



A Bi-objective Model of Research and Development in Battery Manufacturing Industry to Improve Customer Satisfaction

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PAPER INFO

Paper history:

Received: 07 April 2022

Received in revised form: 30 June 2022

Accepted: 04 July 2022

Keywords:

Research and Development

Bi-objective Mathematical Model

Fuzzy Multi-criteria Decision Making

Battery Industry

Uncertainty

ABSTRACT

Reviewing the efficiency of Research and Development (R&D) by giving an equal amount of importance to different R&D actions can make the measuring process too simple, which may cause an inaccurate interpretation of the R&D function and lead to an imprecise interpretation of R&D models. R&D comprises the creative work undertaken on a systematic basis to increase the stock of knowledge, including knowledge of man, culture, and society, and the use of this stock of knowledge to devise new applications. This research provides a two-phase approach to designing an R&D model in the auto battery manufacturing industry based on customer satisfaction. Due to the important role of R&D in customer satisfaction, no study has been conducted in this field and industry. In the first phase, the effective models for R&D management and the indices influencing customer satisfaction in R&D models are identified. In the second phase, the significance coefficients related to the customer satisfaction indices are obtained by using the fuzzy SWARA (Stepwise Weight Assessment Ratio Analysis) as a multi-criteria decision-making method. Furthermore, each model's importance and final priority are calculated by the fuzzy COPRAS (Complex Proportional Assessment) method. Finally, to apply the proposed framework in the battery manufacturing industry, a bi-objective R&D model is presented. The coefficients obtained by the fuzzy COPRAS method are utilized as the input for the proposed model. Therefore, policy-makers and managers can perform their activities based on this method. The obtained results showed that the proposed framework is effective in the case under study.

doi: 10.5829/ije.2022.35.11b.03

NOMENCLATURE

V_m	Significance coefficient of model m	P_{mn}	Probability of risk due to customer dissatisfaction with the implementation of model m in manufacturer n (loss of customer)
W_{mn}	Capital required to select model m in manufacturer n	B_n	The amount of budget available to manufacturer n
L_{mn}	Expected sales through the introduction of a new product by model m in manufacturer n	x_{mn}	Is equal to one if method m is assigned to producer n otherwise it is zero
D_n	Number of models allowed to assign to manufacturer n	R_{mn}	Risk due to customer dissatisfaction with the implementation of model m in manufacturer n

1. INTRODUCTION

The role of knowledge in industrial economics has enhanced in recent decades; thus, industrial economics were named Knowledge-Based Economies (KBE) since the continuation of the growth of these economies relies on speeding up developments in technology and innovation. Hence, Research and Development (R&D) is

an important category of a knowledge-based economy that explains part of the technological revolution's factors [1]. Moreover, many researchers have reported R&D as an important factor in supporting the company's competitiveness and its influence on the competitiveness of the country [2]. Overall, government financial support could be frequently seen in industrialized countries. Indeed, it is argued that government grants will result in

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additional private investment [3]. R&D activities are taken into account as determining factors of productivity, growth, and competitiveness of firms [4].

Generally, R&D in companies embraces numerous activities and resources. These items contain basic research, applied research, development, and support activities like technology intelligence, technology forecasting, and market analysis [5].

The significance of R&D activities makes measuring R&D performance as a principal concern for companies [5-7]. As the complexity and diversity of technical and scientific knowledge have made R&D activities costly and risky, R&D performance measurement has become an essential issue for companies [8]. Overall, R&D managers have numerous reasons for measuring R&D performance: 1) The market is becoming more dynamic, customer needs are changing quickly, and the number of competitors is increasing; 2) Knowledge could be produced very rapidly, and thus the variety of products and services is greater, and 3) The complexity of knowledge in products and services is rising [5].

Employing structures and techniques to measure R&D performance upgrades a company's performance [9]. Nevertheless, uncontrollable factors turn R&D performance measurement into a challenging problem for managers [5]. In a survey in 1999, quantitative indices for assessing R&D in four perspectives on R&D performance, i.e., financial, customer, innovative and learning, and internal business processes were identified [6].

Nowadays, all industrialized or developing countries strive to elevate the volume of their research investments. In the meantime, industrialized countries invest in research for maintaining their position or increasing their superiority in international competition arenas. Developing countries have also understood that they have no choice but to invest in research to accomplish real growth and development and systematic resolving of their economic and social problems. Among the critical factors, which have led to the creation of a gap between countries, is the difference in their capability to carry out continuous innovation in all political, economic, cultural, and social aspects. Concerning the rapid growth of technology in the past two decades and the prediction of this process in the future, the scope of this gap will be undoubtedly aggravated over time in a case that proper measures are not taken. One of the approaches to deal with this challenge is to enhance innovation capability in the country via increasing R&D activities in various economic units [10].

Today, batteries are used in a variety of devices, including cell phones, laptops, and even cars. Just look around to see that almost all homes, work, and public places are filled with all kinds of large and small electronic devices and equipment that work with batteries. The number of batteries has increased so much

that they are considered an invisible part of various devices. The point is that despite the widespread use of batteries and easy access to them in various stores, there are signs that innovation in this area will be extremely exciting in the future. According to the International Energy Agency's Sustainable Development Scenario, batteries with a capacity of nearly 10,000 MWh will be needed annually by 2040. This is while about 200 GWh are needed today. This issue can be studied from the two following aspects:

- An extensive and immediate demand can be a great opportunity for the development of innovations.
- A great need for technological advances is required to find new solutions for energy storage in large quantities and at an affordable price.

The European Patent Office (EPO) and the International Energy Agency (IEA) have conducted a joint study analyzing patents in the field of batteries and electricity storage from 2005 to 2018. According to this report, the patent activity in this area has experienced annual growth of 12%, which is four times faster than the average growth rate in all technology areas [11].

Therefore, about the listed descriptions, the objective of this study was to propose a two-step decision-making approach for evaluating R&D models in the automotive battery industry emphasizing customer satisfaction. In the first section, the models influencing the R&D management and the indicators affecting customer satisfaction on R&D models are detected. In the second section, the weighting coefficients associated with customer satisfaction indices are achieved using the fuzzy Stepwise Weight Assessment Ratio Analysis (SWARA) technique. Additionally, the weight of each model and their ultimate prioritization are calculated using the fuzzy Complex Proportional Assessment (COPRAS) method. In the second step, a Bi-Objective Mathematical Programming (BOMP) model is offered to allocate optimal models to the automotive battery industry. Eventually, due to the bi-objective nature of the proposed model, the Augmented Epsilon Constraint Method will be exploited to solve the mathematical model. Subsequently, the structure of the research is broken down as follows.

The second section deals with the research literature. The third section explains the research methodology. The fourth section provides the case study and the framework of the proposed indexes. The fifth section addresses the discussion on the results of calculations. Finally, an overall conclusion and some recommendations for further studies are presented in the sixth section.

2. THEORETICAL BASIS AND LITERATURE REVIEW

In this section, investigating the theoretical basis, literature review, and the research gap will be addressed.

