EVALUATION OF SMART AND VERTICAL SYSTEMS IN URBAN FARMING VIA FUZZY MCDM METHODS

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LIST OF SYMBOLS

AI	**:** Artificial Intelligence
EC	**:** Electrical Conductivity
EDAS	**:** Evaluation Based on Distance from Average Solution
IDS	**:** Intrusion Detection System
IoT	**:** Internet of Things
HVAC	**:** Heating, Ventilation, and Air Conditioning
LED	**:** Light Emitting Diode
MACBETH	**:** Measuring Attractiveness by a Categorical Based Evaluation Technique
MCDM	**:** Multi-Criteria Decision Making
NASA	**:** National Aeronautical and Space Administration
pH	**:** potential of Hydrogen
UAV	**:** Unmanned Aerial Vehicle
UN	**:** United Nations
WEDBA	**:** Weighted Euclidean Distance Based Approximation

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ABSTRACT

By 2050, the world population is projected to reach over 9 billion inhabitants, with a 50% increase in global food demand. Furthermore, crop productivity could be reduced by 10% because of climate change. People are looking for new ways to feed themselves as the world's population grows. And with a massive increase in the population, clever innovators are searching for new ways to farm more effectively. One of the innovative paths is hydroponics, which is a soilless planting technique. Multi-layered agriculture is a viable option for producing additional food out from unit land since arable land is consistent. The method cuts water consumption by 95% while maintaining crop efficiency at the same time, ensuring long-term sustainability. Traditional farming in remote regions is burdened by high transportation and brokerage prices. Innovators are now creating agricultural practices in vessel containers. Vertical and smart farming, especially in the suburbs of cities, provides new opportunities for food production. The performance of the provided systems is investigated in this thesis by minimizing the investment cost data. There have been many uncertainties in both the structure and the investment area. Fuzzy logic deals with these ambiguities. Different MCDM approaches are used to carry out two applications related to the topic. For the first challenge, selecting production system alternatives, the Fuzzy Evaluation Based on Distance from Average Solution (EDAS) approach aids in the system evaluation decision-making phase. Furthermore, TODIM (an acronym in Portuguese-Tomada de Decisao Iterativa Multicritario) is used to verify the assessment of the three first-problem alternatives and to track how risk analysis influences decision-making processes. In these factory-like farms, smart systems are sensible choices for assisting manufacturing. MCDM methods are employed to test technology alternatives for smart agriculture alternatives in the second issue. To test alternatives, the WEDBA (Weighted Euclidean Distance Based Approximation) and MACBETH (Measuring Attractiveness by a Categorical Based Evaluation Technique) approaches are used.

ÖZET

2050 yılına kadar dünya nüfusunun, küresel gıda talebinde %50'lik bir artışla birlikte, 9 milyardan fazla kişiye ulaşacağı tahmin ediliyor. Ayrıca, iklim değişikliği nedeniyle mahsul verimliliği %10 oranında azalabilir. Dünya nüfusu arttıkça insanlar kendilerini beslemenin yeni yollarını arıyorlar. Ve nüfustaki muazzam artışla birlikte, akıllı yenilikçiler daha etkili bir şekilde tarım yapmanın yeni yollarını arıyorlar. Yenilikçi yollardan biri de topraksız bir tarım tekniği olan hidroponiktir. Dikey tarım, ekilebilir arazi sınırlı olduğu için birim araziden azami gıda üretmek için uygun bir seçenektir. Yöntem, mahsul verimliliğini korurken aynı zamanda su tüketimini %95 oranında azaltarak uzun vadeli sürdürülebilirlik sağlar. Uzak bölgelerdeki geleneksel tarım, yüksek ulaşım ve aracılık fiyatlarının yükünü taşımaktadır. Girişimciler artık gemi konteynerlerinde tarımsal uygulamalar yaratıyorlar. Özellikle şehirlerin banliyölerinde dikey ve akıllı tarım, gıda üretimi için yeni fırsatlar sunuyor. Bu tezde, sağlanan sistemlerin performansı, yatırım maliyeti verileri minimize edilerek araştırılmıştır. Hem kurulum hem de yatırım alanında birçok belirsizlik bulunmaktadır. Bulanık mantık bu belirsizlikleri bertaraf etmektedir. Konuyla ilgili iki uygulamayı değerlendirmek için farklı ÇÖKV yaklaşımları kullanılmaktadır. İlk sorun olan üretim sistemi alternatiflerini değerlendirmek için, Ortalama Çözümden Uzaklığa Dayalı Bulanık Değerlendirme (EDAS) yaklaşımı, alternatiflerin seçimine karar verme aşamasına yardımcı olur. Ayrıca, TODIM (Portekizce-TOmada de Decisao Iterativa Multicritario'nun kısaltması), ilk uygulamadaki üç alternatifin değerlendirmesini doğrulamak ve risk analizinin karar verme süreçlerini nasıl etkilediğini izlemek için kullanıldı. Bu fabrika benzeri çiftliklerde akıllı sistemlerin kullanılması, üretime yardımcı olmak için mantıklı seçeneklerdir. İkinci uygulamada akıllı tarım seçeneklerinde kullanılacak teknoloji alternatiflerini test etmek için ÇÖKV yöntemleri kullanılmaktadır. Alternatifleri test etmek için WEDBA (Ağırlıklı Öklid Mesafeye Dayalı Yaklaşım) ve MACBETH (Kategorik Tabanlı Değerlendirme Tekniği ile Çekicilik Ölçme) yaklaşımları kullanılmıştır.

1. INTRODUCTION

According to the UN Study of World Urbanization Prospects 2018, the rural areas has so far been populated less than the city dwellers after 2007. The urban-rural population ratio continues to rise. A self-sustaining urban population is one option for feeding this growing population. Vertical farming is an alternative option for producing food within city boundaries.

In urban environments, vertical farming is a type of agriculture. According to the Vertical Farm Institute, vertical vegetable farming makes it possible to produce nearly the same amount of crops as 50 square meters of regular land per each one square meter of vertical farming.

The hydroponic model is a method for a low-cost, high-efficiency system with a vertical farming feature that decreases water waste. The hydroponic system's future appears bright due to its design, which might be integrated with nutrients and water delivery automation. Vacant structures in our cities, new buildings built on ecologically degraded land, and even repurposed shipping containers from maritime transportation might all be answers to our space issue. Growing crops in highly controlled indoor habitats with exact light, resources, and temperatures is known as vertical farming. Vertical farming involves growing plants in stages that can reach numerous floors high.

Vertical farms come in a wide range of sizes, from simple two-story structures to multi-story enterprises. All three varieties, however, rely on one of three soilless fertilizer delivery methods: aquaponic, aeroponic, or hydroponic.

Aquaponics: In an aquaponic system, plants and fish occupy the same ecosystem. Fish are reared in enclosed tanks, producing nutritious waste that is used to feed the crops on the vertical farm. Before giving the water to the fish, the plants purify and refresh it.

Aeroponics: Aeroponics is the practice of growing plants in a wet environment without the need of soil or much water. An aeroponic system, which consumes nearly 90% less water, is the most successful plant-growing technology for vertical farms.

Hydroponics: Plants are grown in nutrients without the need of soil, which is the most frequent growing method in vertical farms. The roots are submerged in a nutrient solution that is continually monitored and supplied to maintain the right chemical structure (Birkby, 2019)

Two applications regarding vertical farming is performed for this thesis.

For the first application, fuzzy EDAS and TODIM (a risk sensitive recursive multi-criteria decision-making methodology based on Prospect Theory) approaches will be used to assess three alternatives for vertical farming by metropolitan area: Container, Modular, and Industrial Site Warehouse Systems. Hydroponic agriculture will be used in all setups. When considering those possibilities, considering in one dimension leads us in the incorrect direction. Naturally, this problem requires a multi-dimensional approach, and multi-criteria decision making (MCDM) methodologies are ideal for this procedure. Furthermore, because the issue is new and acquiring cost data is difficult, fuzzy logic, which can calculate with ambiguity, has been included into the Fuzzy EDAS and TODIM procedures, two of the most widely used MCDM approaches. The aforementioned methodologies have gained popularity in recent years as a result of their practicality, with distance to averages giving improved performance in the solution on the EDAS side, and risk sensitive solution on the TODIM side.

Another three alternatives are mentioned in the second application: basic, IoT, and Automated vertical farms. All three alternatives are based on soilless hydroponic systems with an useable area of 200 m2. The first option, Basic, is a simple design. The system functions similarly to that of a regular farm. The farm's essential parameters are manually monitored by the farmer. The farmer pays special attention to pH, EC, humidity, and temperature. IoT is the second option, and it has IoT capabilities. Sensors are used to collect the farm's values, as mentioned above. The farmer interacts with the system based on the information gathered. Because the technology is IoT-enabled, the farmer can monitor the farm from afar. Automation, the third option, combines automation with AI aid. The capacity to automate reduces the need for human involvement. According on the data obtained, the system performs the appropriate measures. When the heat falls below a certain threshold, for example, it automatically activates the heating, ventilation, and air conditioning (HVAC) systems. Artificial intelligence (AI) is being used to improve the manufacturing process. Plant growth data is analysed using machine learning algorithms to harvest the finest plant possible. To analyze such options, MCDM approaches (WEDBA and MACBETH) are used.

2. LITERATURE REVIEW

The research in the field of vertical farming focuses on improving the nutrient solution's strength in order to increase production volume (Schrevens,1993). Morimoto et al. (1985) employ intelligent systems based on genetic algorithms and neural networks to promote long-term plant development plans in a hydroponic system.

Smart farming research covers a wide range of topics, including soil, greenhouses, plant disease, collection robots, and unmanned aerial vehicles (UAV). Articles on automation, farm design, AI applications, and IoT support for smart farms pique my attention.

Yuan et al. (2019) investigated the impact of vertical farming on tropical city ventilation efficiency. Zhang et al. (2018) looked at the viability of establishing vertical agriculture on college campuses. Vertical Smart Farming is a method of producing food vertically using sensors, detectors, and, of course, the Internet of Things (IoT). Sensors are used in IoT farming and agriculture applications to deliver iot - based smart services for smart agriculture. IoT and Big Data advancements continue to improve farming outcomes. As new issues in smart farming emerged, Xin and Zazueta used data integration, farm management, and knowledge-based software. For data security in vertical precision agriculture, Huh suggested the compact intrusion detection system (IDS) (2018).

For various growth procedures, the following research are analyzed. Shamshiri et al. (2018) investigated hydroponic greenhouses; Kodmany (2018) investigated vertical farm techniques; and Graamans et al. (2017) investigated plant factories.

Fernandes et al. (2018) look at how to optimize the environment for best crop development. The research looks at water, lighting, ideal temperature, nutrition, and humidity conditions. The study gives a full model size application.

According to some research, just a portion of the Internet of Things will be implemented. Pincheira et al. (2021) describe how to manage water using blockchain technology. pH and nutrient levels are investigated by Taylor et al. (2019); Graamans et al. (2018) examine hydroponics' energy use; Gwynn-Jones et al. (2018) concentrate on hydroponics economics.

Fully automated, IoT-assisted systems are introduced by De Silvas (2016) and Palande et al. (2018) and used to model size farms. The proposed systems are mostly the equivalent. Sensors gather data from the farm, a microprocessor processes the data, and an Ardunio-like board combines sensors and provides internet and cloud access. The purpose of simple software is to evaluate and distribute data. To receive consistent water readings (temperature, EC, pH, nutrient), humidity, temperature, and lighting, a variety of sensors are used. The farmer is kept up to date on agricultural conditions and has the ability to check current figures. In order to maintain production, systems take precautions such as adding nutrients to flow water when the EC value drops.

