uses historical building data and conventional statistical models to predict the energy performance of a building. In contrast, model-based benchmarking uses physical models or simulation tools to evaluate the performance of a building with a predefined state. It is important to acknowledge that these methods typically rely on certain assumptions and simplifications that can limit their ability to capture the real dynamics of BES. Proper prediction of building energy consumption is a fundamental step in BEM. On the one hand, it can be used to predict the dynamics of energy consumption and help identify potential energy savings and efficiency opportunities. On the other hand, it can help building owners and managers understand the impact of changes in building occupancy, weather patterns, and other factors on energy consumption in order to adjust system performance in response to any changes in a timely manner, thereby preventing energy waste.

Similar to building energy performance assessment, forward-looking models, also known as physics-based models, are often used to predict building energy using fundamental principles and mathematical equations to capture the physical behaviors of a system. By taking into account various factors such as weather conditions, building materials, occupancy patterns, and HVAC systems, these models can provide accurate predictions of building energy consumption. However, developing physical models often requires a significant number of detailed inputs related to specific building parameters, which can be challenging in many situations and requires more efficient strategies to manage this effectively [23].

The present study is applied in terms of purpose and qualitative in terms of method. In this study, MCDM methods were used to identify and prioritize the factors affecting the efficiency of intelligent EMS in high-rise buildings.

# 3 | Research Method

## 3.1 | Population and Statistical Sample

The population of the present study is all experts in the construction industry who have characteristics such as having at least 10 years of experience in the field of intelligentization of construction projects, having a valid scientific and research background, having sufficient information in the field of intelligentization of construction projects, and the exclusion criteria of unwillingness to participate in the research were selected.

Since the number of people and experts who should be in the sample to complete the fuzzy Multi-Attributie Border Approximation area Comparison (MABAC) questionnaire was mentioned based on the inclusion criteria, therefore, the non-probability purposeful judgmental sampling method was used. Accordingly, 10 experts were selected to rank and determine the weight of the criteria.

**Table 1. Experts' profile.**

| Row | Position | History | Degree |
|---|---|---|---|
| 1 | Supervisor | 20 | Master of civil engineering |
| 2 | Workshop supervisor | 10 | Bachelor of civil engineering |
| 3 | Consultant | 25 | PhD in civil engineering |
| 4 | Workshop supervisor | 15 | Bachelor of civil engineering |
| 5 | Employer | 25 | Bachelor of civil engineering |
| 6 | University faculty | 10 | PhD in civil engineering |

**Table 1. Continued.**

| Row | Position | History | Degree |
|---|---|---|---|
| 7 | Designer | 20 | Master of civil engineering |
| 8 | Supervisor | 10 | Master of civil engineering |
| 9 | Employer | 15 | Master of civil engineering |
| 10 | Designer | 16 | Master of architecture |

Decision-making is one of the most vital management activities to achieve organizational goals, which strongly depends on its quality. It includes precisely defining goals, finding different possible solutions and evaluating their feasibility based on constraints, evaluating the results and finally selecting and implementing the best solution. Decision-making based on expert opinion is considered the essence of management. It should be noted that, however, decision-making problems. Due to the increasing level of complexity, it forces decision-makers to use new technologies and tools that simplify decision-making support processes [24].

MCDM approaches include a variety of decision-making methods that have been used and developed for many years at different educational and industrial levels, especially in the fields of management, Industrial Engineering (IE), and Operations Research (OR). MCDM methods are classified into two main groups: 1) Multi-Objective Decision Making (MODM) techniques for finding the best possible solution at the design stage and 2) Multi-Attribute Decision Making (MADM) techniques for selecting the best alternative. Since the practical applications of MADM are higher than MODM, a large number of MADM approaches have been proposed by researchers in the last 60 years and this trend will continue. MADM decision problems involve several main components such as the main objective(s), criteria (sometimes accompanied by sub-criteria) or a set of performance criteria, a decision maker or a team of decision-makers, and a set of decision alternatives along with a set of unknown outcomes and a set of outputs. Today, there are many opportunities to extend existing MADM techniques in order to make them more efficient in dealing with complex and intelligent decision-making systems.