2. 1. Research and Development (R&D) R&D is referred to as a set of novel, creative, innovative, systematic, and planned activities, which generally is carried out to spread the boundaries of scientific cognition and the treasure of human knowledge and human society and the application of this knowledge in various domains to promote human life, briefly for the innovation and establishment of new products, processes, equipment, tools, systems, services, and approaches [12]. At present, R&D activities are recognized as the driving and central factor for all firms' industrial and economic development and are considered among the most crucial agents in strengthening countries' technological potential and economic growth. There are various techniques and mechanisms for technology development through R&D, such as Internal R&D, Joint R&D, R&D Contract, and R&D outsourcing [13].

Similar to R&D units, functional units need a specific model to advance their unit's objectives. These models should be designed in a coordinated and synchronized manner with the models of a company. R&D models comprise the definition of the set of R&D projects needed to accomplish the specified goals in the sphere of technology acquisition set in the framework of a company's overall model. Among the essential R&D models that could be pointed out are the implementation models of R&D. Domestic execution of R&D projects, cooperation, or outsourcing projects are the approaches addressed in various references.

Assessing the success of organizations in the exploitation of the domestic R&D spillover or buying it from foreign companies and the linkage of these two items with the absorptive capacity of organizations demonstrate that organizations with the same absorption capacity placed in more advanced economic conditions and settings are more successful in exploiting R&D spillovers [14]. R&D outsourcing causes an enhancement in the knowledge of organizations. That is, what these organizations can do (competencies) will be upgraded; however, what they should avoid (costs) will be transparent to organizations. Furthermore, conducting R&D in developed countries leads to promoting the level of R&D [15]. There are two primary models in the acquisition and use of knowledge for R&D, one is to limit the scope of knowledge, and the other is its diversity. The results gained from investigations reveal that control on the scope of knowledge flow in particular fields has overall a more significant influence on the sale of new products. Internal and external R&D outsourcing will differently affect innovation performance, and the number of these contracts is impressive on the mode of transfer and the achieved results [16].

2. 2. Customer Satisfaction Customers are people or processes that buy the product or result from a performance that they need and benefit from. Since any performance in an organization is undoubtedly done with

a purpose, so it has customers as well. Customer orientation is taken into account as a critical factor in the success of organizations. One of the most important theoretical and experimental matters for many marketers and marketing researchers is customer satisfaction [17]. Customer satisfaction is regarded as a condition that a person has experienced, which is associated with assessing the hypothetical characteristics of products and expectations of that person about those features. Besides, customer satisfaction is defined as service quality performance levels that meet users' expectations. Assessing customer satisfaction offers a salient and objective view of their choices and beliefs. Customer surveys can contribute to resolving the discrepancy between expectations and satisfaction. The current competition worldwide persuades R&D organizations to maximize customer satisfaction and decipher quality management concepts in the standardization of measures and, consequently, enhancing the quality of services [18].

2. 3. Literature Review Soltanzadeh et al. [19] assessed the impact of government intervention on a company's innovation activities. This paper offers a framework to elaborate on the behavioral changes in the company resulting from government intervention. This investigation intends to estimate the influence of R&D subsidies on Iranian companies (small-, medium-, and large-sized companies) using the Propensity Score Matching (PMS) technique. This article found that R&D subsidies have a substantial impact on the innovation process.

In an investigation, Liu et al. [20] examined the R&D performance of industrial companies in China based on a two-stage data envelopment analysis (DEA) by data from 2009 to 2014. Based on the results gained in this study, several policy proposals for the R&D activities of Chinese industrial companies were provided. Sinimole and Saini [21] in a study, evaluated and compared the R&D performance of Asian countries divided into two groups based on a threshold expenditure of 1% of GDP on R&D. In this study, they exploited an output-oriented DEA model.

Chachuli et al. [22] explored the performance of R&D activities in five renewable energy resources, namely, solar, wind, biomass, biogas, and mini-hydro. The case study is Malaysia and considers the data from 2012 to 2017 concerning two policy thrusts, namely, systematic R&D program and human capital development towards the renewable energy deployment in Malaysia. This research uses the DEA method to evaluate the efficiency of the R&D activities of renewable energy resources considering the variables in the government's renewable energy policy. In a study, Koçak et al. [23] used a data envelopment analysis (DEA) and bootstrap DEA to study the environmental efficiency of R&D expenditures for energy efficiency, renewable energy, hydro and fuel cells, fossil energy,

nuclear energy, and other power and storage technologies in OECD countries. In their study, Matte and Belgin [24] examined the impact of knowledge management (KM) performance on the efficiency of 20 companies operating in R&D in the production of parts and accessories for the motor vehicle industry in Turkey. In their investigation, they employed conventional data envelopment analysis (DEA) and DEA based on weight restrictions for the analysis of data. Based on the results, there is a significant difference between companies' efficiency in R&D with high performance and low performance in terms of knowledge management (KM) dimensions, namely, knowledge creation, information system infrastructure, knowledge culture, and knowledge worker productivity.

Dai et al. [25] reviewed the development of battery management systems in the past and presented a multilayer design architecture for advanced battery management. They also discussed future trends in research and battery management development for future generations. Valacuse [26] examined R&D models for pharmaceutical products following the coronavirus epidemic in the first quarter of 2020. The results of his research show that the COVID -19 crisis highlights the urgent need to reshape global public health for health R&D. Amaskra et al. [27] studied the role of investment in R&D and economic policy uncertainty in Sri Lanka's economic growth. The results of their study show that R&D is crucial to increasing the productivity of all factors in the country. Also, through R&D, EPUs have a significant detrimental effect on the TFP growth, although only in the short run. In 2022, Belderbos et al. [28] studied the international diversity of top management teams and the effectiveness of R&D strategies to increase innovation performance. Their study analyzed the innovation performance of 165 companies in Europe, Japan, and the USA.

Karamasa [29] established the service quality criteria in three-star hotels in Erzurum and ranked the importance levels of the determining criteria. The SWARA method was used to weight the determining criteria. The results of this method show that "Price Availability" was the most important service quality criterion in three-star hotels. This was followed by "Courtesy and Respect Level", "Reliability", "Service and Process Flexibility", "Restaurant Service Quality" and "Cleanliness", respectively. The criteria considered the least important include "Quality of Housekeeping" and "Front Office Service Quality".

Bac [30] proposed a framework to evaluate different smart card systems to determine the best one and additionally validate their benefits while comparing with the traditional fare payment system. For this purpose, an integrated Multi-Criteria Decision-Making (MCDM) framework was used that combines two recent and popular methodologies. The proposed methodology used

the SWARA method for determining the criteria weights in the decision model and the Weighted Additive Sum Product Assessment (WASPAS) method for comparing alternatives. Research results revealed that all smart card systems show improvements in performance, reliability, and user satisfaction-related criteria.