Integrating AI technologies, such as machine learning, with smart farming technologies is a relatively recent approach. According to Kamilaris and Prenafeta-Bold (2018), there was no study on the issue before to 2014. Despite the fact that the topic is new, there have been some research on the issue, such as Alipio et al. (2017)'s research on using Bayesian networks and Mehra et al. (2018)'s study on using Deep Neural Networks to monitor and interfere in plant development in hydroponic farming.

Ecer (2018) investigated a hybrid model with fuzzy EDAS in the third-party logistics service selection method. Ghorabee et al. (2017) expanded EDAS with interval type-2 fuzzy sets and used it to evaluate suppliers based on environmental factors. The goal for that work is to develop a decision support system for selecting among three alternatives using the fuzzy EDAS technique, which includes investment costs (2017).

TODIM is an MCDM technique based on prospect theory that has previously been used in a variety of fields. Tosun and Akyuz (2015) utilized the fuzzy TODIM approach to pick suppliers. For green supplier selection, Qin et al. (2017) employed the TODIM approach based on interval Type-2 fuzzy numbers. TODIM was used by Zhang et al. (2018) to choose a venture capital project. Wang et al. (2016) proposed a TODIM-based strategy for logistics outsourcing. Duarte (2018) used TODIM to assess the worth of six

Brazilian banks. Many studies have been published that combine TODIM with other MCDM approaches, such as Tolga's (2018) study on ERP software assessment using AHP combined TODIM.

Rao et al. (2012) proposed WEDBA as an MCDM approach. This method's distinguishing feature is integrated weights, which are a mixture of objective and subjective weights. The entropy approach is used to calculate objective weights, while the decision-maker is in charge of selecting subjective weights. The WEDBA approach is used to address manufacturing problems (2012), choose the best e-learning website (2017), and rate manufacturing systems based on flexibility (2019). Finally, Al-Hawari et al. (2019) presented and used the fuzzy WEDBA to the issues of supplier assessment and contractor selection.

Bana e Costa and Vansnick (1994) proposed the MACBETH approach, which has been used in a variety of studies including priority evaluation (2013), technology determination (2017), product classification (2017), and performance assessment (2021). The distinctive one-by-one evaluation approach of MACBETH distinguishes it from the other MCDM techniques.

3. VERTICAL FARMING

Vertical farming, with precise illumination, nutrients, and temperatures, involves growing crops in regulated indoor environments. Growing plants are stacked in layers that can reach several stories tall in vertical farming.

Vertical farms exist in various shapes and sizes, from basic two-level or wall-mounted structures to many stories high in massive warehouses. But all vertical farms have one of three soil-free systems, hydroponic, aeroponic, or aquaponic, to provide plants with nutrients. These three growth systems are listed in the following detail:

- **Hydroponics**. Hydroponics, the primary growing method used in vertical farms, includes growing plants with soil-free nutrient solutions. In the nutrient solution, which is frequently checked and circulated to ensure that the correct chemical composition is retained, the plant roots are submerged.

- **Aeroponics**. The creation of this revolutionary indoor rising method is the responsibility of the National Aeronautical and Space Administration (NASA). In the 1990s, NASA was keen to explore successful methods of growing plants in space and introduced the word "aeroponics," defined as "growing plants without soil and hardly any water in an air/mist environment."

In the vertical farming world, aeroponics systems are still an exception, but they attract considerable interest. For vertical farms, an aeroponic system is by far the most effective plant growing system, using up to 90% less water than even the most efficient hydroponic systems. It has also been shown that plants grown in these aeroponic systems consume more nutrients and vitamins, making the plants healthier and possibly more nutritional.

- **Aquaponics.** An aquaponic method carries the hydroponic system a step further, integrating the same habitat with plants and fish. In indoor ponds, fish are raised, producing nutrient-rich manure that is used as a food supplement for vertical farm plants. In turn, the plants filter and clean the waste water that is recycled into the fish ponds. While aquaponics are used in smaller-scale vertical farming systems, only a few fast-growing vegetable crops are developed by most commercial vertical farming systems and do not include an aquaponic portion. This simplifies the issues of economics and development and maximizes effectiveness. New standardized aquaponic systems, however, can contribute to making this closed-cycle system more common.

It is possible to further distinguish vertical farming systems by the sort of structure that houses the system. **Building-based vertical farm**s are frequently housed in abandoned urban buildings, such as vertical farms built in an old packing plant. In vertical farms, modern building construction is also used, such as the new multi-story vertical farm connected to an existing parking lot structure. ***Shipping-container vertical farm***ing is an increasingly common alternative. These vertical farms, typically in use transporting goods around the world, use 40-foot shipping containers. Several companies are refurbishing shipping containers into self-contained vertical farms, complete with LED lamps, drip-irrigation systems, and vertically stacked shelves for a variety of plants to start and expand. These self-contained units have computer-controlled systems for growth management that enables users to remotely track all systems from a smart phone or computer.

3.1 Advantages

Continuous Production— In non-tropical areas, vertical farming technology will ensure crop production year-round. And manufacturing is far more productive than farming on land. When the amount of crops produced per season is taken into account, a single indoor acre of vertical farming can produce yields equivalent to more than 30 acres of farmland.

Elimination of Herbicides and Pesticides— The regulated growing conditions of a vertical farm allow the use of chemical pesticides to be reduced or totally abandoned. When needed to deal with any infestations, some vertical farming operations use ladybugs and other biological controls.

Protection from Weather-Related Variations in Crop Production— Since crops are grown in a managed environment on a vertical farm, they are protected from severe weather events such as droughts, hail, and floods.

Water Conservation and Recycling— In vertical farms, hydroponic growing techniques need about 70 percent less water than regular agriculture.

Climate Friendly— Growing indoor crops reduces or removes the use of tractors and other large-scale farm machinery widely used on outdoor farms, thus reducing fossil fuel combustion. The large-scale implementation of vertical farms could lead to a substantial reduction in air contamination and in CO2 emissions. In addition, carbon emissions will be minimized because, instead of being transported or exported hundreds or thousands of miles from a traditional farm to a market, crops from a vertical farm are normally shipped only a few kilometers from the manufacturing plant.

People Friendly— One of the most dangerous professions on earth is conventional farming. Accidents in the operation of large and hazardous farming equipment and exposure to toxic chemicals are some typical potential dangers that are avoided in vertical farming.

3.2 Disadvantages

Despite these potential benefits of vertical farms, some agronomists are wary of penciling out the costs and benefits. Some think that expensive urban real estate could leave out vertical farms in many cities. And the high use of electricity in a vertical farm to operate lighting and ventilation impacts the economy. A description of the perceived drawbacks of vertical farming is given below.:

Land and Building Costs— Urban locations can be very costly for smart agriculture. Some modern vertical farms, which can be more economical for building, are located in abandoned factories, derelict areas, or superfund sites.

Energy Use— Although the cost of transport could be considerably lower than in traditional agriculture, the energy use of lighting systems and temperature controls in a vertical farm may lead to high cost of operations.

Limited Number of Crop Species— The new vertical farm crop model focuses on high-value, fast-growing, low-footprint, and fast-turning crops such as lettuce, basil, and other salad goods. In a commercial vertical farming system, slower growing crops, as well as grains, aren't as profitable.

Pollination Needs— In vertical farming, crops involving insect pollination will be at a disadvantage, as insects are normally removed from the growing climate. Pollination-requiring plants can need to be fertilized by hand, requiring time and energy for workers (Birkby, 2019).

4. MCDM METHODS

4.1 EDAS Method

Vertical smart farming is a popular issue in the sustainability world right now. Precision data cannot be obtained due to its novelty. The data gathered has a lot of discrepancies. Because of this ambiguity, fuzzy logic logic became obligatory in this thesis. The vertical smart farming assessment dilemma has a hierarchical structure of several dimensions. Multi-criteria decision-making approaches can effectively solve this multi-dimensionality challenge. The EDAS approach with fuzzy logic is chosen because of its stability in this case.

Ghorabee et al. (2017) were the first to create EDAS, and they used it to solve an inventory management challenge. Ghorabee et al. (2014) generalized the crisp EDAS approach to fuzzy logic only a year apart. They attempted to solve the supplier selection problem using the approach described. The same technique that was used in that analysis will be used in ours.

Assume that there are k decision-makers ($D = \{D_1, D_2, \ldots, D_k\}$), each with n alternatives ($A = \{A_1, A_2, \ldots, A_n\}$) and m conditions ($C = \{C_1, C_2, \ldots, C_m\}$). The measures of the extended fuzzy EDAS system are as follows:

Step 1: Create the z$^{\text{th}}$ decision maker's decision matrix DM_z as seen below (gather data presented in Table 4.2 through interviews or surveys):

$$DM_z = \left[\widetilde{P_{ij}^z}\right]_{n\times m} = \begin{bmatrix} P_{11}^z & P_{12}^z & \ldots & P_{1m}^z \\ P_{21}^z & P_{22}^z & \ldots & P_{2m}^z \\ \vdots & \vdots & \vdots & \vdots \\ P_{n1}^z & P_{n2}^z & \ldots & P_{nm}^z \end{bmatrix} \tag{1}$$

where $\widetilde{P_{ij}^z}$ represents the z$^{\text{th}}$ decision maker's output value for alternative a_i on criterion c_j, $1 \le i \le n, 1 \le j \le m$, and $1 \le z \le k$.

Table 4.1: Importance terms in the case of linguistic words for criteria.

Linguistic Terms	Fuzzy number
Lowest (LT)	(0.0, 0.0, 0.0, 0.1)
Very low (VL)	(0.0, 0.1, 0.2, 0.3)
Low (L)	(0.2, 0.3, 0.4, 0.5)
Medium (M)	(0.4, 0.5, 0.5, 0.6)
High (H)	(0.5, 0.6, 0.7, 0.8)
Very High (VH)	(0.7, 0.8, 0.9, 1.0)
Highest (HT)	(0.9, 1.0, 1.0, 1.0)

Table 4.2: Preference ratings in case of linguistic terms for alternatives.

Linguistic Terms	Fuzzy number
Very Poor (VP)	(0, 0, 0, 1)
Poor (P)	(0, 1, 2, 3)
Medium Poor (MP)	(2, 3, 4, 5)
Medium/Fair (M)	(4, 5, 5, 6)
Medium Good (MG)	(5, 6, 7, 8)
Good (G)	(7, 8, 9, 10)
Very Good (VG)	(9, 10, 10, 10)

Step 2: Assemble the $\overline{G}$ average decision matrix as follows:

$$\widetilde{P_{ij}} = \left(\left(\widetilde{P_{ij}^1} \oplus \widetilde{P_{ij}^2} \oplus \ldots \oplus \widetilde{P_{ij}^k}\right)/k\right) \tag{2}$$

$$\overline{G} = [\widetilde{P_{ij}}]_{n\times m} \tag{3}$$

where $\widetilde{P_{ij}}$ represents the average criterion c_j output value of alternative a_i, $1 \leq i \leq n, 1 \leq j \leq m$.

Step 3: Create the W_z weighting matrix for the z^th decision maker's criteria (using the linguistic terminology in Table 3), as seen below:

$$W_z = [\widetilde{w}_j^{\,z}]_{m\times 1} = \begin{bmatrix} \widetilde{w_1^z} \\ \widetilde{w_2^z} \\ \vdots \\ \widetilde{w_m^z} \end{bmatrix} \tag{4}$$

where w_j^z is the weight given by the z^th decision maker to criterion c_j , $1 \leq j \leq m, 1 \leq z \leq k.$

Step 4: Assemble the $\overline{W}$ average weighting matrix as follows:

$$\widetilde{w_j} = \left(\left(\widetilde{w_j^1} \oplus \widetilde{w_j^2} \oplus \ldots \oplus \widetilde{w_j^{\mathrm{k}}}\right)/k\right) \tag{5}$$

$$\overline{W} = [w_j]_{1\times m} \tag{6}$$

Step 5: Build the matrix of average solutions., AV:

$$AV = [\widetilde{av}_j]_{1\times m} \tag{7}$$

$$\widetilde{av}_j = \frac{1}{n}\sum_{i=1}^{n} \tilde{P}_{ij} \tag{8}$$

The average solutions for each criterion are denoted by $\widetilde{av}_j$.