On the other hand, the concept of sustainable development along with the circular economy approach, has recently become a focus for governments, industries, and researchers to carry out decision-making processes. In fact, addressing these unavoidable issues along with other decisions leads to complex multidimensional decision-making. In view of this, this study tries to address these concepts in line with the application of MCDM approaches, in which MABAC is considered one of the most powerful methods to deal with intelligent decision-making systems. The following sections examine MABAC from a comprehensive perspective to address various real-world applications [25].

Decision-making for sustainability and circularity: sustainability is the ability to keep pace with a tangible behavior for an indefinite period. In order to provide a clear definition, three domains related to economic, environmental, and social aspects should be considered simultaneously. Effective economic decision-making has always been an important issue in private or public organizations.

The intrinsic link between the environment and economic growth originates from the study conducted by Nordhaus [26], where he stated that reducing emissions limits its impact and ensures higher economic growth in the future. In the past two decades, the research community has pursued and modeled the relationships between economic growth, environmental sustainability and human well-being as a fundamental issue. Over the years, the dramatic increase in economic activities and high levels of consumption have created problems for long-term planning and have prevented the emergence and adequate growth of sustainable management [27].

It is becoming increasingly necessary to integrate the interests of the various stakeholders involved in or affected by long-term planning measures in order to balance their requirements, including economic development with environmental, social and future generations. Sustainable decision-making models can be considered as a basic condition for achieving sustainable development, as economic agents often turn to decision-making processes to improve their organization's performance. *Fig. 1* Annual evolution of scientific efforts in MCDM programs to address the SDGs between 2016 and 2020, according to 143 articles reviewed by Sousa et al. [28]. As can be seen, a steep upward trend has started since 2019, indicating the importance of sustainability in addressing decision-making problems. Sousa et al. [28] also defined the 2030 agenda framework for different SDG classifications to be addressed by MCDM methods.

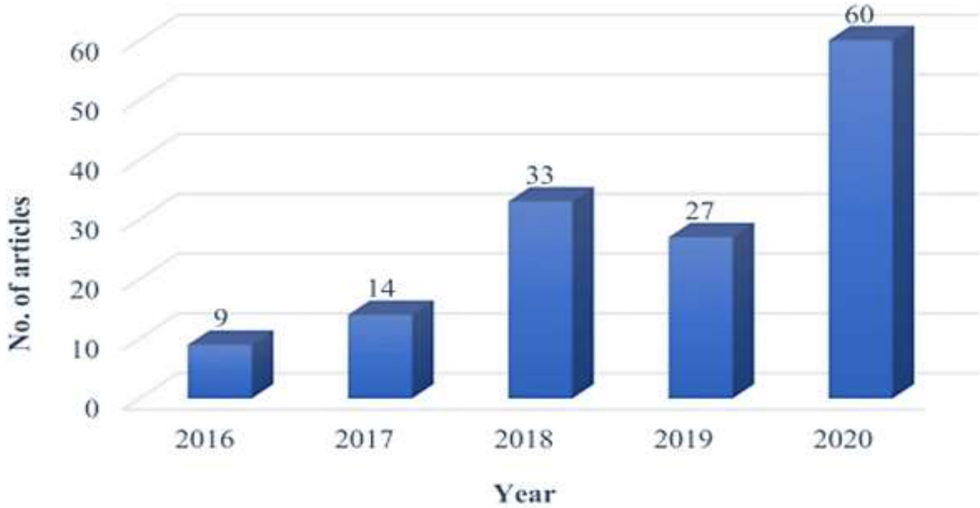


**Fig. 1. Annual scientific production from 2016 to 2020 on the use of multi-criteria decision-making methods to address sustainable development goals [28].**

Decision makers (policymakers and public/private implementers) seek appropriate trade-offs while reconciling economic, social and environmental criteria or objectives. Accordingly, each stakeholder must treat diverse and conflicting criteria/objectives, which makes MCDM complex and intelligent. Many researchers have relied on and used MADM and MODM models as formal and standard methods using available technical information to balance and evaluate stakeholder values, develop solutions and enhance environmental and social sustainability. One of the most studied areas is Supply Chain Management (SCM) [18]. In the meantime, and with the search for alternative solutions as a tool to create more sustainable economies, the concept of circular economy emerged. The circular economy aims not only to use resources wisely but also to minimize the demand for their production and to reuse existing resources. Following this framework, it replaces the linear approach of the end-of-life economy with new circular flows through reuse, repair and regeneration within.