Khalili and Alinezhad [31] evaluated the performance of Aggregate Production Planning (APP). In this regard, the optimal values were determined by the multi-objective Grey Aggregate Production Planning (GAPP) model, and the weights of the input and output indicators for the performance evaluation were characterized by the SWARA method. Further, the efficiency of Decision-Making Units (DMUs) was determined by the Ratio Efficiency Dominance (RED) mode, and then, DMUs were ranked. As a result, the efficiency and resource loss increased and decreased, respectively.

2. 4. Research Gap As seen from the literature review, the problem of research and development (R&D) is still among the most critical scientific challenges and especially a vital matter in Iran. Therefore, in this study, we intend to design an R&D model in the automotive battery industry by proposing a new framework based on the SWARA method, the fuzzy COPRAS method, and a BOMP model, taking into account the dimensions of customer satisfaction.

3. FRAMEWORK OF THE PROPOSED ASSESSMENT APPROACH

In this section, the basic definitions associated with the suggested decision-making approach are briefly expressed. Besides, a bi-objective mixed-integer linear programming (MILP) model is formulated. By these core concepts, a new hybrid approach of fuzzy multi-criteria decision making (MCDM) - mathematical optimization (mathematical programming) is proposed.

3. 1. Fuzzy Set Theory The triangular fuzzy number is defined as a triple (a_1, a_2, a_3) , which its membership function is equal to [32]:

$$\mu_{\tilde{a}}(x) = \begin{cases} (x-a_1)/(a_2-a_1), & \text{if } a_1 \leq x \leq a_2 \\ (a_3-x)/(a_3-a_2), & \text{if } a_2 \leq x \leq a_3 \\ 0, & \text{Otherwise} \end{cases} \quad (1)$$

So, a_1 , a_2 , and a_3 are the minimum possible, the highest, and the maximum possible values, respectively.

If $\tilde{A}=(a_1,a_2,a_3)$ and $\tilde{B}=(b_1,b_2,b_3)$ are two fuzzy triangular numbers so that $a_1 \leq a_2 \leq a_3$ and $b_1 \leq b_2 \leq b_3$, and β is also a number greater than zero, then the basic operations of fuzzy triangular numbers will be [33]:

$$\tilde{A} \oplus \tilde{B} = (a_1+b_1, a_2+b_2, a_3+b_3) \quad (2)$$

$$\tilde{A} \otimes \tilde{B} = (a_1b_1, a_2b_2, a_3b_3) \quad (3)$$

$$\tilde{A} \ominus \tilde{B} = (a_1 - b_3, a_2 - b_2, a_3 - b_1) \tag{4}$$

$$\tilde{A} \oslash \tilde{B} = (a_1/b_3, a_2/b_2, a_3/b_1) \tag{5}$$

$$\beta \tilde{A} = (\beta a_1, \beta a_2, \beta a_3) \tag{6}$$

If $\tilde{A} = (a_1, a_2, a_3)$ is a triangular fuzzy number, then the best non-fuzzy performance is calculated by [34, 35]:

$$R(\tilde{A}) = \frac{1}{6} (a_1 + 4a_2 + a_3) \tag{7}$$

3.2. Fuzzy SWARA Method Overall, the procedure for achieving the relative weights of the criteria using the fuzzy SWARA technique is as follows:

Step 1: The criteria are arranged in a sequence from the highest degree of importance (priority) to the lowest degree of importance (priority) according to experts' opinions and based on the purpose of the decision. As decision-making about real-world problems is always associated with uncertainties, the language scale provides more freedom to experts. These linguistic scales can be provided by Triangular Fuzzy Numbers (TFNs) according to Table 1.

Step 2: This process starts from the second criterion where the experts allocate a linguistic variable for each criterion to criterion j with the previous criterion ($j-1$). This ratio is recognized as the comparative importance of the average value [36].

Step 3: Calculate the fuzzy coefficient \tilde{k}_j by:

$$\tilde{k}_j = \begin{cases} 1, & j=1 \\ \tilde{s}_{j+1}, & \>1 \end{cases} \tag{8}$$

Step 4: Calculate the fuzzy weight (\tilde{q}_j) by:

$$\tilde{q}_j = \begin{cases} 1, & j=1 \\ \frac{\tilde{q}_{j-1}}{\tilde{k}_j}, & \>1 \end{cases} \tag{9}$$

Step 5: Calculate the fuzzy relative weights of evaluation criteria by:

$$\tilde{w}_j = \frac{\tilde{q}_j}{\sum_{k=1}^n \tilde{q}_k} \tag{10}$$

TABLE 1. Verbal phrase for pairwise comparison of criteria

Verbal phase	Fuzzy scale
No matter (EU)	(0.0,0.0,0.1)
Importance is very weak (NVI)	(0.0,0.1,0.3)
Poor importance (NI)	(0.1,0.3,0.5)
Relative importance (F)	(0.3,0.5,0.7)
Important (I)	(0.5,0.7,0.9)
Very important (VI)	(0.7,0.9,1.0)
Absolute importance (EI)	(0.9,1.0,1.0)

where \tilde{w}_j represents the relative weights of criteria j and n represents the total number of criteria.

Step 6: Defascularization of fuzzy relative weights of criterion j that results from Equation (7).

3.3. Fuzzy COPRAS Method

The steps of the COPRAS technique are as follows:

Step 1: Creating a fuzzy decision matrix using the fuzzy membership functions presented in Table 2 based on the following equation.

$$\tilde{X} = \begin{bmatrix} (x_{11}^l, x_{11}^m, x_{11}^u) & \dots & (x_{1n}^l, x_{1n}^m, x_{1n}^u) \\ \vdots & \ddots & \vdots \\ (x_{m1}^l, x_{m1}^m, x_{m1}^u) & \dots & (x_{mn}^l, x_{mn}^m, x_{mn}^u) \end{bmatrix} \tag{11}$$

where m is the number of options, n is the number of criteria, and x_{mn} represents the performance of option i in relation to criterion j . Conversion instructions for fuzzy membership functions are indicated in Table 2 [37].

Step 2: Normalize the fuzzy decision matrix using Equations (12) – (14) to enhance its comparability. The normalized value of the fuzzy decision matrix is calculated using the procedure adopted in the research [38]. This normalization approach of the initial fuzzy decision matrix improves the computational process and upgrades the accuracy of numbers [39].

As: $\tilde{s}_{ij} = (s_{ij}^l, s_{ij}^m, s_{ij}^u)$ $\forall ij$

$$s_{ij}^l = x_{ij}^l / \sqrt{\sum_{i=1}^m [(x_{ij}^l)^2 + (x_{ij}^m)^2 + (x_{ij}^u)^2]} \tag{12}$$

$$s_{ij}^m = x_{ij}^m / \sqrt{\sum_{i=1}^m [(x_{ij}^l)^2 + (x_{ij}^m)^2 + (x_{ij}^u)^2]} \tag{13}$$

$$s_{ij}^u = x_{ij}^u / \sqrt{\sum_{i=1}^m [(x_{ij}^l)^2 + (x_{ij}^m)^2 + (x_{ij}^u)^2]} \tag{14}$$

Step 3: Calculate the weighted normalized fuzzy decision matrix. This matrix is obtained by multiplying the weights gained for each criterion by the cumulative weighted method in the normal fuzzy decision matrix.