Step 6: Assume that *B* represents the set of beneficial criteria and *N* represents the set of non-beneficial criteria. Consider the form of criteria (*B* or *N*) when calculating the positive distance to average (*PDA*) and negative distance to average (*NDA*) matrices, as shown below:

$$PDA = [\widetilde{pda}_{ij}]_{n \times m} \tag{9}$$

$$NDA = [\widetilde{nda}_{ij}]_{n \times m} \tag{10}$$

$$\widetilde{pda}_{ij} = \begin{cases} \dfrac{\psi(\tilde{P}_{ij} \ominus \widetilde{av}_j)}{\kappa(\widetilde{av}_j)} & if \;\; j \;\in\; B \\[2ex] \dfrac{\psi(\widetilde{av}_j \ominus \tilde{P}_{ij})}{\kappa(\widetilde{av}_j)} & if \;\; j \;\in\; N \end{cases} \tag{11}$$

$$\widetilde{nda}_{ij} = \begin{cases} \dfrac{\psi(\widetilde{av}_j \ominus \tilde{P}_{ij})}{\kappa(\widetilde{av}_j)} & if \;\; j \;\in\; B \\[2ex] \dfrac{\psi(\tilde{P}_{ij} \ominus \widetilde{av}_j)}{\kappa(\widetilde{av}_j)} & if \;\; j \;\in\; N \end{cases} \tag{12}$$

Here, $\widetilde{pda}_{ij}$ and $\widetilde{nda}_{ij}$ denote the estimated value of the i^{th} alternative in terms of the j^{th} criterion's positive and negative ranges from the average solution, respectively.

Step 7: Calculate the weighted average of the positive and negative distances for the entire alternatives, as seen below:

$$\widetilde{ps}_i = \sum_{j=1}^{m} (\widetilde{w}_j \otimes \widetilde{pda}_{ij}) \tag{13}$$

$$\widetilde{ns}_i = \sum_{j=1}^{m} (\widetilde{w}_j \otimes \widetilde{nda}_{ij}) \tag{14}$$

Step 8: Calculate the $\widetilde{ps}_i$ and $\widetilde{ns}_i$ normalized values across all alternatives as follows:

$$\widetilde{nps}_i = \frac{\widetilde{ps}_i}{\max_i(\kappa(\widetilde{ps}_i))} \tag{15}$$

$$\widetilde{nns}_i = 1 - \frac{\widetilde{ns}_i}{\max_i(\kappa(\widetilde{ns}_i))} \tag{16}$$

Step 9: Calculate the assessment score ($\widetilde{as}_i$) for each alternative as follows:

$$\widetilde{as}_i = \frac{(\widetilde{nps}_i \oplus \widetilde{nns}_i)}{2} \tag{17}$$

Step 10: According to $\kappa(\widetilde{as}_i)$, list the alternatives in order of declining assessment scores. To put it another way, the alternative with the highest assessment score is the superior option of the candidate alternatives.

4.2 TODIM Method

TODIM is an MCDM approach that relies on the Nobel Laureate in Economics, Prospect Theory, which states that individuals are more willing to take risk in the event of a loss and less willing in the event of a gain.On the basis of crisp numbers, Gomes and Lima (1992) suggested TODIM for the first time. Fuzzy TODIM is a fuzzy-numbers-based system. The TODIM approach compares each alternative to the others in terms of gains and losses under each criterion.

To make the extended EDAS system more accessible and to avoid breaking the rhetoric, all of the notations would be used in the same manner. And the approaches' first two steps are similar, despite the fact that the majority of the steps are different.

Step 1: Separately build the decision makers' matrix based on the survey findings (collect the data from Table 4.1 by interviews or surveys, excluding the Cost criterion) as in Eq. 1. The output value of alternativea_i on criterion c_j given by the z^{th} decision maker is denoted by P_{ij}^{z}., $1 \leq i \leq n, 1 \leq j \leq m$, and $1 \leq z \leq k$.

Step 2: As the result of Eqs. 2 and 3, combine all of the decision makers' views to construct the average decision matrix, $\overline{G}$. The average performance level of alternative a_i on criterion c_j is denoted by P_{ij}., $1 \leq i \leq n, 1 \leq j \leq m$.

Step 3: Create an average weight matrix using the professional opinion from Table 4.1 and Eq. 6 to calculate the weight matrix.

Step 4: As seen in Eq. below, calculate the normalized $\overline{G}^{\nu}$ matrix with peak normalization for beneficial criteria and minimal normalization for cost criteria:

$$\overline{G}^{\nu} = \left[\tilde{P}^{\nu}{}_{ij}\right]_{n\times m} = \begin{cases} \left[\tilde{P}_{ij} \oslash \tilde{P}_{ij}^{c_j}{}_{max}\right]_{n\times m} & for\ \ beneficial\ \ criteria \\ \left[\tilde{P}_{ij}^{c_j}{}_{min} \oslash \tilde{P}_{ij}\right]_{n\times m} & for\ \ non-beneficial\ \ criteria \end{cases} \tag{18}$$

This step should be applied to all criteria, c_j, and $1 \leq j \leq m$.

Step 5: Determine the relative criteria weights w_{rc_j} by normalizing the average weights obtained from experts' perspectives, as seen in folowing Eq.

$$\left[\widetilde{w}_{rc_j}\right]_{1\times m} = \left[\widetilde{w}_{c_j} \oslash \widetilde{w}_r\right]_{1\times m} \tag{19}$$

Where $\widetilde{w}_r$ is the weight of reference criterion for the most substantial value. And $\widetilde{w}_{c_j}$ is described as the weights of each criterion, and $1 \leq j \leq m$.

Step 6: Get any criterion's c_j relation to the superiority of one alternative A_{a_i} over each alternative A_i; $\tilde{\phi}_{c_j}(A_{a_i}, A_i)$, using following Eq. :

$$\tilde{\phi}_{c_j}(A_{a_i}, A_i) = \begin{cases} \sqrt{\dfrac{\widetilde{w}_{rc_j}}{\sum_{j=1}^{m} \widetilde{w}_{rc_j}} d(\tilde{P}^v_{a_ij}, \tilde{P}^v_{ij})}, & if \quad \kappa(\tilde{P}^v_{a_ij}) - \kappa(\tilde{P}^v_{ij}) > 0 \\ 0, & if \quad \kappa(\tilde{P}^v_{a_ij}) - \kappa(\tilde{P}^v_{ij}) = 0 \\ -\dfrac{1}{\theta}\sqrt{\dfrac{\sum_{j=1}^{m} \widetilde{w}_{rc_j}}{\widetilde{w}_{rc_j}} d(\tilde{P}^v_{a_ij}, \tilde{P}^v_{ij})}, & if \quad \kappa(\tilde{P}^v_{a_ij}) - \kappa(\tilde{P}^v_{ij}) < 0 \end{cases} \tag{20}$$

Where (A_{a_i}, A_i) shows the referred one alternative to other *i* alternatives, $d(\tilde{P}^v_{a_ij}, \tilde{P}^v_{ij})$ represents the distance across each criterion *j*'s performance values to each alternative *i*. $\kappa(\tilde{P}^v_{a_ij})$, and $\kappa(\tilde{P}^v_{ij})$ reflect, respectively and are extracted from Eq. 3, the decreased crisp values of the associated performance values.

Step 7: Calculate each alternative's dominance position over each other using the following Eq:

$$\tilde{\delta}(A_{a_i}, A_i) = \sum_{j=1}^{m} \tilde{\phi}_{c_j}(A_{a_i}, A_i) \quad \forall(a_i, c_j) \tag{21}$$

where $1 \leq i \leq n$, also $1 \leq j \leq m$.

Step 8: Transpose the domination values to make the $\left[\tilde{\delta}(A_{a_i}, A_{a_i})\right]_{n\times n}$ matrix easy to calculate.

Step 9: Using the equation below, determine the normalized global value of alternative i:

$$\tilde{\xi}_i = \frac{\sum \tilde{\delta}(A_{a_i}, A_i) - min \sum \tilde{\delta}(A_{a_i}, A_i)}{max \sum \tilde{\delta}(A_{a_i}, A_i) - min \sum \tilde{\delta}(A_{a_i}, A_i)} \tag{22}$$

Where $min \sum \{\tilde{\delta}(A_{a_i}, A_i)$ denotes the least proportion of sum of each alternative's dominance value and $max \sum \tilde{\delta}(A_{a_i}, A_i)$ denotes the most proportion of sum of each alternative's dominance value. $1 \leq i \leq n$.

Step 10: Eq. 3 will be used to get the type-reduced global values $\kappa(\tilde{\xi}_i)$, for every alternative i, then list them in descending order to determine the appropriate one or the most precise ordering.

4.3 WEDBA

The WEDBA strategy is a multi-criteria decision-making method based on the Euclidian interval between the best and worst situations. The ideal point is the best case, and the anti-ideal point is the worst. The distance between the optimal and anti-ideal points is used to value the alternatives. The success of an alternative is mirrored with its index score. A numerical comparison is used to measure the index score. A higher index score indicates improved results and a closer proximity to the ideal point. When it comes to using criterion weights, the WEDBA approach offers a lot of options. The WEDBA approach allows for three different kinds of criteria weighting: subjective criteria weights, quantitative criteria weights, and combined criteria weights. For this thesis, I used combined weights. The following is a short description of how to use the WEDBA system from Rao and Singh (2012)'s study:

Step 1: Make the decision matrix. The properties of alternatives are seen in the average decision matrix. The output of the i^{th} alternative for property '*j*' as d_{ij} is seen in the decision matrix. The size of the average decision matrix is determined by attribute data of *m* alternatives with *n* properties as *mxn*. Just one decision-maker is included in Rao and Singh's analysis (2012). I opted to use Ghorabee et al. (2016)'s analysis for planning decision matrix in order to include a community of decision-makers in the assessment process. The measures for creating a decision matrix are as follows:

$$D = \left[\tilde{d}_{ij}\right]_{nxm} \tag{23}$$

$$\tilde{d}_{ij} = \frac{1}{z} \sum_{i=1}^{z} \tilde{d}_{ij}^{p} \tag{24}$$

Where $\tilde{d}_{ij}^{p}$ represents the efficiency assessment of the i^{th} alternative for the j^{th} property by the p^{th} decision-maker. For the preference scores of the alternatives, Table 4.2 includes verbal phrases and fuzzy counterparts. To test the alternatives, decision-makers use the oral expressions seen in Table 4.2. To continue the standardization process, fuzzy equivalents of decision-makers' verbal phrases for alternatives should be defuzzified. The research of Zeng et al. (2007) gives a basic method for defuzzifying trapezoidal fuzzy numbers:

$$\mathrm{x} = \frac{x_1 + 2x_2 + 2x_3 + x_4}{6} \tag{25}$$

Step 2: Standardization. The basic decision matrix, *D'*, is a simplified version of the average decision matrix, with standard scores representing standardized attribute data. The standard deviation of standard scores is one, and the mean is zero. The following is the standardization procedure:

$$D' = [Z_{ij}]_{nxm} \tag{26}$$

$$z_{ij} = \frac{x_{ij} - \mu_j}{\sigma_j} \tag{27}$$

$$X_{ij} = \frac{d_{ij}}{\max j\,(d_{ij})}, for\ beneficial\ attributes, \tag{28}$$

$$X_{ij} = \frac{\max j\,(d_{ij})}{d_{ij}}, for\ non - beneficial\ attributes, \tag{29}$$

$$\mu_j = \frac{1}{m}\sum_{i=1}^{m} x_{ij} \tag{30}$$

$$\sigma_j = \sqrt{\frac{\sum_{i=1}^{m}\left(x_{ij} - \mu_{ij}\right)^2}{m}} \tag{31}$$

Step 3: Establish the ideal and anti-optimal points. On a standard decision matrix, the ideal point represents the optimal attribute value for criterion *'j'*. On a standard decision matrix, the anti-ideal point represents the worst attribute value for criterion *'j'*. The ideal point is denoted by the letter '*a**', while the anti-ideal point is denoted by the letter '*b**'.

$$\mathrm{a}^* = \{\mathrm{a}_j^*\} \text{ and } \mathrm{b}^* = \{\mathrm{b}_j^*\} \text{ and } \mathrm{j} = \{1,2,3,\ldots,\mathrm{n}\} \tag{32}$$

Step 4: Attribute weights. WEDBA gives the decision-maker the option of using various attribute weights. The decision-maker may choose to employ objective or subjective weights when making a decision. The integrated attribute weights can also be generated by combining the objective and subjective weights.