The integrated and fundamental processes of the circular economy, in support of the decoupling of economic growth from the increasing consumption of resources, a relationship that is otherwise recognized as inevitable, reformulate the functional flows of production chains and cast doubt on the hegemonic model of waste and disposal.

A decisive aspect of the creation of any circular economy involves waste management tools. According to this framework, recycling plays a key and fundamental role in transforming such waste into new raw materials/products with the possibility of reuse. Given the application of recycling to this process, there are major demands for a significant increase in waste recycling rates, mainly in major cities and suburbs. For example, the application of integrated multi-criteria assessment to present a circular city can be shown in *Fig. 2*.

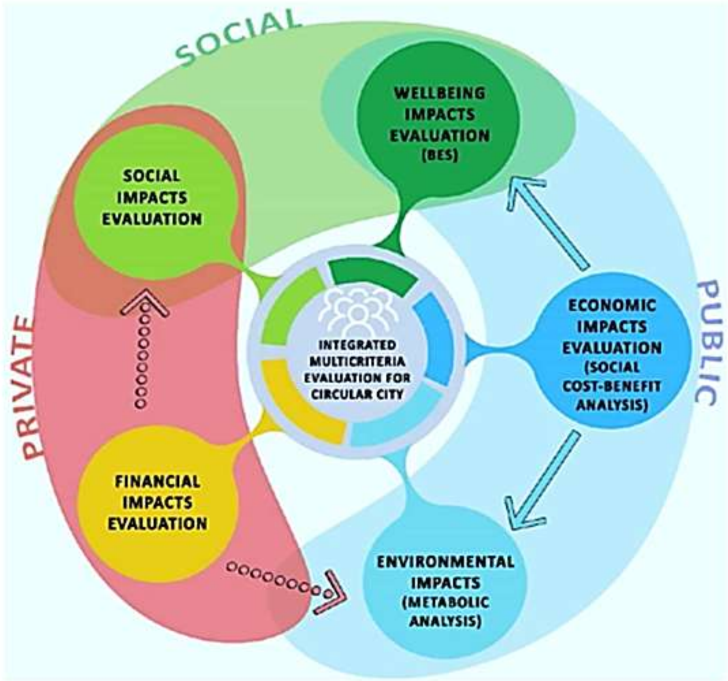


**Fig. 2. Integrated multi-criteria framework for a circular city.**

In line with sustainable development, there is a growing consensus on the need for a gradual and continuous transition to more sustainable economic growth, and almost all countries are facing this emerging challenge [29]. The proposed mechanism sets clear targets for waste reduction at all stages of the value chain from production to consumption, recycling, repair and remanufacturing, recycling and management of waste and secondary raw materials, which affect economic development. Furthermore, this approach provides a long-term direction for waste recycling and management.

Over the past few years, the application of MCDM techniques to assess the prospects for the circular economy and sustainability issues has increased dramatically, and to the best of our knowledge, we can claim that these methods can be effectively used to address them.

The application of MCDM techniques in sustainable development and the circular economy is much less than its application in other academic disciplines. The MABAC technique is recognized as one of the newest MADM techniques and the literature has not kept up with the rapid expansion of knowledge in this field. As a result, there is still a need for a comprehensive review of the applications of the MABAC method with a sustainability perspective in various application domains as one of the most efficient methods in expert decision-making. This research systematically reviews previous attempts to investigate the application of MABAC in decision-making problems. By considering a variety of new perspectives in the evaluation of the articles, including the classification of published studies based on time trends, journals, locations, application domains, and MCDM objectives, it provides significant insights into and adds to the MABAC literature and other common MCDM approaches.

Pamučar and Ćirović [30] developed the MABAC method in 2015, and to date, this multi-criteria method has found wide application to tackle numerous real-world problems. The main advantages of the MABAC multi-criteria framework are: 1) the MABAC method provides stable results when the units of measurement used to represent the values of the criteria of the options change, 2) the MABAC method provides stable solutions when the type of criterion formula changes, i.e. when the criterion changes from a benefit type to a cost type, and 3) the MABAC algorithm is suitable for solving multi-criteria problems that include many criteria and options because the mathematical formulation of the problem does not become complicated with an increase in the number of options and criteria. The mathematical formulation of the MABAC method is based on determining the distance of the options from the approximate boundary area. By definition, the MABAC method is one of the new MCDM methods presented by Pamučar and Ćirović [30]. The purpose of this method is to rank the options in an MCDM model. The fuzzy MABAC technique examines this model in a fuzzy environment, which eliminates uncertainties and ambiguity in decision-making, resulting in more accurate results [31]. The steps of this method are given below.