Fuzzy multiplication is illustrated as Equation (2).

TABLE 2. Verbal phrase to evaluate the R&D models

Verbal phase	Fuzzy scale
Very poor (VP)	(0.0,0.0,1.0)
Poor (P)	(0.5,1.0,2.5)
Medium poor (MP)	(1.5,3.0,4.5)
Medium (M)	(3.5,5.0,6.5)
Medium important (MG)	(5.5,7.0,8.0)
Important (G)	(7.5,9.0,9.5)
Very important (VG)	(9.5,10,10)

Step 4: Calculate the sum of all the criteria according to Equation (15) so that their maximum value is preferred for each further option.

$$\tilde{P}_i = \sum_{j=1}^k \tilde{x}_{ij} \quad i=1,2,\dots,m; j=1,2,\dots,n \quad (15)$$

Step 5: Calculate the sum of all the criteria based on Equation (16) so that the minimum value is preferred for each further option.

$$\tilde{R}_i = \sum_{j=k+1}^n \tilde{x}_{ij} \quad \begin{matrix} i=1,2,\dots,m; \\ j=k+1,k+2,\dots,n \end{matrix} \quad (16)$$

where in the above equations, k is equal to the number of criteria of utility, and $n-k$ is the number of criteria of cost.

Step 6: Non-Fuzzy values of \tilde{P}_i and \tilde{R}_i are calculated by utilizing equation 7.

Step 7: Calculate the minimum value of R_i through Equation (17).

$$R_{min} = \min_i R_i; \quad i=1, \dots, m \quad (17)$$

Step 8: Calculate the options' relative importance values through Equation (18).

$$Q_i = P_i + \frac{R_{min} \sum_{i=1}^m R_i}{R_i \sum_{i=1}^m R_{min}}; \quad i=1, \dots, m \quad (18)$$

Step 9: Calculate the degree of each option. The utility of desirability of each option is calculated by comparing it with the ideal option based on the following equations.

$$Q_{max} = \max_i Q_i; \quad i=1, \dots, m \quad (19)$$

$$N_i = \frac{Q_i}{Q_{max}} \times 100 \quad (20)$$

where Q_i is the non-fuzzy relative weight for each option, and Q_{max} is the ideal option value. Eventually, the options are ranked based on the value N_i so that the option with a high value of N_i is optimal and is placed in the first rank.

3. 4. Suggested Mathematical Model In this section, a bi-objective mathematical model is proposed to assign R&D models to automobile battery manufacturing companies, taking profit and risk objectives into account. To model the problem, like other mathematical models, hypotheses need to be considered. The assumptions employed in this study are as follows:

- The number of R&D models is specific and limited.
- The number of battery manufacturing factories is specified and limited
- The expenditure for executing each model, the degree of customer satisfaction with each model and the total budget considered for the models are different and specific values.
- There is the possibility of choosing several models for each manufacturer.
- The values associated with the model parameters are certain.

- Each model has a coefficient of importance in the model, the value of which is a definite number between zero and one, which results from the characteristic of the fuzzy COPRAS method.

3. 4. 1. Mathematical Modeling

$$\text{Max } Z_1 = \sum_{m=1}^p \sum_{n=1}^q V_m L_{mn} x_{mn} \quad (21)$$

$$\text{Min } Z_2 = \sum_{m=1}^p \sum_{n=1}^q P_{mn} R_{mn} x_{mn} \quad (22)$$

s.t.

$$\sum_{m=1}^p W_{mn} x_{mn} \leq B_n \quad \forall n \quad (23)$$

$$\sum_{m=1}^p x_{mn} \leq D_n \quad \forall n \quad (24)$$

$$\sum_{m=1}^p x_{mn} \geq 1 \quad \forall n \quad (25)$$

$$x_{mn} \in \{0,1\} \quad \forall m,n \quad (26)$$

The offered model has two objective functions that will be elaborated below. The first objective function (21) maximizes the expected sales of the new product from the execution of R&D models in battery manufacturers. The second objective function (22) addresses minimizing the risk of customer loss via implementing R&D models in battery manufacturers. Also, the model has four constraints. Phrase (23) estimates the constraint associated with the budget. Phrase (24) ensures that the number of models assigned to each manufacturer does not exceed the allowable limit. Constraint (25) ensures that each manufacturer is allocated at least one model. Ultimately, Constraint (26) specifies the type of variables applied to the problem.

3. 4. 2. Constraint Method The constraint ϵ method formula is as follows: The first objective is introduced as the main objective [40, 41].

$$\text{Min } f_1(X) \quad (27)$$

$$x \in X \quad (28)$$

$$\begin{matrix} f_2(X) \leq \epsilon_2 \\ f_n(X) \leq \epsilon_n \end{matrix} \quad (29)$$

In the proposed query of this study, the initial objective is considered the primary objective, and other objectives are viewed as secondary objectives. Hence, according to the constraint method, the new formula of the proposed model culminates in the following optimization problem.

$$\text{Min } Obj_1 \quad (30)$$

$$Obj_2 \geq \epsilon_2 \quad (31)$$

Equation (29) represents the main objective function of the problem, and Equation 30 adds to the problem’s set of constraints. The constraint ε method’s steps/stages are as follows:

- Select one of the objective functions as the primary objective function.
- Solve the problem each time according to one of the selected objective functions, and obtain the optimal values of each objective function.
- Divide the interval between the two optimal values of the sub-objective functions into a predetermined number and obtain a table of values for $\varepsilon_2, \dots, \varepsilon_n$
- Solve the problem with the main objective function with each of the values of each time $\varepsilon_2, \dots, \varepsilon_n$
- Report the Pareto findings.

We calculate the size of the objective function 2, ..., p for each objective function, and then, we divide the limit k of the objective function into equal distances q_k, r_k of the scope becomes the objective function of k ($k=2, \dots, p$). The decoupling step for this objective function is defined by:

$$step_k = r_k / q_k \tag{32}$$

The values on the right-hand side for the corresponding constraint on t iterations in a given objective function correspond to Equation (33).

$$e_{kt} = fmin_k + t \times step_k \tag{33}$$

where $fmin_k$ is a half function and t counter is a specific objective function. After optimization, the excess variable is obtained and the passage coefficient is calculated so that $int()$ is a function of the integer Component (34).

$$b = int(s_2 / step_2) \tag{34}$$

In the proposed constraint ε method, as mentioned, the initial objective function is presumed as the primary objective function and the second objective function as the sub-objective function; Thereafter, the n number of failures is presumed for each objective, and a total of $2n$

Pareto points are generated for each problem. Next, the best answer for the objective functions is presented between the Pareto points of the ε -constraint method.