Objective attribute weights. The following diagram depicts the method of determining the objective attribute weights:

$$r_{ij} = \frac{d_{ij}}{\sum_{i=1}^{m} d_{ij}} \tag{33}$$

$$E_j = \frac{-\left(\sum_{i=1}^{m} r_{ij} \ln r_{ij}\right)}{\ln m} \tag{34}$$

$$l_{ij} = 1 - E_j \tag{35}$$

$$w_j = \frac{l_{ij}}{\sum_{i=1}^{m} l_{ij}} \tag{36}$$

Subjective attribute weights. As previously mentioned, I used the analysis of Ghorabee et al. (2016) to construct an average decision matrix. To calculate subjective weights, I used the procedure described in the same study (Ghorabee et al., 2016).

$$W = \left[\widetilde{w}_j\right]_{1xm} \tag{37}$$

$$\widetilde{w}_j = \frac{1}{z}\sum_{i=1}^{z} \widetilde{w}_j \tag{38}$$

where $\widetilde{w}_j^p$ represents the significance assessment of criterion C_j by the p^{th} decision-maker. For the value scores of the criterion, Table 4.1 includes verbal phrases and fuzzy counterparts. To measure Weighted Euclidian Distances (WED), fuzzy equivalents of decision-makers' verbal expressions for alternatives should be defuzzified. Again, Zeng et al.'s (2007) above mentioned formula is employed to defuzzify trapezoidal fuzzy numbers.

Integrated attribute weights. The objective and subjective attribute weights are combined in integrated attribute weights. The objective attribute weight of attribute '*j*' is represented by w_j^o, as well as the subjective attribute weight is represented by w_j^s. The integrated attribute weight of attribute *'j'* is represented as weight w_j^i, which can be found as follows:

$$w_j^i = \frac{w_j^o * w_j^s}{\sum_{i=1}^{m}\left(w_j^o * w_j^s\right)} \tag{39}$$

Step 5: To order the alternatives, the WEDBA approach employs Euclidian distance. Simply put, the shortest distance between two points in Euclidian space is known as the Euclidian distance. The method relies on the identification of two reference points. The first point (ideal point) is the most desirable condition, and the second point (anti-ideal point) is the least desirable situation. If the reference points have been established, the distance between each alternative and the reference points can be measured. The optimal option would be the one that is nearest to the ideal point and farthest from the anti-ideal point. WED_i^+ depicts the WED of each alternative to the ideal point, $a*$, while WED_i^- depicts the WED of each alternative to the anti-ideal point, $b*$.

$$WED_i^+ = \left[\sum_{j=1}^{n} \left\{w_j.\left(Z_{ij} - a_i^*\right)\right\}^2\right]^{1/2} \tag{40}$$

$$WED_i^- = \left[\sum_{j=1}^{n} \left\{w_j.\left(Z_{ij} - b_i^*\right)\right\}^2\right]^{1/2} \tag{41}$$

$$Index\ Score_i = \frac{WED_i^-}{WED_i^+ + WED_i^-} \tag{42}$$

The index score indicates how similar an alternative is to the optimal solution. The better solution is the one with the highest index score.

4.4 MACBETH

The MACBETH approach is a common MCDM technique based on multi-attribute value theory. This approach compares and contrasts alternatives based on the decision maker's assessment of their attraction to one another. The method's key approach is to evaluate the success of alternatives using qualitatively calculated criteria.

The attractiveness of each parameter is assessed using a seven-leveled qualitative measure by the decision-maker. The approach aids decision-makers in making consistent decisions. The decision-maker is alert of uncertainty where there is a contradiction. The qualitative judgments of decision makers are translated to the quantitative MACBETH scale using linear programming. To rate the alternatives, an aggregated algorithm calculates their overall attractiveness ratings.

The steps of the MACBETH approach are derived from Tosun (2017)'s analysis and are seen below:

Step 1: Make a decision tree from the information you've gathered. Criteria are organized as nodes in a decision tree. Decision-maker may use both quantitative and qualitative criteria. Verbal values are used to determine qualitative parameters. The maximum and minimum numerical quantities are used to determine quantitative parameters.

Step 2: Attractiveness is determined. By comparing each criterion to some other criterion, the degree of attractiveness is validated for each. The MACBETH approach uses a linguistic scale for contextual analysis of criteria (Table 4.3), where "extreme" indicates a strong preference for one choice over another and "none" indicates the same degree of preference. An assessment matrix for criteria is formed, and criteria are arranged from left to right as per their significance level. Each criterion is rated on a linguistic scale by the decision-maker.

Table 4.3: MACBETH semantic scale.

Semantic Scale	Significance level of difference between options' attractiveness
Null	Same level of attractiveness
Very Weak	Very weak difference between options
Weak	Weak difference between options
Moderate	Moderate difference between options
Strong	Strong difference between options
Very Strong	Very strong difference between options
Extreme	Extreme difference between options

Step 3: Linear programming. The attractiveness degree is determined by evaluating the decision maker's judgments using linear programming for the comparison. When solving this linear program seems impossible, MACBETH alerts the decision-maker of a potential contradiction. If practicable alternatives are found, MACBETH creates the MACBETH scale using averages. With a scale ranging from 0 to 100, attractiveness is shown.

Step 4: Weighting. The weight of every criterion is determined by the judgement of decision maker's for its significance. The total weight of the parameters is equal 100.

Step 5: Attractiveness and rating in general. The graded criteria's comparison with the attractiveness scale determines the total ranking of alternatives. These cumulative ratings are used to rate the alternatives.

5. APPLICATION

The multi-criteria decision making approaches described in the previous part are used in this thesis to choose the best option across vertical farming projects in a metropolitan area. There are two applications performed. First application is evaluating three hydropic vertical farm alternatives; Container, Modular and Industrial site warehouse. EDAS and TODIM methods are applied to select the best alternative. Second application is evaluating three smart vertical farm alternatives; Basic, IoT and Auto. WEDBA and MACBETH methods are applied to select the best alternative.

Detailed information on selected criteria and MCDM method applications to given problems are given below.

5.1 Vertical Farm Alternative Evaluation

First application is to determine an indoor vertical farm alternative in a city region. As stated earlier indoor farming alternatives are not feasible solutions yet. Already existing indoor farms around the globe are focused on producing mainly on rare herbs and greens. Experts are kindly asked to evaluate alternatives to produce high valued and rare herbs to be selled to top restaurants in city.

The very first alternative is a container-based system with LEDs, six vertical farming spaces, a water tank, air conditioning system, fridge, and other essential equipment, as well as a 21-meter square space. The second alternative is a new Modular system, which includes identical technology to the first alternative but is less expensive owing to its flexibility in installation. The last alternative is a setup in a warehouse on an industrial site with additional equipment and a 200-meter square space. The criteria were found in the literature and confirmed by experts. Five hydroponic farming professionals (two of whom are agricultural engineers and three of whom are farmers) were requested to participate in a survey to assess the criteria and alternatives. A product development laboratory was founded by one of the producers in the Buyukcekmece region who had previously worked in the tissue (seedling) industry. In the same region of Istanbul, other producer uses hydroponic gardening to cultivate strawberries in a greenhouse. The hydroponic farming was created by a consultant/expert, who now advertises the technique and helps others. Agricultural engineers watch and advise farmers who are using precise farming practices.

Expenditure data is gathered from the market (as TL values of 2019) and calculated based on the individual designs of each system. The container option offers a 21 m2 space, whilst the industrial site option has a 200 m2 space. In addition, in order to fairly compare the alternatives, I used the area of the modular option, which was the same as the area of the container option. As a non-benefit criteria, the whole data in Table 5.1 is incorporated into the solution procedures in their Step 2. Despite the fact that cost estimates for container and modular options are quite comparable, two systems differ on other parameters. As seen in Table 5.2, decision makers' perceptions about these two alternatives differ. These figures represent the expenses per square meter of the each alternative.

The problem is initially examined using the fuzzy EDAS approach. Then, because my inquiry into the problem is in an unexplored territory, it must be validated with a risk-sensitive procedure known as fuzzy TODIM. This section contains all of the solution processes for the two MCDM approaches.

Table 5.1: Cost Estimations of Vertical Farming System Alternatives (TL, 2019)

Cost Item	Container	Modular	Ind. Site W.
LED (150 m / 1170 m))	(2533.2, 2831.2, 3129.2, 3427.2)	(2533.2, 2831.2, 3129.2, 3427.2)	(98793.6, 110416.4, 122039.2, 133662.0)
Water hose (40 m / 240 m)	(467.5, 522.5, 577.5, 632.5)	(467.5, 522.5, 577.5, 632.5)	(2805.0, 3135.0, 3465.0, 3795,0)
Water hose elbow (6 pieces)	(76.5, 85.5, 94.5, 103.5)	(76.5, 85.5, 94.5, 103,5)	

Capillary water hose (30 m)	(80.1, 89.5, 98.9, 108.3)	(80.1, 89.5, 98.9, 108.3)	
Suspension rope (30 m)	(34.0, 38.0, 42.0, 46.0)	(34.0, 38.0, 42.0, 46.0)	
Hook (300 pieces)	(453.9, 507.3, 560.7, 614.1)	(453.9, 507.3, 560.7, 614.1)	
Plastic Velcro Clamp (100 pieces)	(4.3, 4.8, 5.4, 5.9)	(4.3, 4.8, 5.4, 5.9)	
PVC (150 m)	(3187.5, 3562.5, 3937.5, 4312.5)	(3187.5, 3562.5, 3937.5, 4312.5)	
Water tank (500 / 2000 liters)	(425.0, 475.0, 525.0, 575.0)	(425.0, 475.0, 525.0, 575.0)	(1700.0, 1900.0, 2100.0, 2300.0)
Shutter / Container (21 m^2)	(8500.0, 9500.0, 10500.0, 11500.0)	(6375.0, 7125.0, 7875.0, 8625.0)	
Small Water Tanks (for nutrients)	(212.5, 237.5, 262.5, 287.5)	(212.5, 237.5, 262.5, 287.5)	
Oxygen Cylinder	(467.5, 522.5, 577.5, 632.5)	(467.5, 522.5, 577.5, 632.5)	
Air conditioning	(4250.0, 4750.0, 5250.0, 5750,0)	(4250.0, 4750.0, 5250.0, 5750.0)	(42500.0, 47500.0, 52500.0, 57500.0)
Electrical Installation and Equipment	(1700.0, 1900.0, 2100.0, 2300.0)	(1700.0, 1900.0, 2100.0, 2300.0)	(4250.0, 4750.0, 5250.0, 5750.0)
Counter type refrigerator (1 / 3 pieces)	(5185.0, 5795.0, 6405.0, 7015.0)	(5185.0, 5795.0, 6405.0, 7015.0)	(15555.0, 17385.0, 19215.0, 21045.0)
Rack (117 pieces)			(64642.5, 72247.5, 79852.5, 87457.5)
Cornice (130 m)			(1270.8, 1420.3, 1569.8, 1719.3)
Recirculation pump			(212.5, 237.5, 262.5, 287.5)
Total	(27577.0, 30821.3, 34065.7, 37310.0)	(25452.0, 28446.3, 31440.7, 34435.0)	(231729.4, 258991.7, 286253.9, 313516.2)
Total per 1 m^2	(1313.2, 1467.7, 1622.2, 1776.7)	(1212.0, 1354.6, 1497.2, 1639.8)	(1158.6, 1295.0, 1431.3, 1567.6)

5.1.1 Criteria

At first, criteria for valuation must be defined in the evaluation process of hydroponic alternatives. The literature was combed through, and systematic interviews with persons involved in vertical agriculture on the outskirts of town were conducted. For the evaluation procedure, the following criteria were identified.