**Step 1.** Forming the initial decision matrix (X)

Suppose the decision matrix of people's opinions is as follows:

$$\tilde{G} = \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \cdots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \cdots & \tilde{x}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \cdots & \tilde{x}_{mn} \end{bmatrix}. \quad (1)$$

Each column represents a measurement index, and each row represents an option. $X_{ij}$ represents the quantity of the i-th option in the j-th subcriterion. Also, the sub-criterion may be negative or positive depending on their impact on the options. In this study, verbal expressions and fuzzy numbers were used to evaluate the options against each criterion, as shown in *Table 2*.

**Table 2. Verbal expressions and corresponding fuzzy numbers for evaluating options.**

| Verbal Phrase | Corresponding Fuzzy Number |
|---|---|
| Very poor | (0, 0, 1) |
| Poor | (0, 1, 3) |
| A little poor | (1, 3, 5) |
| Average | (3, 5, 7) |
| A little good | (5, 7, 9) |
| Good | (7, 9, 10) |
| Very good | (9, 10, 10) |

**Step 2.** Normalize the elements of the initial decision matrix (N).

Since the gender of each criterion may be different, in Step 2, the decision matrix is normalized to neutralize the effect of the different scales of the criteria. In order to do this, and considering the gender of each criterion, *Eq. (3)* is used to normalize the positive criteria and *Eq. (4)* is used to normalize the negative criteria. The normal decision matrix is denoted by N.

$$N = \begin{bmatrix} n_{11} & \cdots & n_{1n} \\ \vdots & \ddots & \vdots \\ n_{m1} & \cdots & n_{mn} \end{bmatrix}. \quad (2)$$

.: The elements of the normalized matrix N are calculated using the following relations:

$$\tilde{t}_{ij} = \frac{\tilde{x}_{ij} - x_i^-}{x_i^+ - x_i^-}, \quad (3)$$

$$\tilde{t}_{ij} = \frac{\tilde{x}_{ij} - x_i^+}{x_i^- - x_i^+}. \quad (4)$$

In *Eq. (3)* and *Eq. (4)*, $x_{ij}$ are the elements of the initial decision matrix (X) and $x_i^-$ and $x_i^+$ are defined as follows:

I. $x_i^+=\max(x_1,x_2,\ldots,x_m)$ indicates the maximum value of the upper limit of the phase observed in a given criterion among the options.

II. $x_i^-=\min(x_1,x_2,\ldots,x_m)$ indicates the minimum value of the lower limit of the phase observed in a given criterion among the options.

**Step 3.** Formation of the weighted normal matrix (V).

Since the criteria have different weights in the evaluation process, in Step 3, the elements of the weighted normal matrix should be calculated based on *Eq. (5)*.

$$\tilde{v}_{ij} = w_i.\left(\tilde{t}_{ij} + 1\right), \tag{5}$$

In this relation, $t_{ij}$ are the elements of the normal matrix, and $w_i$ is the weight of the i-th criterion. Also, $v_{ij}$ forms the elements of the weighted matrix V.

**Step 4.** Specify the boundary matrix of the estimation area (G).

In Step 4, the boundary matrix of the estimation area (G) is calculated based on *Eq. (6)*. In other words, the geometric mean of the elements of each criterion column in the weighted matrix must be calculated:

$$\tilde{g}_i = \left(\prod_{i=1}^{m} \tilde{v}_{ij}\right)^{\frac{1}{m}}. \tag{6}$$

**Step 5.** Calculate the distance of the options from the area estimation boundary (Q).

The distance of the options from the area estimation boundary is determined according to *Eq. (7)*, which is equal to the difference between the weighted matrix elements (V) and the area estimation boundary value (G).