4. CASE STUDY

In this survey, the population under study included experts from battery companies (i.e., $a-1$). There are numerous indices and criteria in conjunction with the assessment of R&D models. The classification provided in this study has put together the indicators that are closer to the intended problem by the concept. Therefore, in this phase, a list of relevant criteria to assess R&D models (Figure 1) is initially detected in Table 3 through the revision and literature review, and in-person interviews with experts.

5. RESULTS

This section describes the result of implementing the proposed approach.

5. 1. Determining the Weights of Criteria: Fuzzy SWARA Technique

As previously mentioned, the final list of criteria and sub-criteria relating to the assessment of R&D models in the automotive battery industry for the decision-making board (experts) is offered. This committee includes experts from the most important manufacturers in the country’s battery industry. In the next step, the experts determine the relative weight of the main criteria and the relevant sub-criteria.

After several rounds of discussion, the board of experts formed a common consensus and arranged the main criteria from the most important criteria to the least important criteria, respectively. Next, the relative importance of the mean value (\tilde{J}_j) for each of the criteria of quality, market, technical, and process is assessed by experts using the fuzzy verbal scale presented in Table 1.

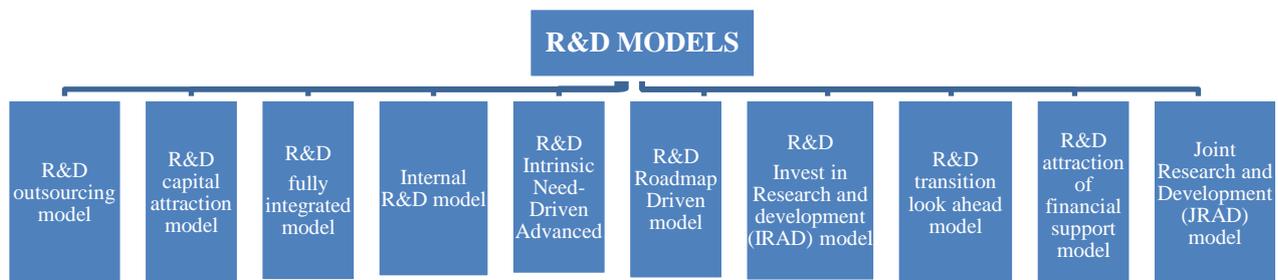


Figure 1. Conceptual model of the R&D models in the battery industry

Next, the fuzzy coefficient $\tilde{\lambda}_j$ for each criterion is calculated using Equation (8). After that, the calculated fuzzy weight \tilde{q}_j and the relative fuzzy weight \tilde{w}_j for the main criteria are specified by employing Equations (9) and (10), respectively.

The results associated with these steps are given in Table 3. As can be inferred from the results, the order of

importance (priority) of the main criteria in the experts' opinion is so that the most important criterion belongs to the criterion of Technical. Then, the criteria of Market, Process, and Quality are placed, respectively. Similarly, a pairwise comparison of the sub-criteria of each of the four main criteria, the defuzzified local weight, is provided in Table 4. Eventually, the optimized overall weights for the indicators affecting the R&D models in the automotive battery industry are achieved, as demonstrated in Table 5.

TABLE 3. Evaluation framework for the R&D models

Criterion /index	Main dimensions
Durability and longevity (R ₁₁)	Quality (R ₁)
Weight and dimensions (R ₁₂)	
Service & product innovation (R ₁₃)	
Market share (R ₂₁)	Market (R ₂)
Price (R ₂₂)	
Brand (R ₂₃)	
Amount of combination with other operations (R ₃₁)	Technical (R ₃)
Compatibility with technology (R ₃₂)	
Safety (R ₃₃)	
Warranty (R ₄₁)	Process (R ₄)
Ease of access to sales centers (R ₄₂)	
Cooperation with car assistance (R ₄₃)	

5. 2. Assessment of R&D models: a Fuzzy COPRAS Method

In the previous steps, the weights of evaluation indicators of R&D models in the automotive battery industry were determined. In this section, the performance characteristic of each model could be measured by converting verbal variables into quantitative values using the fuzzy COPRAS technique. For this purpose, by distributing and collecting the relevant questionnaires and implementing them step by step, the proposed method of ranking 10 models identified as:

- 1- R&D outsourcing model (A1);
- 2- R&D capital attraction model (A2);
- 3- R&D fully integrated model (A3);
- 4- Internal R&D model (A4);
- 5- R&D intrinsic need-driven advanced (A5);
- 6- R&D roadmap driven model (A6);

TABLE 4. Results related to local optimal weights of the main criteria

	\tilde{S}_j	\tilde{k}_j	\tilde{q}_j	\tilde{w}_j	w_j^{Crisp}
Technical (R ₃)		(1,1,1)	(1,1,1)	(0.328,0.335,0.404)	0.335
Market (R ₂)	(0.283,0.333,0.408)	(1.283,1.333,1.408)	(0.710,0.750,0.779)	(0.254,0.325,0.345)	0.325
Process (R ₄)	(0.377,0.467,0.613)	(1.377,1.467,1.613)	(0.440,0.511,0.566)	(0.158,0.208,0.229)	0.208
Quality (R ₁)	(0.260,0.300,0.354)	(1.260,1.1300,1.354)	(0.325,0.393,0.449)	(0.116,0.132,0.181)	0.132

TABLE 5. Optimal global weights indicators evaluation models

Main dimensions	Local weight main dimensions	Under the criteria	Local weight of each sub-criterion	w_j^{Final}	Rank
Quality (R ₁)	0.132	Durability and longevity (R ₁₁)	0.589	0.078	6
		Weight and dimensions (R ₁₂)	0.167	0.022	12
		Service & product innovation (R ₁₃)	0.224	0.032	11
Market (R ₂)	0.325	Market share (R ₂₁)	0.167	0.054	8
		Price (R ₂₂)	0.461	0.150	2
		Brand (R ₂₃)	0.372	0.121	3
Technical (R ₃)	0.335	Amount of combination with other operations (R ₃₁)	0.567	0.190	1
		Compatibility with technology (R ₃₂)	0.290	0.097	4
		Safety (R ₃₃)	0.144	0.048	9
Process (R ₄)	0.208	Warranty (R ₄₁)	0.461	0.096	5
		Ease of access to sales centers (R ₄₂)	0.372	0.077	7
		Cooperation with car assistance (R ₄₃)	0.167	0.035	10

- 7- Invest in R&D (IRAD) model (A7);
- 8- R&D transition look ahead model (A8);
- 9- R&D attraction of financial support model (A9);
- 10- Joint R&D (JRAD) model (A10).

After achieving the priority of each expert, in the next step, the average of the degrees is calculated, and the average fuzzy decision matrix is obtained according to Table 6. The initial gray decision matrix needs to be converted to a comparable scale to ensure consistency between the evaluation criteria.

Therefore, the normal weighted fuzzy decision matrix is obtained by using Equations (12)-(14) as shown in Table 7. Ultimately, following Table 8, the performance values \hat{R}_i , \hat{P}_i and the features Q_i and N_i are calculated employing Equations (15), (16), (18), and (20), respectively.