C1) Number of Crop Types: In theory, almost any crop may be produced in a vertical farming system. In general, lettuce species, cherry tomatoes (less than 2.5 cm), and strawberries are now being produced. Other crops that can be grown include tree fruits and salad tomatoes (5-7.5 cm). However, these may necessitate a larger separation and spacing. It's crucial for a farmer to be able to adapt to market demand. Because crop prices fluctuate throughout the year, the farmer's ability to produce a variety of crops is a valuable advantage. Because hydroponics allows for quick maturity timeframes, farmers may harvest the most valuable produce at the right time of year.

C2) Production Volume: It should be highlighted that more building factories surrounding the city can attain higher output volumes. On the other side, when the number of plants grows, a more complex organizational system may be required. Increased production quantities may allow the manufacturer to improve profit and market share. However, in order for the harvested products to be sold while still fresh, market orientation is also necessary.

C3) Venture Capital Attractiveness: Indoor agriculture, particularly vertical farming, is a viable sector for government, entrepreneurs, and universities to engage in. However, the level of interest varies depending on the sort of vertical farming. The issue is growing prominence throughout the world, and because it is still relatively new, more start-ups are entering the market. Agricultural initiatives are frequently supported by multi-national entities such as the European Union (EU).

C4) Sustainability: Farm equipment such as tractors, lorries, and haulers, which boost the carbon emissions, are unnecessary. The site of agricultural production, on the other hand, has a direct impact on carbon footprint due to transportation. Hydroponics uses less water, and because there is no soil involved in the manufacturing process, pesticides are rarely employed. There is no known impact to the environment as a result of the system as a whole.

C5) Flexibility (Modularity and Scalability): The capacity to adapt to any workplace is a property of a structure's modularity. In addition, the structure's dimensions might be altered if necessary. The manufacturing area and capacity may be scaled as needed by the producer.

C6) Workforce Requirement: Even though some alternatives give smaller planting grounds, they all require labor, at the very least for plant collection. Because the suggested technologies are more difficult than traditional food production methods, a well-educated staff is critical. This circumstance raises the cost of labor and lengthens the time it takes to train new employees.

C7) Stock-Out Cost: If a consumer refuses to queue for their purchase to be delivered, they may back order the item, resulting in customer loss. As a result of the stock-out, the seller will suffer certain charges.

C8) Transportation Costs: Food production being located closer to customers in cities is an intriguing concept that results in lower transportation costs. In order to be used in urban settings, transportation vehicles must likewise get smaller.

C9) Investment Costs: Start-up expenses in many cities, such as Istanbul and Ankara, are mostly due to the high cost of real estate in metropolitan areas opposed to the rural land, as well as depreciation charges on equipment and machinery.

5.1.2 Fuzzy EDAS Application

The theoretical framework for the fuzzy EDAS approach was presented above; in this section, the context is applied to vertical farming alternative evaluation.

Step 1 of the protocol requires the development of a decision matrix: Decision-makers are politely invited to assess each alternative's success against pre-determined criteria. To assess each alternative's predicted results, decision makers used the qualitative scores in Table 4.2. Table 5.2 illustrates how decision makers rated each choice overall.

Table 5.2: Decision Makers Evaluation for each alternative.

		C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
	A_1	P	P	P	P	P	VG	VG	VG
D_1	A_2	MG	MG	MG	MG	MG	MG	MG	MG
	A_3	VG	VG	VG	VG	VG	P	P	P
	A_1	MP	P	MP	VG	G	VG	MP	VG
D_2	A_2	MG	M	G	VG	VG	G	G	MP
	A_3	VG	VG	VG	VG	MP	M	VG	G
	A_1	MG	MG	G	G	VG	VG	MG	VG
D_3	A_2	VG	VG	VG	G	VG	MG	VG	VG
	A_3	VG	G	VG	G	G	G	G	MG
	A_1	MP	MP	P	VG	VG	MG	MP	VG
D_4	A_2	MG	MG	M	M	M	MG	M	MG
	A_3	G	VG	VG	G	MP	G	VG	M
	A_1	G	G	G	G	G	P	VG	VG
D_5	A_2	MP	MP	G	G	G	P	MP	P
	A_3	M	M	MG	MG	MG	P	MP	MP

The average decision matrix is defined in Step 2 as follows: To create an average decision matrix, the total rates of decision makers must be averaged. The average values of alternatives are calculated using Eq. 2. For example, the success of the first alternative on the first criterion can be calculated as follows:

$$\tilde{P}_{11} = \left(\left(\tilde{P}_{11}^{1} \oplus \tilde{P}_{11}^{2} \oplus \tilde{P}_{11}^{3} \oplus \tilde{P}_{11}^{4} \oplus \tilde{P}_{11}^{5} \right) / 5 \right)$$

$$\tilde{P}_{11} = ((0,1,2,3) \oplus (2,3,4,5) \oplus (5,6,7,8) \oplus (2,3,4,5) \oplus (7,8,9,10)) / 5$$

$\tilde{P}_{11} = (3.2, 4.2, 5.2, 6.2)$

Table 5.3 displays the calculated performance matrix:

Table 5.3: Performance Matrix

	A_1	A_2	A_3
C_1	(3.2, 4.2, 5.2, 6.2)	(5.2, 6.2, 7, 7.8)	(7.6, 8.6, 8.8, 9.2)
C_2	(2.8, 3.8, 4.8, 5.8)	(5, 6, 6.6, 7.4)	(7.6, 8.6, 8.8, 9.2)
C_3	(3.2, 4.2, 5.2, 6.2)	(6.4, 7.4, 8, 8.8)	(8.2, 9.2, 9.4, 9,6)
C_4	(6.4, 7.4, 8, 8.6)	(6.4, 7.4, 8, 8.8)	(7.4, 8.4, 9, 9.6)
C_5	(6.4, 7.4, 8, 8.6)	(6.8, 7.8, 8.2, 8.8)	(5, 6, 6.8, 7.6)
C_6	(6.4, 7.4, 7.8, 8.2)	(4.4, 5.4, 6.4, 7.4)	(3.6, 4.6, 5.4, 6.4)
C_7	(5.4, 6.4, 7, 7.6)	(5.4, 6.4, 7, 7.8)	(5.4, 6.4, 7, 7.6)
C_8	(9, 10, 10, 10)	(4.2, 5.2, 6, 6.8)	(3.6, 4.6, 5.4, 6.4)
C_9	(1313.2,1467.7, 1622.2, 1776.7)	(1212.0, 1354.6, 1497.2, 1639.8)	(1158.6, 1294.9, 1431.2, 1567.5)

The following technique is used to construct the weighting matrix in step 3: Table 4.1 is also available for decision makers to use to assign a rating to each criterion. Table 5.4 shows the views of decision makers on various criteria. Eq. 5 can be used to measure the weight of each criterion, and Eq. 6 can be used to integrate the average weighting matrix in step 4. To make it clearer, w_1 is calculated as follow:

$$\widetilde{w}_1 = (((0, 0, 0, 0.1) \oplus (0.5, 0.6, 0.7, 0.8) \oplus (0.7, 0.8, 0.9, 1) \oplus \ldots$$
$$(0.4, 0.5, 0.5, 0.6) \oplus (0.2, 0.3, 0.4, 0.5)) / 5)$$
$$\widetilde{w}_1 = (0.36, 0.44, 0.5, 0.6)$$
$$\kappa(\widetilde{w}_1) = (0.36 + 0.44 + 0.5 + 0.6 - ((0.5 \text{ x } 0.6 - 0.36 \text{ x } 0.44) / \ldots$$
$$(0.5 + 0.6 - (0.36 + 0.44)) /3$$
$$\widetilde{w}_1 = 0.476$$

Table 5.4: Decision Makers' Opinions on Criteria importance

	D_1	D_2	D_3	D_4	D_5
C_1	LT	H	VH	M	L
C_2	M	HT	H	HT	HT

C_3	HT	HT	HT	VH	HT
C_4	HT	HT	VH	HT	HT
C_5	HT	HT	HT	VH	HT
C_6	VL	HT	VH	HT	HT
C_7	H	VH	VH	HT	HT
C_8	M	H	VH	VH	VL
C_9	H	H	H	VH	H

The average solutions matrix is created in step 5 as follows: The average solutions matrix displays average output values for each criterion. The following is an example of a calculation for the first alternative:

$$\widetilde{av}_1 = (((3.2, 4.2, 5.2, 6.2) \oplus (5.2, 6.2, 7, 7.8) \oplus (7.6, 8.6, 8.8, 9.2)) / 3)$$

$$\widetilde{av}_1 = (5.33, 6.33, 7, 7.73)$$

As in step 6, distance from averages matrices are calculated as follows: In terms of each criterion, the positive and negative deviations from the average solution are determined for each alternative. If the criterion is beneficial or not, the calculations vary. Calculations of the $\widetilde{pda}$ is the inverse of calculations of the $\widetilde{nda}$. The below are examples of estimates both for non-beneficial and beneficial criteria:

$\widetilde{pda}$ for beneficial criterion:

$$\widetilde{pda}_{31} = ((7.6, 8.6, 8.8, 9.2) \ominus (5.33, 6.33, 7, 7.73)) / 6.59$$

$$\widetilde{pda}_{31} = (-0.02, 0.24, 0.37, 0.59)$$

$\widetilde{pda}$ for cost criterion:

$$\widetilde{pda}_{39} = ((1227.94, 1372.41, 1516.87, 1661.34) \ominus (1158.65, 1294.96, 1431.27, 1567.58)) / 1444.64$$

$$\widetilde{pda}_{39} = (-0.348, -0.154, 0.041, 0.235)$$

The weighted sums of distances are computed in step 7 using the values from the previous step. Eqs. 13 and 14 will be used to measure the weighted total of both positive and negative distances for each alternative. The values for the third alternative are seen in the calculations below.

$$\tilde{w}_1 \otimes \widetilde{pda}_{31} = (0.36, 0.44, 0.5, 0.6) \otimes (-0.02, 0.24, 0.37, 0.59)$$

$$\tilde{w}_1 \otimes \widetilde{pda}_{31} = (-0.0073, 0.1069, 0.1872, 0.352185)$$

$$\widetilde{ps}_3 = (-1.307, -0.087, 0.920, 2.519)$$

In step 8, the weighted sums of distances are normalized. The maximum crisp value for $\widetilde{ps}_i$ in the third choice is determined to be 0.529709. This value would be used to normalize each alternative's $\widetilde{ps}_i$ values. The maximum crisp value for $\widetilde{ns}_i$ in the first alternative is determined to be 0.383094. This value will also be used to normalize each alternative's $\widetilde{ns}_i$ values. The $\widetilde{nps}_i$ and $\widetilde{nns}_i$ calculations for the third alternative are given below as explanations:

$$\widetilde{nps}_3 = (-1.307, -0.087, 0.920, 2.519) / 0.529709$$

$\widetilde{nps}_3 = (-2.468, -0.164, 1.738, 4.755)$

$\widetilde{nps}_3 = 1 - (-0.181, 0.035, 0.225, 0.459) / 0.383094$

$\widetilde{nps}_3 = (-0.197, 0.413, 0.908, 1.474)$

Step 9 calculates the assessment scores ($\widetilde{as}_i$) for each alternative, as seen below:

$\widetilde{as}_1 = ((-0.912, -0.211, 0.392, 1.262) \oplus (-4.652, -0.947, 1.587, 4.212)) /2$

$\widetilde{as}_1 = (-2.8415, -0.9584, 0.3927, 1.9944)$

$\widetilde{as}_2 = ((-2.141, -0.713, 0.730, 2.860) \oplus (-2.048, 0.116, 1.534, 3.216)) / 2$

$\widetilde{as}_2 = (-2.094, -0.298, 1.132, 3.038)$

$\widetilde{as}_3 = ((-2.468, -0.164, 1.738, 4.755) \oplus (-0.197, 0.413, 0.908, 1.474)) / 2$

$\widetilde{as}_3 = (-1.333, 0.125, 1.323, 3.114)$

In the final step of the fuzzy EDAS process, step 10, the alternatives will be ranked using the defuzzification technique described in Eq. 3. The highest ($\widetilde{as}_i$) score indicates the best alternative:

$\kappa(\widetilde{as}_1)$ = 0.0703

$\kappa(\widetilde{as}_2)$ = 0.4496

$\kappa(\widetilde{as}_3)$ = 0,8234

The survey data and cost data are added in the direction determined in the previous section. As per the fuzzy EDAS method, the pioneering alternative is the industrial site warehouse, which has more benefits in production volume and stock-out cost criteria could be seen from above.

5.1.3 Fuzzy TODIM Application

As previously said, the very first steps of fuzzy EDAS & fuzzy TODIM methods are similar; hence, the very same criteria weighting and performance evaluation phases used in fuzzy EDAS can be used in fuzzy TODIM. We'll go forward to normalizing performance metrics. Eq. 18 is used for normalizing the value of performance. The below is a brief sample of normalization with both benefit and cost criteria:

For benefit criteria:

$$\tilde{P}_{11} = \frac{3.2}{9.2}, \frac{4.2}{8.8}, \frac{5.2}{8.6}, \frac{6.2}{7.6}$$

$$\tilde{P}_{11} = \frac{3.2}{9.2}, \frac{4.2}{8.8}, \frac{5.2}{8.6}, \frac{6.2}{7.6} = (0.348, 0.477, 0.605, 0.816)$$

For cost criteria:

$$\tilde{P}_{19} = \frac{1776.67}{1158.65}, \frac{1622.18}{1294.96}, \frac{1467.68}{1431.27}, \frac{1313.19}{1567.58} = (0.652, 0.798, 0.975, 1.194)$$

In step 4, the normalization technique is extended to all criteria based on the alternatives, and a normalized $\overline{G}^{v}$ matrix is formed, as can be seen in Table 5.5:

Table 5.5: Normalized $\overline{G}^{v}$ matrix

	A_1	A_2	A_3
C_1	(0.348, 0.477, 0.605, 0.816)	(0.565, 0.705, 0.814, 1.026)	(0. 826, 0.977, 1.023, 1.211)

C_2	(0.304, 0.432, 0.558, 0.763)	(0.543, 0.682, 0.767, 0.974)	(0.826, 0.977, 1.023, 1.211)
C_3	(0.333, 0.447, 0.565, 0.756)	(0.667, 0.787, 0.870, 1.073)	(0.854, 0.979, 1.022, 1.171)
C_4	(0.667, 0.822, 0.952, 1.162)	(0.667, 0.822, 0.952, 1.189)	(0.771, 0.933, 1.071, 1.297)
C_5	(0.727, 0.902, 1.026, 1.265)	(0.773, 0.951, 1.051, 1.294)	(0.568, 0.732, 0.872, 1.118)
C_6	(0.780, 0.949, 1.054, 1.281)	(0.537, 0.692, 0.865, 1.156)	(0.439, 0.590, 0.730, 1.000)
C_7	(0.692, 0.914, 1.094, 1.407)	(0.692, 0.914, 1.094, 1.444)	(0.692, 0.914, 1.094, 1.407)
C_8	(0.900, 1.000, 1.000, 1.111)	(0.420, 0.520, 0.600, 0.756)	(0.360, 0.460, 0.540, 0.711)
C_9	(0.652, 0.798, 0.975, 1.194)	(0.707, 0.865, 1.056, 1.293)	(0.739, 0.905, 1.105, 1.353)

Phase 5 involves calculating relative criteria weights based on expert perspectives on criteria importance. As shown below, relative criteria weights are calculated by dividing normalized criteria weights by the reference criterion weight in Eq. 19:

$$\tilde{w}_{c_1} = (0.360, 0.440, 0.500, 0.600\ )$$

$$\tilde{w}_r = (\ 0.860, 0.960, 0.980, 1.000\ )$$

$$\tilde{w}_{rc_1} = \tilde{w}_{c_1} \oslash \tilde{w}_r = (0.360, 0.449, 0.521, 0.698\ )$$

The preceding formula yields the total relative criteria weights, which are shown in Table 5.6.

Table 5.6: Relative Criteria Weights

	$\widetilde{w}_{c_j}$	$\widetilde{w}_{rc_j}$
C_1	(0.360, 0.440, 0.500, 0.600)	(0.360, 0.449, 0.521, 0.698)
C_2	(0.720, 0.820, 0.840, 0.880)	(0.720, 0.837, 0.875, 1.023)
C_3	(0.860, 0.960, 0.980, 1.000)	(0.860, 0.980, 1.021, 1.163)
C_4	(0.860, 0.960, 0.980, 1.000)	(0.860, 0.980, 1.021, 1.163)
C_5	(0.860, 0.960, 0.980, 1.000)	(0.860, 0.980, 1.021, 1.163)
C_6	(0.680, 0.780, 0.820, 0.860)	(0.680, 0.796, 0.854, 1.000)
C_7	(0.740, 0.840, 0.900, 0.960)	(0.740, 0.857, 0.938, 1.116)
C_8	(0.460, 0.560, 0.640, 0.740)	(0.460, 0.571, 0.667, 0.860)
C_9	(0.540, 0.640, 0.740, 0.840)	(0.540, 0.653, 0.771, 0.977)

In step 6, dominance matrices are generated for each criterion. This move shows how each alternative stacks up against the others for a criteria provided. Dominance matrices are calculated using Eq. 20, and the dominance matrix for the first criterion when θ is equal to 1 can be seen below.

$$\tilde{P}_{21} = (0.565, 0.705, 0.814, 1.026)$$

$$\tilde{P}_{12} = (0.348, 0.477, 0.605, 0.816)$$

$$\tilde{P}_{21} > \tilde{P}_{12}$$

$$\mathrm{d}(\tilde{P}_{21}, \tilde{P}_{12}) = \sqrt{\frac{[\ (0.565 - 0.348\ )^2 + 2\,(0.705 - 0.477)^2 + 2(0.814 - 0.605)^2\ + (1.026 - 0.816\ )^2]}{6}} = 0.21698$$

$$\tilde{\phi}_{c_1}(A_{a_2}, A_1) = \sqrt{\frac{(0.36,\ 0.44897,\ 0.52083,\ 0.69767)}{(6.08, 7.10204, 7.6875, 9.16279)}} * \ 0.21698$$

$$= (0.09233, 0.11257, 0.12614, 0.15779)$$

$$\tilde{\phi}_{c_1}(A_{a_1}, A_2) = -\frac{1}{1}\sqrt{\frac{(6.08,\ \ 7.10204,\ \ 7.6875,\ \ 9.16279)}{(0.36,\ \ 0.44897,\ \ 0.52083,\ \ 0.69767)} * 0.21698}$$

$$= (-2.35006, -1.92751, -1.72012, -1.37513)$$

$$\tilde{\phi}_{c_1} = \begin{bmatrix} (0,0,0,0) & (0.092, 0.112, 0.126, 0.157) & (0.116, 0.142, 0.159, 0.199) \\ (-2.350, -1.927, -1.720, -1.375) & (0,0,0,0) & (0.085, 0.104, 0.117, 0.146) \\ (-3.398, -2.787, -2.487, -1.988) & (-2.458, -2.016, -1.799, -1.438) & (0,0,0,0) \end{bmatrix}$$

Eq. 21 is used to calculate the overall dominance matrix in step 7, as seen in the example below. We averaged these dominance values after measuring each alternative's dominance with each criterion to arrive at an aggregate dominance score for each alternative. The below are the figures for the overall dominance matrix:

$\tilde{\delta}(A_{a_1}, A_2) = \tilde{\phi}_{c_1}(A_{a_1}, A_2) + \tilde{\phi}_{c_2}(A_{a_1}, A_2) + \ldots + \tilde{\phi}_{c_9}(A_{a_1}, A_2)$

= (0.092, 0.112, 0.126, 0.157) + (0.134, 0.157, 0.167, 0.196) + ... +(0.067, 0.080, 0.091, 0.111)

$= (-4.053, -3.160, -2.732, -1.999)$

The dominance values matrix becomes transposed in step 8 and introduced as follows:

$$\Delta = \begin{bmatrix} (0,0,0,0) & (-8.2, -6.8, -6.2, -5.1) & (-10.3, -8.5, -7.7, -6.3) \\ (-4.1, -3.2, -2.7, -2.0) & (0,0,0,0) & (-7.3, -6.0, -5.5, -4.5) \\ (-5.1, -4.0, -3.5, -2.7) & (-3.0, -2.4, -2.1, -1.6) & (0,0,0,0) \end{bmatrix}$$

In phase 8, total values are calculated across all alternatives: Each alternative is represented by a row in the overall dominance matrix. The total value of each row is used to calculate the average ranking value of each alternative. As an example, the overall ranking value of the first alternative is determined as follows:

$\sum \tilde{\delta}(A_{a_1}, A_{a_i})$ = [(0, 0, 0, 0) ⊕ (-8.196, -6.804, -6.194, -5.073) ⊕ (-10.319, -8.524, -7.740, -6.290)] = (-18.515, -15.328, -13.934, -11.363)

$$\sum \tilde{\delta}(A_{a_2}, A_i) = (-11.351, -9.188, -8.212, -6.458)$$

$$\sum \tilde{\delta}(A_{a_3}, A_i) = (-8.059, -6.399, -5.654, -4.293)$$

The following is how to calculate the normalized global values of the each alternative in step 9:

$$\tilde{\xi}_1 = \frac{(-18.515,-15.328,-13.934,-11.363)\ominus(-18.515,-15.328,-13.934,-11.363)}{(-8.059,-6.399,-5.654,-4.293)\ominus(-18.515,-15.328,-13.934,-11.363)}$$

= (-0.503, -0.144, 0.185, 2.165)

$$\tilde{\xi}_2 = \frac{(-11.351,-9.188,-8.212,-6.458)\ominus(-18.515,-15.328,-13.934,-11.363)}{((-8.059,-6.399,-5.654,-4.293)\ominus(-18.515,-15.328,-13.934,-11.363)}$$

= (0.001, 0.491, 0.944, 3.650)

$$\tilde{\xi}_3 = \frac{(-8.059,-6.399,-5.654,-4.293)\ominus(-18.515,-15.328,-13.934,-11.363)}{(-8.059,-6.399,-5.654,-4.293)\ominus(-18.515,-15.328,-13.934,-11.363)}$$

= (0.232, 0.779, 1.284, 4.305)

The defuzzification procedure is extended to $\kappa(\xi_i)$ values in order to list the alternatives as in step 10. In this stage, the alternative with the best score is the best alternative.