$$\tilde{Q} = \tilde{V} - \tilde{G} = \begin{bmatrix} v_{11} & \cdots & v_{1n} \\ \vdots & \ddots & \vdots \\ v_{m1} & \cdots & v_{mn} \end{bmatrix} - \begin{bmatrix} g_{11} & \cdots & g_{1n} \\ \vdots & \ddots & \vdots \\ g_{m1} & \cdots & g_{mn} \end{bmatrix}. \tag{7}$$

**Step 6.** Ranking the options

In the last step of the MABAC method, the value of the criterion functions is calculated based on the sum of the distances of the options from the area estimation vector ($q_i$) for each, according to *Eq. (8)*. By calculating the sum of the elements of the matrix Q in rows, the final value of the criterion functions for each option is determined and is the basis for ranking the options.

$$\tilde{S}_i = \sum_{j=1}^{n} \tilde{q}_{ij}. \tag{8}$$

To defuzzify the final scores, *Eq. (9)* is used, where l is the lower limit of the fuzzy number, m is the middle limit, and u is the upper limit of the fuzzy number.

$$s = \frac{l + m + u}{3}. \tag{9}$$

# 4 | Findings

This section analyzed the research data. The goal of this study was to identify and prioritize the factors affecting the efficiency of smart EMS in high-rise buildings in Mazandaran using the fuzzy MABAC approach. To achieve this goal, first, from a review of the research literature and background, the factors affecting the efficiency of smart EMS were extracted, and these factors were ranked using the MABAC method. Also, to evaluate each factor, three criteria of cost, time and quality were used for optimization. The weight of these three criteria was calculated using the fuzzy ANP method, which was obtained for the quality criteria with fuzzy weight (0.59, 0.62, 0.62), time with fuzzy weight (0.12, 0.14, 0.15) and cost with fuzzy weight (0.17, 0.23, 0.27), respectively. Using each of these weights obtained, MABAC calculations were performed.

## 4.1 | Calculating the Weight of the Criteria

**Step 1.** Forming the initial decision matrix.

In this step, we form the decision matrix of the opinions. The decision matrix of the TOPSIS method is a matrix consisting of criteria and research options (10 criteria), where each option was used for each criterion based on the 1 to 7 fuzzy spectrum of *Table 3*. 10 experts completed this decision matrix, and then the experts' opinions were combined using the arithmetic averaging method. The decision matrix in question is shown in *Table 4*.

**Table 3. Fuzzy expressions.**

| Verbal Phrase | Corresponding Fuzzy Number |
|---|---|
| Very poor | (0, 0, 1) |
| Poor | (0, 1, 3) |
| A little poor | (1, 3, 5) |
| Average | (3, 5, 7) |
| A little good | (5, 7, 9) |
| Good | (7, 9, 10) |
| Very good | (9, 10, 10) |

**Table 4. Fuzzy multi-attribute border approximation area comparison decision matrix.**

| | Quality | | | Cost | | | Time | | |
|---|---|---|---|---|---|---|---|---|---|
| $A_1$ | 4.9333 | 6.7333 | 8.2000 | 0.8000 | 2.1333 | 3.9333 | 0.9333 | 2.1333 | 4.0000 |
| $A_2$ | 1.2667 | 2.7333 | 4.6000 | 3.6000 | 5.5333 | 7.4000 | 5.4000 | 7.2667 | 8.6667 |
| $A_3$ | 2.4667 | 4.3333 | 6.2667 | 2.9333 | 4.8667 | 6.6667 | 2.6000 | 4.4667 | 6.4000 |
| $A_4$ | 1.0000 | 2.2667 | 4.1333 | 6.3333 | 8.1333 | 9.3333 | 5.6667 | 7.5333 | 8.9333 |
| $A_5$ | 4.6000 | 6.6000 | 8.2000 | 2.2667 | 4.0667 | 6.0667 | 1.2000 | 2.6667 | 4.7333 |
| $A_6$ | 0.6667 | 1.8667 | 3.6667 | 0.8000 | 1.9333 | 3.6667 | 4.2000 | 6.2000 | 8.0000 |
| $A_7$ | 5.5333 | 7.4000 | 8.8000 | 0.6000 | 1.6000 | 3.2000 | 1.2000 | 2.7333 | 4.6000 |
| $A_8$ | 2.0000 | 3.7333 | 5.6667 | 2.2667 | 4.0667 | 6.0667 | 2.5333 | 4.3333 | 6.2667 |
| $A_9$ | 0.4000 | 1.3333 | 3.0000 | 3.9333 | 5.9333 | 7.8000 | 6.2000 | 8.0000 | 9.2667 |
| $A_{10}$ | 5.1333 | 7.0000 | 8.4667 | 0.8000 | 2.1333 | 3.9333 | 1.3333 | 2.5333 | 4.3333 |
| | $W_1$ | $W_2$ | $W_3$ | $W_1$ | $W_2$ | $W_3$ | $W_1$ | $W_2$ | $W_3$ |
| | 0.59 | 0.62 | 0.62 | 0.59 | 0.62 | 0.62 | 0.59 | 0.62 | 0.62 |