As is deduced from the results, the “joint R&D model (JRAD)” is chosen as the optimal model because of enjoying the highest degree of desirability (utility).

5. 3. Optimal Allocation of Models: Solving Mathematical Model

In this part, a set of R&D

models will be allocated to each manufacturer via solving a mathematical programming model. It is worth mentioning that the collection of manufacturers includes the companies, namely Saba battery, Faraz battery, Pasargad battery, Durna Aras battery, Aco battery, Azar battery, Niru Gostaran battery, and Vaya battery.

The input parameters of the examined problem can be observed in Tables 9-14. Subsequently, the results of how to allocate R&D models to each manufacturer are provided after solving the problem.

The ϵ -constraint method is exploited in GAMS software version 24.3 and the CPLEX solver to solve the suggested mathematical model. To solve the problem and reach the ideal positive and negative values, each time one of the objective functions is used as the basis, and the next objective function is inserted into the bounds with the limit ϵ . After solving the model based on the described method, the upper bound is determined by the basis of the first objective function (*i.e.*, maximization) and the lower bound by the basis of the second objective function (*i.e.*, minimization).

TABLE 6. Fuzzy initial decision matrix option-criterion

	R₁₁	R₁₂	R₁₃	R₂₁	R₂₂	R₂₃
A ₁	(10,16,22)	(18,23,27.5)	(19,26,30)	(14,20,26)	(14,20,26)	(10,16,22)
A ₂	(20,26,32)	(16,22,28)	(12,16,21)	(18,24,30)	(30,35,37.5)	(32,37,38.5)
A ₃	(12,18,24)	(26,31,35.5)	(24,30,35)	(26,32,35)	(22,28,32)	(20,26,30)
A ₄	(16,22,28)	(18,24,30)	(7,12,18)	(12,18,24)	(18,23,27.5)	(24,30,35)
A ₅	(24,30,33)	(24,30,35)	(16,22,27)	(22,28,33)	(22,28,32)	(22,28,33)
A ₆	(26,30,33)	(10,16,22)	(18,24,30)	(20,26,31)	(24,30,34)	(26,31,34.5)
A ₇	(20,26,31)	(16,22,27)	(14,20,26)	(14,20,25)	(18,24,29)	(24,30,35)
A ₈	(14,20,26)	(16,22,28)	(18,24,30)	(20,26,31)	(24,30,35)	(24,29,33.5)
A ₉	(20,26,31)	(20,26,31)	(24,29,32.5)	(22,27,31.5)	(28,34,37)	(36,39,39.5)
A ₁₀	(14,20,25)	(22,28,33)	(26,31,35.5)	(30,35,37.5)	(26,32,35)	(30,35,37.5)
	R₃₁	R₃₂	R₃₃	R₄₁	R₄₂	R₄₃
A ₁	(10,16,22)	(20,25,28.5)	(18,24,29)	(16,22,28)	(14,20,25)	(10,16,22)
A ₂	(20,26,31)	(15,20,26)	(16,20,24)	(13,18,24)	(34,37,38.5)	(30,36,38)
A ₃	(14,20,25)	(24,30,34)	(24,30,34)	(20,26,30)	(20,26,30)	(18,24,29)
A ₄	(16,22,28)	(10,14,20)	(15,20,26)	(16,22,28)	(22,27,31.5)	(32,36,38)
A ₅	(14,20,26)	(24,30,34)	(14,18,23)	(18,24,28)	(30,34,36)	(28,33,35.5)
A ₆	(20,25,29.5)	(17,22,27)	(19,24,28)	(24,30,34)	(18,23,27.5)	(10,16,22)
A ₇	(22,28,32)	(26,32,35)	(20,26,31)	(22,28,32)	(16,22,28)	(18,23,27.5)
A ₈	(24,29,32.5)	(17,21,25.5)	(11,16,22)	(18,24,30)	(20,25,28.5)	(14,20,26)
A ₉	(28,32,34)	(10,14,20)	(16,20,24)	(15,20,26)	(26,30,33)	(14,20,25)
A ₁₀	(28,34,37)	(24,30,34)	(23,28,31)	(26,32,35)	(6,12,18)	(20,26,32)

TABLE 7. Normalized decision matrix option-criterion

	R₁₁	R₁₂	R₁₃	R₂₁	R₂₂	R₂₃
A ₁	(0.005,0.008,0.011)	(0.004,0.005,0.006)	(0.007,0.01,0.011)	(0.006,0.009,0.011)	(0.011,0.016,0.021)	(0.006,0.009,0.012)
A ₂	(0.01,0.013,0.016)	(0.004,0.005,0.007)	(0.005,0.006,0.008)	(0.008,0.011,0.013)	(0.025,0.029,0.031)	(0.018,0.02,0.021)
A ₃	(0.006,0.009,0.012)	(0.006,0.007,0.008)	(0.009,0.011,0.013)	(0.011,0.014,0.015)	(0.018,0.023,0.026)	(0.011,0.014,0.017)
A ₄	(0.008,0.011,0.014)	(0.004,0.006,0.007)	(0.003,0.005,0.007)	(0.005,0.008,0.011)	(0.015,0.019,0.023)	(0.013,0.017,0.019)
A ₅	(0.012,0.015,0.017)	(0.006,0.007,0.008)	(0.006,0.008,0.01)	(0.01,0.012,0.015)	(0.018,0.023,0.026)	(0.012,0.015,0.018)
A ₆	(0.013,0.015,0.017)	(0.002,0.004,0.005)	(0.007,0.009,0.011)	(0.009,0.011,0.014)	(0.02,0.025,0.028)	(0.014,0.017,0.019)
A ₇	(0.01,0.013,0.016)	(0.004,0.005,0.006)	(0.005,0.008,0.01)	(0.006,0.009,0.011)	(0.015,0.02,0.024)	(0.013,0.017,0.019)
A ₈	(0.007,0.01,0.013)	(0.004,0.005,0.007)	(0.007,0.009,0.011)	(0.009,0.011,0.014)	(0.02,0.025,0.029)	(0.013,0.016,0.019)
A ₉	(0.01,0.013,0.016)	(0.005,0.006,0.007)	(0.009,0.011,0.012)	(0.01,0.012,0.014)	(0.023,0.028,0.03)	(0.02,0.022,0.022)
A ₁₀	(0.007,0.01,0.013)	(0.005,0.007,0.008)	(0.01,0.012,0.013)	(0.013,0.015,0.017)	(0.021,0.026,0.029)	(0.017,0.019,0.021)
	R₃₁	R₃₂	R₃₃	R₄₁	R₄₂	R₄₃
A ₁	(0.012,0.019,0.026)	(0.018,0.023,0.026)	(0.013,0.017,0.021)	(0.01,0.014,0.018)	(0.006,0.008,0.011)	(0.003,0.005,0.007)
A ₂	(0.023,0.03,0.036)	(0.014,0.018,0.024)	(0.011,0.014,0.017)	(0.008,0.011,0.015)	(0.014,0.016,0.016)	(0.01,0.011,0.012)
A ₃	(0.016,0.023,0.029)	(0.022,0.027,0.031)	(0.017,0.021,0.024)	(0.013,0.017,0.019)	(0.008,0.011,0.013)	(0.006,0.008,0.009)
A ₄	(0.019,0.026,0.033)	(0.009,0.013,0.018)	(0.011,0.014,0.018)	(0.01,0.014,0.018)	(0.009,0.011,0.013)	(0.01,0.011,0.012)
A ₅	(0.016,0.023,0.03)	(0.022,0.027,0.031)	(0.01,0.013,0.016)	(0.011,0.015,0.018)	(0.013,0.014,0.015)	(0.009,0.01,0.011)
A ₆	(0.023,0.029,0.035)	(0.015,0.02,0.025)	(0.013,0.017,0.02)	(0.015,0.019,0.022)	(0.008,0.01,0.012)	(0.003,0.005,0.007)
A ₇	(0.026,0.033,0.037)	(0.024,0.029,0.032)	(0.014,0.018,0.022)	(0.014,0.018,0.02)	(0.007,0.009,0.012)	(0.006,0.007,0.009)
A ₈	(0.028,0.034,0.038)	(0.015,0.019,0.023)	(0.008,0.011,0.016)	(0.011,0.015,0.019)	(0.008,0.011,0.012)	(0.004,0.006,0.008)
A ₉	(0.033,0.037,0.04)	(0.009,0.013,0.018)	(0.011,0.014,0.017)	(0.01,0.013,0.017)	(0.011,0.013,0.014)	(0.004,0.006,0.008)
A ₁₀	(0.033,0.04,0.043)	(0.022,0.027,0.031)	(0.016,0.02,0.022)	(0.017,0.02,0.022)	(0.003,0.005,0.008)	(0.006,0.008,0.01)