$$\kappa(\xi_1) = \frac{1}{3}\left(-0.503 - 0.144 + 0.185 + 2.165 - \frac{0.185 * 2.165 - (-0.503 * -0.144)}{(0.185 + 2.165\ ) - (\ -0.503 - 0.144\ )}\right)$$

$$= 0.5312$$

$$\kappa(\xi_2) = \frac{1}{3}\left(0.01 + 0.491 + 0.944 + 3.650 - \frac{0.944 * 3.650 - 0.001 * 0.491}{(0.944 + 3.650\ ) - (\ 0.001 + 0.491)}\right) = 1.4151$$

$$\kappa(\xi_3) = \frac{1}{3}\left(0.232 + 0.779 + 1.284 + 4.305 - \frac{1.284 * 4.305 - 0.232 * 0.779}{(\ 1.284 + 4.305\ ) - (\ 0.232 + 0.779\ )}\right) = 1.8106$$

To determine the impact of risk on outcomes, a sensitivity analysis is used. 2, 2.5, 4, and 7 are the new values for the θ parameter. Table 5.7 shows the findings:

Table 5.7: Sensitivity Analysis of overall values for different θ values

	$\kappa(\xi_i)$values				
Alternatives	θ = 1	θ = 2.5	θ = 3	θ = 4	θ = 7
Container	0.531	0.602	0.626	0.675	0.826
Modular	1.415	1.521	1.557	1.631	1.866
Ind. Site W.	1.811	1.959	2.010	2.114	2.441

5.2 Smart Vertical Farm Technology Selection

In an urban setting, the WEDBA and MACBETH methodologies are used to evaluate three smart farm solutions. To begin, the WEDBA technique is used to rank the alternatives. Then, to check the answer, we used the MACBETH approach, which mainly relies on qualitative judgements.

A panel of decision-makers evaluated three urban farm possibilities for previous application. The first option was to build a hydroponics in a vessel container that could be placed anywhere. The second option was to design a modular farm in a scalable facility that could be moved around depending on the available space. The last option was to convert an industrial site warehouse into a plant factory. Within the possibilities, the last choice was chosen as the finest.

For this application, I evaluated three smart farm choices and asked a panel of three experts for their thoughts. A farmer is the first expert, an entrepreneur is the second, and a data scientist is the third. Alternatives are planned as hydroponic farms erected on an industrial site warehouse, based on the prior assessment. LED lighting, climate control, vertically arranged farming slots, a 200 m2 space, and harvest equipment are all common aspects among the alternatives.

The very first alternative, Basic, is just a simple design. The system functions similarly to that of a regular farm. The farm's essential parameters are manually maintained by the farmer. The farmer pays special attention to pH, EC, moisture, and heat. IoT is the second option, and it has IoT capabilities. Sensors are used to collect the farm's data, as mentioned above. The farmer interacts with the system based on the information gathered. Because the technology is IoT-enabled, the farmer can monitor the farm from afar. The third option, Automation, combines automation with AI aid. The ability to automate reduces the need for human involvement. According on the data obtained, the system performs the appropriate measures. When the heat falls below a certain threshold, for example, it automatically activates the air conditioning system. AI is being used to improve the manufacturing process. Plant development data is analysed using machine learning algorithms in order to harvest the finest crop possible.

Each option has its own set of setup expenses. Table 5.8 shows a quick cost calculation of the various options. Due to high energy and advanced technology requirements, indoor farming is not an economically feasible method in Turkey yet. I tried to avoid detailed calculations for alternatives and simply added today’s technology costs to cost data given in Table 5.1 for Industrial site warehouse alternative As a non-beneficial feature, cost is included in the computations.

Table 5.8: Expected cost data of alternatives

Alternative	Cost (TL, 2020)
Basic	(1227,1371,1516,1660)
IoT	(1240,1386,1532,1678)
Automation	(1278,1429,1579,1730)

5.2.1 Criteria

Researchers are interested in smart farming and related fields, however there has been no prior research on technology selection and MCDM in precision agriculture. Experts and scholars are the primary contributors to developing evaluation criteria given the lack of previous literature. For the purpose of evaluating alternatives, the following criteria have been established:

(C1) Venture Capital Attractiveness: Indoor agriculture, particularly vertical farming, is a viable sector for government, entrepreneurs, and universities to engage in. However, the level of interest varies depending on the sort of vertical farming. The issue is growing prominence throughout the world, and because it is still relatively new, more start-ups are entering the market. Agricultural initiatives are frequently supported by multi-national entities such as the European Union (EU).

(C2) Effective Manufacturing Processes: The most significant advantage of urban farming is the production environment. A farmer may create the ideal environment for plant development. The producer should keep an eye on the market and adjust the production pace and variety as needed.

(C3) Workforce Requirement: Even though some alternatives give smaller planting grounds, they all require labor, at the very least for plant collection. Because the suggested technologies are more difficult than traditional food production methods, a well-educated staff is critical. This circumstance raises the cost of labor and lengthens the time it takes to train new employees.

(C4) Security: Plant production that may be customized and a flexible production method that varies by firm. The company's manufacturing method, cybersecurity, and agricultural rotations are all valuable assets.

(C5) Space Requirement: Smart farming maximizes crop yield per unit of land. Land in the city is both expensive and scarce. The producer must determine how the available space will be distributed.

(C6) R&D Capabilities: It is feasible to grow new species, produce local plants, and unique plants since environmental elements are entirely changeable. Alternatives provide a variety of benefits in terms of reducing crop cycles and improving product quality.

(C7) Expansion Opportunities: Manufacturers may adjust production output in response to market demand. Initial investment expenditures and set-up time are factors in expanding a firm and establishing new plant facilities.

(C8) Investment and Maintenance Costs: Urban agriculture is a complicated process that necessitates the use of pricey production equipment as well as valuable urban area. The initial investment varies depending on the options.

5.2.2 WEDBA Application

The theoretical foundations of the WEBDA method are outlined above. The implementation of the given protocol will be demonstrated in this section:
Step 1 : Average Decision Matrix. The first step, according to the procedure, is to create a decision matrix. Table 4.1 provides qualitative assessments for decision-makers to use in evaluating alternatives. Table 5.9 shows decision-makers' evaluations of alternatives based on every criterion.

Table 5.9: DM's evaluation on performance of each alternative

	DM_1			DM_2			DM_3		
	A_1	A_2	A_3	A_1	A_2	A_3	A_1	A_2	A_3
C_1	MG	G	MG	MG	G	VG	MG	G	VG
C_2	M	G	VG	M	G	VG	G	G	VG
C_3	MP	MG	VG	M	G	G	MG	MG	G
C_4	G	MG	MG	VG	G	G	G	MG	MG
C_5	P	M	M	MG	G	VG	M	MG	G
C_6	MP	G	VG	MG	G	VG	MG	VG	VG
C_7	M	G	G	VG	G	MG	VG	G	G

Eq (24) is used to assess the overall decision matrix. The following is an example calculation for $\tilde{d}_{13}$:

$$\tilde{d}_{13} = \frac{1}{3}((2, 3, 4, 5) + (4, 5, 5, 6) + (5, 6, 7, 8)) = (3.67, 4.67, 5.33, 6.33)$$

Table 5.10 demonstrates the average decision matrix.

Table 5.10: Average Decision Matrix

	DM_1	DM_2	DM_3
	(5, 6, 7, 8)	(7, 8, 9, 10)	(7.67, 8.67, 9, 9.33)
C_1	(5, 6, 6.33, 7.33)	(7, 8, 9, 10)	(9, 10, 10, 10)
C_2	(3.67, 4.67, 5.33, 6.33)	(5.67, 6.67, 7.67, 8.67)	(7.67, 8.67, 9.33, 10)
C_3	(7.67, 8.67, 9.33, 10)	(5.67, 6.67, 7.67, 8.67)	(5.67, 6.67, 7.67, 8.67)
C_4	(3, 4, 4.67, 5.67)	(5.33, 6.33, 7, 8)	(6.67, 7.67, 8, 8.67)
C_5	(4, 5, 6, 7)	(7.67, 8.67, 9.33, 10)	(9, 10, 10, 10)
C_6	(7.33, 8.33, 8.33, 8.67)	(7, 8, 9, 10)	(6.33, 7.33, 8.33, 9.33)
C_7	(5, 6, 7, 8)	(7, 8, 9, 10)	(7.67, 8.67, 9, 9.33)

Eq (25) is used to measure the defuzzied values from the judgments. The following is an example of calculation for d_{13}:

$$d_{13} = \frac{3.67 + 2*4.67 + 2*5.33 + 6.33}{6} = 5$$

Table 5.11 demonstrates the defuzzied average decision matrix.

Table 5.11: Standardized decision matrix

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	-1.41	-1.32	-1.26	1.41	-1.34	-1.39	0.14	0.99
A_2	0.59	0.22	0.08	-0.71	0.28	0.46	1.15	0.38
A_3	0.82	1.1	1.18	-0.71	1.06	0.93	-1.29	-1.37

In step 3 ideal and anti-ideal points are determined for each criterion from the standardized decision matrix. Ideal point (a) is the highest attribute value and anti-ideal point (b) is the lowest attribute value of each criterion. For C_1:

In step 3, the standardized decision matrix is used to establish ideal (a^*) and anti-ideal (b^*) points for every criterion. Each criterion's ideal point is the highest attribute score, while the anti-ideal point is the lowest. Following are the ideal and anti-ideal points for C_1:

a_1^* = 0.815

b_1^* = -1.408

Calculating criteria weights is the next step. The weights of objective and subjective criteria are combined to create integrated criteria weights. The objective criteria weights are determined using equations (33) to (36) as previously stated. The following is an example of how to calculate C_1's objective criterion weight:

$r_{11} = \frac{6.5}{6.5+8.5+8.72} = 0.274$

$E_1 = \frac{-(0.274*ln0.274+ 0.358*ln0.358+0.368*ln0.368)}{\ln 3} = 0.992$

$l_1 = 1- E_1 = 1-0.992 = 0.008$

$w_1 = \frac{0.008}{0.105} = 0.72$

The process outlined above is used to measure subjective criteria weights. The significance of criteria as judged by decision-makers is seen in Table 5.12. The following is an example of how to calculate C_1's subjective criteria weight:

Table 5.12: Decision maker’s evaluation for each criterion

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
D_1	VH	M	H	M	H	VH	H	VH
D_2	HT	M	M	VH	M	H	HT	HT
D_3	H	VH	VH	M	L	HT	VH	HT

$\widetilde{w}_1 = \frac{1}{3}$ ((0.7, 0.8, 0.9, 1.0) + (0.9, 1.0, 1.0, 1.0) + (0.5, 0.6, 0.7, 0.8))

= (0.7, 0.8, 0.87, 0.93)

$w_1 = \frac{0.7+ 2*0.8 + 2*0.87 + 0.93}{6} = 0.828$

The weights of integrated criteria are determined using Eq (39). As an example, the integrated criterion weight for C_1 is computed as follows:

$w_1^i = \frac{0.72 * 0.828}{0.669} = 0.089$

w_j^i = [0.089, 0.142, 0.233, 0.046, 0.179, 0.304, 0.006, 0.002]

Calculating WED’s of alternatives and calculating index scores are the final steps of the WEDBA. Eqs (40) and (41) measure the distances between alternatives and ideal and anti-ideal points, respectively.

$$WED_1^+ = [\,\{0.89 * (-1.408 - 0.815)\}^2 + \{0.142 * (-1.32 - 1.1)\}^2 + \cdots]^{1/2}$$

$= 1.078$

$WED_2^+ = 0.362$

$WED_3^+ = 0.099$

$WED_1^- = [\{0.89 * (-1.408 - 1.408)\}^2 + \{0.142 * (-1.32 - 1.32)\}^2 + \cdots]^{1/2}$

$= 0.097$

$WED_2^- = 0.759$

$WED_3^- = 1.078$

Index Score$_1 = \frac{0.097}{1.078 + 0.097} = 0.083$

Index Score$_2 = 0.677$

Index Score$_3 = 0.917$

As previously stated, a higher index score suggests closer proximity to the ideal point, while the highest index score signifies the best option. Alternatives are ranked using index scores as Auto (Alt 3) – IoT (Alt 2) – Basic (Alt 1).