**Step 2.** Normalize the elements of the initial decision matrix.
In the second step, the decision matrix is normalized using the formula of Steps 3 and 4 of the fuzzy MABAC method. If the criterion is positive, in this study, since the aim is to examine the factors in terms of the greatest impact on the criteria, then all the criteria will be positive in nature. On this basis, first, in the quality criterion column, the highest upper limit value and the lowest lower limit value are determined, which are 8.8 and 0.4, respectively. Then, based on the relationship of Step 4 of the fuzzy MABAC method, the normal matrix is obtained.

Similarly, calculations are performed for other cells in the same way:

**Table 5. Determining the maximum and minimum values.**

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **MAX** | 8.8000 | | | 9.3333 | | | 9.2667 | | |
| **MIN** | 0.4000 | | | 0.6000 | | | 0.9333 | | |
| **MAX** | 8.800 | 8.800 | 8.800 | 9.333 | 9.333 | 9.333 | 9.267 | 9.267 | 9.267 |
| **MIN** | 0.400 | 0.400 | 0.400 | 0.600 | 0.600 | 0.600 | 0.933 | 0.933 | 0.933 |
| **MAX-MIN** | 8.400 | 8.400 | 8.400 | 8.733 | 8.733 | 8.733 | 8.333 | 8.333 | 8.333 |
| **MIN-MAX** | -8.400 | -8.40 | -8.40 | -8.733 | -8.73 | -8.73 | -8.33 | -8.33 | -8.33 |
| **Kind of criteria** | 1 | 1 | 1 | -1 | -1 | -1 | -1 | -1 | -1 |

**Table 6. Multi-attribute border approximation area comparison normal matrix.**

| | **Quality** | | | **Cost** | | | **Time** | | |
|---|---|---|---|---|---|---|---|---|---|
| $A_1$ | 0.5397 | 0.7540 | 0.9286 | 0.6183 | 0.8244 | 0.9771 | 0.6320 | 0.8560 | 1.0000 |
| $A_2$ | 0.1032 | 0.2778 | 0.5000 | 0.2214 | 0.4351 | 0.6565 | 0.0720 | 0.2400 | 0.4640 |
| $A_3$ | 0.2460 | 0.4683 | 0.6984 | 0.3053 | 0.5115 | 0.7328 | 0.3440 | 0.5760 | 0.8000 |
| $A_4$ | 0.0714 | 0.2222 | 0.4444 | 0.0000 | 0.1374 | 0.3435 | 0.0400 | 0.2080 | 0.4320 |
| $A_5$ | 0.5000 | 0.7381 | 0.9286 | 0.3740 | 0.6031 | 0.8092 | 0.5440 | 0.7920 | 0.9680 |
| $A_6$ | 0.0317 | 0.1746 | 0.3889 | 0.6489 | 0.8473 | 0.9771 | 0.1520 | 0.3680 | 0.6080 |
| $A_7$ | 0.6111 | 0.8333 | 1.0000 | 0.7023 | 0.8855 | 1.0000 | 0.5600 | 0.7840 | 0.9680 |
| $A_8$ | 0.1905 | 0.3968 | 0.6270 | 0.3740 | 0.6031 | 0.8092 | 0.3600 | 0.5920 | 0.8080 |
| $A_9$ | 0.0000 | 0.1111 | 0.3095 | 0.1756 | 0.3893 | 0.6183 | 0.0000 | 0.1520 | 0.3680 |
| $A_{10}$ | 0.5635 | 0.7857 | 0.9603 | 0.6183 | 0.8244 | 0.9771 | 0.5920 | 0.8080 | 0.9520 |
| | **$W_1$** | | | **$W_2$** | | | **$W_3$** | | |
| | 0.59 | 0.62 | 0.62 | 0.12 | 0.14 | 0.15 | 0.17 | 0.23 | 0.27 |