TABLE 8. Degree of the desirability of the R&D models

	P_i^{Crisp}	R_i^{Crisp}	Q_i	N_i	Rank
A ₁	0.135	0.008	0.151	72%	10
A ₂	0.171	0.013	0.181	86%	4
A ₃	0.175	0.009	0.190	90%	2
A ₄	0.143	0.011	0.155	74%	9
A ₅	0.168	0.015	0.177	84%	6
A ₆	0.165	0.015	0.174	83%	8
A ₇	0.171	0.013	0.181	86%	5
A ₈	0.162	0.010	0.175	83%	7
A ₉	0.174	0.013	0.184	87%	3
A ₁₀	0.198	0.010	0.211	100%	1

As previously described, the ϵ -constraint method solves the evolved constraint by considering one of the objective functions as the main objective function and the other objective functions in the constraint problem, and it remains to be seen what effect this approach will have on the objective function values. Based on this

information, the mathematical problem designed by the 200 iterations of the Epsilon constraint method is solved, and the Pareto front gained from the two objective functions is shown in Figure 2. The number of cuts is assumed to be 100 and considering that the problem model is zero and one, each cut is a single step.

TABLE 9. Capital required to implement the model in the manufacturer

W_{mn}	M_1	M_2	M_3	M_4	M_5	M_6	M_7	M_8
A ₁	17,600	27,164	13,306	13,252	16,736	23,504	12,202	28,340
A ₂	20,676	15,645	13,168	19,956	20,727	24,689	14,196	18,205
A ₃	10,159	17,964	14,547	10,868	14,699	11,146	16,226	20,011
A ₄	14,727	24,801	19,047	26,852	11,867	25,400	23,871	25,711
A ₅	24,102	19,156	24,945	27,905	26,957	22,437	23,582	26,316
A ₆	28,810	20,392	13,714	15,729	11,999	15,339	23,180	14,405
A ₇	25,074	11,448	12,084	27,917	29,406	11,837	29,109	21,003
A ₈	26,402	14,550	25,184	21,199	28,946	23,065	20,320	27,216
A ₉	16,582	26,763	17,841	28,148	13,177	11,488	27,798	16,569
A ₁₀	27,853	16,767	20,497	20,556	12,048	26,560	14,700	21,890

TABLE 10. Number of sales expected from the implementation of the model in the manufacturer

L_{mn}	M_1	M_2	M_3	M_4	M_5	M_6	M_7	M_8
A ₁	26,524	13,452	25,167	20,354	27,523	19,318	23,197	12,360
A ₂	10,076	29,112	28,759	25,523	11,988	10,441	18,194	23,524
A ₃	13,573	16,586	22,882	19,472	13,072	19,130	14,054	15,423
A ₄	24,086	25,912	21,147	12,677	13,210	11,601	20,172	14,555
A ₅	16,678	23,654	17,300	28,989	25,848	27,050	16,793	25,229
A ₆	16,844	12,169	25,134	13,251	18,991	20,231	29,227	12,477
A ₇	27,421	25,603	10,631	26,478	12,407	15,761	17,100	26,314
A ₈	29,638	19,141	17,526	16,826	23,851	12,286	23,949	10,879
A ₉	17,497	26,385	11,393	29,989	13,550	19,292	29,060	29,258
A ₁₀	21,585	22,801	21,506	11,317	28,285	13,383	27,172	17,623

TABLE 11. Risk of customer dissatisfaction with the implementation of the model in the manufacturer

R_{mn}	M_1	M_2	M_3	M_4	M_5	M_6	M_7	M_8
A ₁	0.6138	0.6552	0.8635	0.8012	0.6844	0.7898	0.9141	0.7500
A ₂	0.6477	0.8741	0.8118	0.8142	0.6281	0.6075	0.7765	0.6699
A ₃	0.9338	0.6784	0.6071	0.8645	0.8791	0.6446	0.8580	0.6914
A ₄	0.6951	0.7340	0.9102	0.8676	0.6427	0.6479	0.6218	0.9456
A ₅	0.9335	0.6649	0.8782	0.8792	0.8157	0.7533	0.8530	0.6573
A ₆	0.8844	0.7209	0.6821	0.6310	0.9265	0.7555	0.7558	0.6090
A ₇	0.6811	0.8733	0.6550	0.6304	0.8265	0.7831	0.9216	0.6468
A ₈	0.8621	0.6728	0.7405	0.8698	0.6108	0.8620	0.9243	0.6613
A ₉	0.9474	0.6862	0.8123	0.8310	0.6622	0.7302	0.9451	0.7605
A ₁₀	0.6543	0.7919	0.8437	0.8247	0.7586	0.8954	0.7200	0.8787

TABLE 12. Probability of risk of customer dissatisfaction with the implementation of the model in the manufacturer