5.2.3 MACBETH Application

The MACBETH Method is also applied to solve the same problem. The M-MACBETH package is a useful tool for MACBETH problems. As discussed in the theoretical part, the implementation began with the creation of a decision tree. Figure 5.1 depicts the decision tree of criteria:

Figure 5.1: Decision Tree

The type of criterion and scale should be implemented to M-MACBETH as seen in Figure 5.2 so MACBETH assists the researcher to use either a quantitative or qualitative comparative basis.

Decision-makers expressed their opinions on alternative performance using the phrases mentioned in Table 4.3. M-MACBETH program is used to join qualitative evaluations for each criterion. A criterion's appraisal scale is seen in Figure 5.3. For advantageous criteria, ‘VG' denotes the most appealing result, while ‘VP' denotes the least appealing performance. When it comes to cost criteria, the assessment process is reversed. The attractiveness levels are inserted in decreasing order, as seen in Figure 5.3. The relationship between performance standards is determined by the decision-maker. By providing frequent accuracy notifications and preparing the evaluation scale accordingly, the app assists decision-makers in staying within a feasible area.

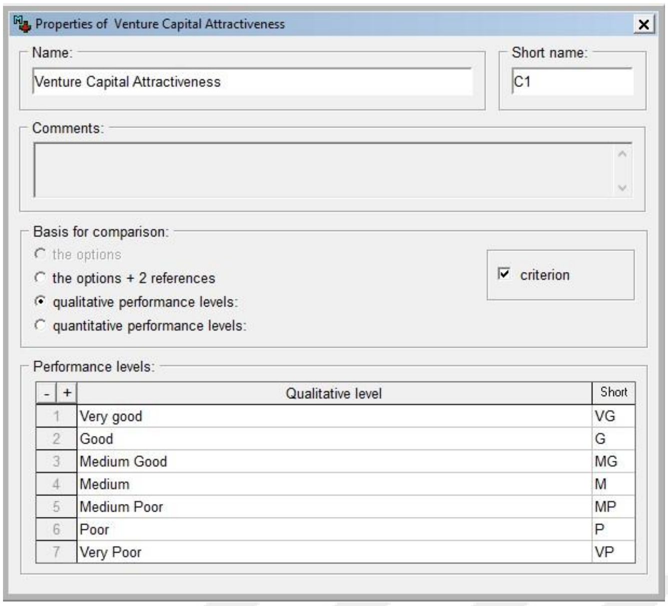
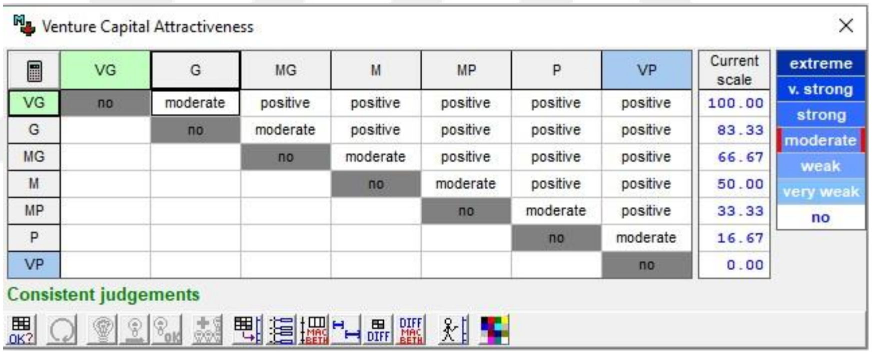


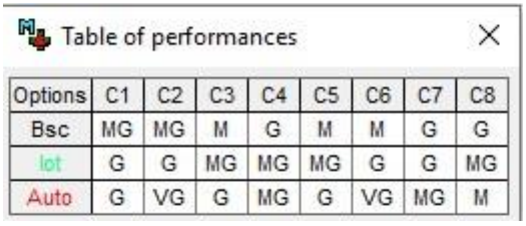
Figure 5.2: Criteria assessment levels



	VG	G	MG	M	MP	P	VP	Current scale
VG	no	moderate	positive	positive	positive	positive	positive	100.00
G		no	moderate	positive	positive	positive	positive	83.33
MG			no	moderate	positive	positive	positive	66.67
M				no	moderate	positive	positive	50.00
MP					no	moderate	positive	33.33
P						no	moderate	16.67
VP							no	0.00

Figure 5.3: Scaling of assessment levels

Following the preparation of assessment scales with each criterion, the decision-maker assesses each alternative's success on each criterion using the assessment scales. Figure 5.4 shows the output values of the various alternatives.



Options	C1	C2	C3	C4	C5	C6	C7	C8
Bsc	MG	MG	M	G	M	M	G	G
Iot	G	G	MG	MG	MG	G	G	MG
Auto	G	VG	G	MG	G	VG	MG	M

Figure 5.4: Table of Performances

Creating assessment scales for criteria is quite close to preparing criteria weighting. The criteria should be sorted in ascending order by the decision-maker. M-MACBETH creates a weight scale based on the relative value of the criteria. Figure 5.5 depicts the significance of criteria and the total weighting of criteria.

Weighting (Hydroponics selection criteria)

	[C6]	[C3]	[C5]	[C2]	[C1]	[C4]	[C7]	[C8]	VERY POOR	Current scale
[C6]	no	moderate	positive	positive	positive	positive	positive	positive	positive	25.00
[C3]		no	weak	positive	positive	positive	positive	positive	positive	20.31
[C5]			no	very weak	positive	positive	positive	positive	positive	17.18
[C2]				no	moderate	positive	positive	positive	positive	15.62
[C1]					no	moderate	positive	positive	positive	10.94
[C4]						no	weak	positive	positive	6.25
[C7]							no	very weak	positive	3.13
[C8]								no	positive	1.57
VERY POOR									no	0.00

extreme
v. strong
strong
moderate
weak
very weak
no

Consistent judgements

Figure 5.5: Criteria weighting

Figure 5.6 shows the overall results and ranking of the alternatives. Alternatives are ranked using the MACBETH process as Auto (Alt 3) – IoT (Alt 2) – Basic (Alt 1).

Table of scores

Options	Overall	C1	C2	C3	C4	C5	C6	C7	C8
VERY GOOD	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Auto	88.02	83.33	100.00	83.33	66.67	83.33	100.00	66.67	50.00
Iot	75.78	83.33	83.33	66.67	66.67	66.67	83.33	83.33	66.67
Bsc	58.08	66.67	66.67	50.00	83.33	50.00	50.00	83.33	83.33
VERY POOR	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Weights :		0.1094	0.1562	0.2031	0.0625	0.1718	0.2500	0.0313	0.0157

Figure 5.6: Overall scores and ranking of alternatives

5.3 Inferences and Discussions

Both applications provides valuable insights regarding the urban aggriculture. For first application, in the implementation of sustainable agriculture in urban areas, the industrial site warehouse alternative is picked in both of the solution approaches -fuzzy EDAS and fuzzy TODIM. Although this option has the greatest starting cost, comparing it to the others in total would be inappropriate due to its 200 m2 space. As a result, I computed the unit meter square cost of each choice. Of course, the industrial site warehouse option was the cheapest in that scenario. The beginning cost criteria has greater weight in the decision-making process in both ways, and that is why this alternative is chosen as the best. The modular option is the second best option since it offers greater flexibility and is less expensive. Although two or more containers might be combined, the container option is also versatile, but it imposes a volume limitation. Although the outcome is unexpected, in the market, stock-out costs are significant, and in order to make money, you must sell more in accordance with the product volume requirement. The fuzzy EDAS approach guarantees intervals based on the criteria's means, whereas the fuzzy TODIM approach assures a solution process for dangerous issues. The investment strategy in this vertical urban farming application field is undoubtedly hazy and risky. That is why I used the fuzzy EDAS approach and compared the findings with the fuzzy TODIM approach. Furthermore, the fuzzy TODIM approach guarantees that we use sensitivity analysis to guarantee that the results are reliable. As shown by the the Table 5.7 above, the appropriate sequence remains the same in all other risky possibilities. Both solution strategies provide outcomes that are more realistic.

In the second application, the auto option is selected as the preferred option in both approaches. R&D capabilities was given top priority by decision-makers. Investment expenses showed a surprising lack of influence on decision-makers. Due to high R&D competence expectations and small staff needs, the auto option performs effectively. Due to the low critical weight attributed to the cost criteria, the large initial investment cost of the alternative had minimal influence on the outcome. In terms of average investment cost and ease of growth, the IoT option came in second. Even though it has the lowest investment cost, the basic option is selected as the third option. The WEDBA technique rates the alternatives based on their lengths from the best and worst conceivable scenarios. The MACBETH approach assesses the options based on how appealing they are in comparison to one another. These findings are for only three possibilities; but, in my opinion, if the number of options or criteria is raised, the results given by two approaches may change.

6. CONCLUSION

As a conclusion, Agriculture has altered as a result of the industrial revolution and the use of synthetic fertilizers. For decades, mechanized agriculture has been the standard. Precision farming is set to become the standard in the Information age. Climate change, rising temperatures, and the expanding urban population are all pressing issues that need to be addressed. Sustainable agriculture in the city center or on the outskirts of a city is a sensible solution to the problem of food scarcity, especially in rapidly increasing and chaotic metropoles.

In this thesis, I attempted to present numerous solutions to the aforementioned challenge. As far as I know, this is the first time in the literature that an assessment procedure using MCDM approaches on technology selection for agricultural operations is presented. Furthermore, when the matter is fresh and ambiguous, there are unreliable data and viewpoints. After doing a literature search, the criteria for the assessment process were defined by a consensus among vertical farming farmers and agricultural engineers. Due of the ambiguity of the procedure, fuzzy MCDM was proposed for selection.

The fuzzy EDAS approach adapts to imprecise conditions in the first application, and it delivers superior results in this scenario since it measures deviations from the mean. Container, Modular, and Industrial Site Warehouse are the three options; the final one is selected using the fuzzy EDAS Method. This is appropriate since the production capacity and stock-out cost criteria were given high priority by all decision makers.

The Industrial Site Warehouse was also identified as the best option using the Fuzzy TODIM algorithm. Furthermore, owing to TODIM's risk-aware calculating procedure, the other two choices did not alter their rankings. The result's validity was guaranteed by the sensitivity analysis.

Throughout the second application, the Automation option outperformed the other options using both the MACBETH and WEDBA methodologies. The conclusions are plausible since decision-makers placed a high value on R&D capabilities and labor requirements.

I modified the earlier approach of the WEDBA method to incorporate multiple decision-makers and fuzzy linguistic ratings in the assessment process. The method responded nicely to my changes, and I was able to get regular results. The MACBETH approach is also used to test the proposed approach's accuracy. Because the MACBETH approach analyzes each choice with the others, discrepancies may be detected early in the process. Using both strategies, I was able to get the same outcomes.

Real-option Evaluation or the net present value methodology may be included in future research to solve the problem. Alternatives may be subjected to design and optimization studies. Modified alternatives can be subjected to a variety of MCDM approaches. For each option, many improved optimization offers may be available. Another future research proposal could be a location selection study for all options individually.

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BIOGRAPHICAL SKETCH

Murat Başar was born in İstanbul in 1989. He graduated from Bursa Işıklar Military High school and Turkish Military Academy with honor. He served in Turkish Army until 2019.

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