**Step 3.** Forming a weighted matrix.

In this step, using the formula from Step 5 of the MABAC method, a weighted matrix is formed. In other words, we must multiply the final weight of the criteria by the normal matrix. The results can be seen in the table below:

**Table 7. Multi-attribute border approximation area comparison weighted matrix.**

| | **$X_1$** | | | **$X_2$** | | | **$X_3$** | | |
|---|---|---|---|---|---|---|---|---|---|
| $A_1$ | 1.1856 | 1.6312 | 1.9286 | 1.2461 | 1.6967 | 1.9771 | 1.2566 | 1.7261 | 2.0000 |
| $A_2$ | 0.8494 | 1.1883 | 1.5000 | 0.9405 | 1.3347 | 1.6565 | 0.8254 | 1.1532 | 1.4640 |
| $A_3$ | 0.9594 | 1.3655 | 1.6984 | 1.0051 | 1.4056 | 1.7328 | 1.0349 | 1.4657 | 1.8000 |
| $A_4$ | 0.8250 | 1.1367 | 1.4444 | 0.7700 | 1.0578 | 1.3435 | 0.8008 | 1.1234 | 1.4320 |
| $A_5$ | 1.1550 | 1.6164 | 1.9286 | 1.0580 | 1.4908 | 1.8092 | 1.1889 | 1.6666 | 1.9680 |
| $A_6$ | 0.7944 | 1.0924 | 1.3889 | 1.2696 | 1.7180 | 1.9771 | 0.8870 | 1.2722 | 1.6080 |
| $A_7$ | 1.2406 | 1.7050 | 2.0000 | 1.3108 | 1.7535 | 2.0000 | 1.2012 | 1.6591 | 1.9680 |
| $A_8$ | 0.9167 | 1.2990 | 1.6270 | 1.0580 | 1.4908 | 1.8092 | 1.0472 | 1.4806 | 1.8080 |
| $A_9$ | 0.7700 | 1.0333 | 1.3095 | 0.9052 | 1.2921 | 1.6183 | 0.7700 | 1.0714 | 1.3680 |
| $A_{10}$ | 1.2039 | 1.6607 | 1.9603 | 1.2461 | 1.6967 | 1.9771 | 1.2258 | 1.6814 | 1.9520 |

**Step 4.** Determine the boundary matrix of the estimation area.

In this step, the boundary matrix of the estimation area (G) is calculated based on *Eq. (6)* of the MABAC method. In other words, the geometric weighted average of the elements of each criterion column in the weighted matrix must be calculated.

**Table 8. Estimation area boundary matrix.**

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Border approximation area matrix (G) | 0.7466 | 0.90 | 1.029 | 0.166 | 0.222 | 0.26 | 0.222 | 0.348 | 0.464 |

**Step 5.** Determining the distance of each option from the boundary of the estimation area.

In this step, the distance of each option from the boundary of the estimation area is calculated using the formula in Step 7 of the MABAC method. In other words, we must subtract the elements of the weighted matrix from the value of G calculated in the previous step.