P_{mn}	M ₁	M ₂	M ₃	M ₄	M ₅	M ₆	M ₇	M ₈
A ₁	0.7191	0.6575	0.7187	0.7307	0.5926	0.7009	0.6343	0.6820
A ₂	0.6617	0.6193	0.5592	0.7039	0.5601	0.6493	0.5510	0.7464
A ₃	0.6558	0.6399	0.5606	0.7121	0.6431	0.5896	0.6673	0.7159
A ₄	0.6702	0.5623	0.7335	0.6111	0.7437	0.7492	0.7297	0.6910
A ₅	0.6622	0.7261	0.7040	0.5975	0.6245	0.6327	0.6135	0.6132
A ₆	0.6814	0.5840	0.6105	0.6115	0.6088	0.5943	0.5868	0.7411
A ₇	0.6679	0.6919	0.5618	0.6721	0.5500	0.7058	0.6524	0.5532
A ₈	0.6807	0.6324	0.7237	0.7113	0.5798	0.6130	0.7477	0.6353
A ₉	0.5849	0.6254	0.6812	0.6379	0.6439	0.6722	0.6005	0.5782
A ₁₀	0.7239	0.7389	0.7026	0.5758	0.6298	0.7077	0.6757	0.5702

TABLE 13. Number of models allowed to be assigned to each manufacturer

	M ₁	M ₂	M ₃	M ₄	M ₅	M ₆	M ₇	M ₈
D_n	2	3	1	2	3	3	2	1

TABLE 14. Budget available to any manufacturer

M ₁	M ₂	M ₃	M ₄
68,000	73,250	51,050	65,500
M ₅	M ₆	M ₇	M ₈
49,500	56,850	63,250	65,250

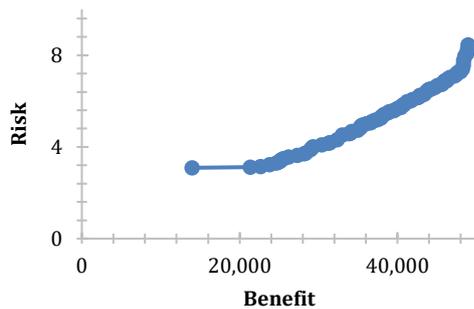


Figure 2. Pareto chart created based on benefit and risk goals

After presenting the results to the experts and considering the values obtained for the objective functions, the experts found consensus on choosing the best answer from the 76 points on the Pareto front, presented in Table 15. Also, the mode of allocation of

models to each manufacturer will be described in Table 16.

TABLE 15. Optimal value of the objective function based on the common opinion of experts

Benefit (Z_1)	Risk(Z_2)
37,152	5.17

TABLE 16. Assigning the R&D models to each manufacture

Model	Manufacturer							
	1	2	3	4	5	6	7	8
A ₁								
A ₂	✓							
A ₃								
A ₄		✓						
A ₅								
A ₆			✓					
A ₇				✓				
A ₈							✓	
A ₉		✓						
A ₁₀	✓	✓				✓		

6. CONCLUSION AND FURTHER SUGGESTIONS

Nowadays, numerous firms have encountered challenges in strengthening and enhancing their competitiveness to survive in a competitive business environment. In the meantime, only companies that take advantage of key capabilities and comparative advantages have achieved sustainable success. In creating competitive advantages, R&D model formulation activities play a very important

role. Because the model planning process of R&D must be done before product design and development, so far limited structured methodologies have been used in this field. Therefore, in this study, a new fuzzy model for evaluating and selecting R&D models in the automotive battery industry is proposed. First, expert and research committees were selected. According to the previous literature as well as the opinion of experts, the final indicators for evaluating R&D models using the Delphi technique and brainstorming in four categories of quality, market, technical and process were identified and finalized.

In the second stage, after allocating the experts' subjective preferences to the criteria, the final weight of the criteria was calculated through the fuzzy SWARA (Stepwise Weight Assessment Ratio Analysis) technique. In addition, the weight of each model and their final prioritization were determined using the fuzzy Complex Proportional Assessment (COPRAS) method. Based on the results obtained from the fuzzy SWARA method, the three influential factors in evaluating R&D models in the automotive battery industry include the following items, respectively: "The amount of combination with other operations", "Price", and "Brand". Furthermore, the "joint R&D model" was recognized as the superior model because of the optimal level of the optimal membership. Also, the "R&D outsourcing model" gained the least importance among R&D models in the automotive battery industry. Eventually, Zero-One Goal Programming (ZOGP) in an assignment of each model to the manufacturers of the country's battery industry was obtained by presenting and solving a bi-objective mathematical model. Accordingly, the "joint R&D model" in companies 1, 2 and 5 enjoys the highest numbers of frequency.

Some other Multi-Criteria Decision-Making (MCDM) approaches in other uncertainty environments, such as fuzzy intuitions, Z numbers, etc., could be employed in further studies and compared the obtained results with each other. Besides, some inputs of the proposed mathematical model (e.g., the parameter of cost) in uncertainty conditions could be considered. Fuzzy Goal Programming (FGP) or robust Programming could be exploited to fix this problem.

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Persian Abstract

چکیده

اندازه گیری عملکرد تحقیق و توسعه و تخصیص میزان اهمیت یکسان به اقدامات مختلف تحقیق و توسعه می تواند فرآیند اندازه گیری آن را بیش از حد ساده کند، که ممکن است منجر به تفسیر نادرست از عملکرد و در نتیجه منجر به تفسیر اشتباه مدل های تحقیق و توسعه شود. تحقیق و توسعه شامل کار های خلاقانه ای است که به صورت سیستماتیک به منظور افزایش ذخایر دانش از جمله دانش انسان، فرهنگ و جامعه و استفاده از این انبار دانش برای ابداع برنامه های کاربردی جدید انجام می شود. هدف از این پژوهش ارائه رویکردی دو مرحله ای جهت طراحی مدل تحقیق و توسعه در صنایع باتری سازی خودرو با تأکید بر رضایت مشتریان است. با توجه به نقش مهم تحقیق و توسعه در رضایت مشتری، مطالعه ای در این زمینه و صنعت انجام نشده است. در بخش نخست ابتدا مدل های مؤثر بر مدیریت تحقیق و توسعه و شاخص های اثرگذار رضایت مندی مشتریان بر مدل های تحقیق و توسعه شناسایی می شوند. در بخش دوم ضرایب معنی داری مربوط به شاخص های رضایت مندی مشتریان از طریق به کارگیری روش تصمیم گیری چند معیاره سوارا فازی نتیجه می گردد. علاوه بر این اهمیت و اولویت نهایی هر مدل با استفاده از روش کوپراس فازی محاسبه می شوند. در نهایت، برای اعمال چارچوب پیشنهادی در صنعت تولید باتری، یک مدل تحقیق و توسعه دو هدفه ارائه شده است. ضرایب به دست آمده با روش کوپراس فازی به عنوان ورودی برای مدل پیشنهادی استفاده می شود. بنابراین، سیاست گذاران و مدیران می توانند فعالیت های خود را براساس این روش انجام دهند. نتایج به دست آمده نشان داد چارچوب پیشنهادی کارایی مؤثری در مسئله مورد بررسی را دارد.