**Table 9. Distance matrix of each option from the estimation area.**

| | $X_1$ | | | $X_2$ | | | $X_3$ | | |
|---|---|---|---|---|---|---|---|---|---|
| $A_1$ | -0.12 | 0.19 | 0.45 | -0.07 | 0.03 | 0.13 | -0.19 | 0.08 | 0.32 |
| $A_2$ | -0.38 | -0.11 | 0.18 | -0.12 | -0.02 | 0.08 | -0.28 | -0.06 | 0.17 |
| $A_3$ | -0.29 | 0.01 | 0.31 | -0.11 | -0.01 | 0.09 | -0.24 | 0.01 | 0.26 |
| $A_4$ | -0.40 | -0.14 | 0.15 | -0.15 | -0.06 | 0.04 | -0.29 | -0.07 | 0.16 |
| $A_5$ | -0.14 | 0.18 | 0.45 | -0.10 | 0.00 | 0.11 | -0.20 | 0.06 | 0.31 |
| $A_6$ | -0.42 | -0.17 | 0.11 | -0.07 | 0.04 | 0.13 | -0.27 | -0.03 | 0.21 |
| $A_7$ | -0.08 | 0.24 | 0.49 | -0.06 | 0.04 | 0.13 | -0.20 | 0.06 | 0.31 |
| $A_8$ | -0.33 | -0.03 | 0.26 | -0.10 | 0.00 | 0.11 | -0.23 | 0.02 | 0.27 |
| $A_9$ | -0.44 | -0.21 | 0.07 | -0.13 | -0.03 | 0.08 | -0.29 | -0.08 | 0.15 |
| $A_{10}$ | -0.11 | 0.21 | 0.47 | -0.07 | 0.03 | 0.13 | -0.19 | 0.07 | 0.30 |

**Step 6.** Determine the final score and rank of each option.

In this step, we calculate the final score of each option using *Eq. (8)* and rank it based on it. In fact, this relationship states that the score of each option is obtained from the row sum of the Q matrix.

**Table 10. Final score and ranking of each option.**

| Alternative | Si | | | Defuzzification of Si | Defuzzification of Si | Ranking |
|---|---|---|---|---|---|---|
| $A_1$ | -1.125 | 0.239 | 1.543 | 0.219 | 0.219 | 2 |
| $A_2$ | -1.277 | 0.070 | 1.384 | 0.059 | 0.059 | 4 |
| $A_3$ | -1.348 | 0.019 | 1.372 | 0.014 | 0.014 | 6 |
| $A_4$ | -1.194 | 0.125 | 1.396 | 0.109 | 0.109 | 3 |
| $A_5$ | -1.314 | 0.000 | 1.304 | -0.003 | -0.003 | 8 |
| $A_6$ | -1.460 | -0.164 | 1.173 | -0.150 | -0.150 | 9 |
| $A_7$ | -1.212 | 0.053 | 1.306 | 0.049 | 0.049 | 5 |
| $A_8$ | -1.479 | -0.184 | 1.153 | -0.170 | -0.170 | 10 |
| $A_9$ | -1.295 | 0.005 | 1.289 | 0.000 | 0.000 | 7 |
| $A_{10}$ | -1.118 | 0.247 | 1.550 | 0.226 | 0.226 | 1 |

According to the results obtained, the order of importance of each criterion is:

I. Environmental conditions

II. Internet of Things (IoT)

III. Technology acceptance

IV. Home automation

V. Economic factors

VI. Employee comfort and health

VII. Infrastructure

VIII. Structural strength

IX. Structure size

X. Development factors

**Validation**

Cronbach's alpha was used to validate the questionnaire used. This method determines the internal consistency or average correlation of items in a tool to measure the reliability of the questionnaire. For this purpose, SPSS27 software was used in this study to calculate Cronbach's alpha coefficient, which was obtained as 0.78 for the questionnaire used.

# 5 | Conclusion

This study addresses the importance of smart energy management in the construction industry and shows that smart heating and cooling devices, along with environmental data analysis, can help reduce energy consumption and optimize the performance of energy systems in buildings. Studies in an office building have shown that the use of these systems is not only economically viable but also has positive environmental impacts. Also, challenges such as high initial costs and the need to build a culture to accept new technologies have been examined.

Based on the research findings, environmental conditions, IoT, technology adoption, home automation, and economic factors are among the most important factors affecting the efficiency of smart EMS in high-rise buildings in Mazandaran. These technologies reduce energy consumption and increase efficiency by automatically adjusting heating, cooling, and lighting. Also, the IoT enables smart control and energy optimization by collecting real-time data. On the other hand, the acceptance of these technologies by users and organizations, along with financial and economic support, has a significant impact on their success. In addition, communication infrastructure and cybersecurity, structural strength, building size and construction factors are also important factors in the efficiency of these systems. Building design using appropriate insulation, natural ventilation and optimal space layout helps reduce energy consumption. Also, resilient buildings with smart infrastructure have better performance in energy management. Finally, combining these factors with modern technologies can play an important role in reducing costs, optimizing energy consumption and achieving SDGs.

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# Data Availability

The data used in this study are available upon request.

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