Research Article

A Complete MCDM Model for NPD Performance Assessment in an LED-Based Lighting Plant Factory

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Globally, industries and economies have undergone rapid development and expansion over the last several decades. As a result, global warming and environmental contaminations have resulted in climate change and jeopardized food security. In many developing countries, already decreasing crop yields are threatened by extreme weather and soil damaged by genetically modified food, making environmental problems worse and increasing food and organic product prices. For these reasons, this study proposes a hybrid multicriteria decision-making (MCDM) model for new product development (NPD) in the light-emitting diode- (LED-) based lighting plant factory. First, literature reviews and expert interviews are employed in constructing a list of decision-making objectives and criteria for new product development. Then, a fuzzy Delphi method (FDM) is used to screen the elements of the objectives and criteria, while a fuzzy decision-making trial and evaluation laboratory (FDEMATEL) is used to determine the relationships among the objectives and criteria. Finally, a fuzzy analytic network process (FANP) and a composite priority vector (CPV) are manipulated to determine the relative importance weights of the critical objectives and criteria. Results show that the proposed method can create a useful and assessable MCDM model for decision-making applications in new product development, and a case study is herein performed to validate the feasibility of the proposed model in a Taiwanese LED-based lighting plant factory, which not only provides the decision-makers with a feasible hierarchical data structure for decision-making guidance but also increases the competitive advantages of trade-offs on developing novel products.

1. Introduction

Global resource demands are constantly on the rise as a result of global population growth and the development and expansion of economies worldwide. People now face the danger of depleting fossil fuel reserves. Since the industrial revolution, industrial and economic prosperity came at the cost of severe environmental problems like global warming, ozone depletion, air and water pollution, and more. The effects of the weather warming include the melting of the ice sheet in the Arctic and climate change. In addition to dwindling resources and global warming, reduced food security resulting from overuse of land and chemicals is a very serious problem. A 2007 Intergovernmental Panel on

Climate Change (IPCC) climate report predicted that the global surface temperature is likely to rise a further 1.1 to 6.4°C between 2007 and 2100. It is also predicted that 15.0% to 40.0% of the Earth's species will become extinct if the average temperature of Earth's atmosphere rises by about 2°C. If Earth's mean surface temperature increases by 4°C, around 3 billion people will lose access to safe drinking water. The Kyoto Protocol or Kyoto Treaty hoped to coordinate a response to global warming, including mitigation by emission reduction, in an international convention attended by more than 50 countries in Kyoto, Japan, on December 11, 1997. The treaty was validated in 2002 and the resolution was passed on February 2005, with countries committing to endeavor to reduce emissions of CO₂, CH₄, N₂O, HFC, PFC,

and SF₆ to 5.2% of the amount in 1990. The Copenhagen Accord was created by the COP 15 on December 7 and 8, 2009, to further strengthen the commitment of countries party to the Kyoto Agreement's goals. Afterwards, IPCC's Working Group II (WGII) did the literature survey on the wide range of impacts and risks of climate change and identified impediments and opportunities and warned that failure to make "substantial and sustained" reductions in greenhouse gas (GHG) emissions will increase the likelihood of severe and irreversible impacts [1]. In February 2015, they further assessed submissions related to the frequency and scheduling of reports in light of structure and operations [2]. However, three actions are to be suggested for the IPCC's decision-makers: (1) incorporating more practitioners to enhance the awareness and understanding in terms of climate change; (2) allowing a practitioner-led IPCC Special Report representing good-practice responses to climate change; (3) reporting good practices on timely climate response strategies [3]. Above all, understanding anthropogenic factors to assist decision-makers in implementing policies and actions on a weather event or climatic process and abiding by the Paris Agreement, enhanced understanding, action, and support, are needed in several areas related to addressing loss and damage, including comprehensive risk assessment and building the resilience of communities, livelihoods, and ecosystems, which can reduce the likelihood of extreme events happening [4].

In recent years, the environmental problems described above have prompted countries to develop green-related products and enterprises and to adopt strategies of renewable energy for new product development. Climate change and food security are among those threats considered to have the most significant impact on people, especially in the Afro-Asian regions, and so any new product able to overcome or alleviate these problems will be distinguished in the mainstream market. Since new product development in the 21st century needs to meet emission reduction and energy saving requirements, light-emitting diodes (LEDs), a semiconductor light source, are a typical choice and are being increasingly used for most forms of artificial lighting. For example, LEDs are used in traffic lights at intersections, outdoor billboards, landscape design, mobile phones, laptops, vehicles, televisions, and vegetative growth controlled by considerable parameters variability under different LED spectrum supplementation [5]. In other words, it seems that LEDs have become the new light sources for modern ecoenergy. The Fukushima Daiichi nuclear disaster served as a dire warning that high pollution and nonrenewable energy pose a lasting threat to the environment and must be replaced. Even though Taiwan has been deficient in many kinds of energy resources and highly dependent on imported energy, it has mature optic engineering and agriculture technology. Efforts to integrate these advantages that meet green-related product criteria have thus received significant attention recently.

Enterprises have to seek beneficial investments such as international cooperation, new product development, and equipment maintenance in order to survive in this highly competitive global economy. New product development

FIGURE 1: The schematic structure of an LED-based lighting plant factory.

(NPD) is deemed the most difficult of such investments. In general, the cost of new product development, the number of development team members, and the duration of a project are in direct proportion. In addition, enterprises need to pay for equipment and tools for manufacturing. It is not easy for enterprises to develop an unflawed product, and it actually takes a great deal of time and money to successfully develop a new product. New product development challenges include decision-making, regulation change, manufacturing details, time stress, market economy, producing schedule, customer needs, member diversity, and team work. As a result, performance assessment for new product development is very important in any industry.

The proposed LED-based lighting plant factory can be composed of a light source system, an environmental control system, and a nutrient liquid feeding system, as shown in Figure 1. The light source system includes variations for the light quality, amount, and photoperiod. The environment control system controls the air temperature, humidity, and carbon dioxide concentration. The nutrient liquid feeding system controls fertilizer concentration, pH levels, and the quantity of dissolved oxygen.

Team members working on the new product development usually work in a specific project group. Bad decisions by the group will result in significant financial losses for the enterprise. Thus, the financial risks involved in decision-making must be reduced as far as possible, and this can be achieved with an assessment system. LEDs are likely to be in the spotlight in the 21st century since illumination products are becoming popular, lighting technologies are improving, and costs are decreasing. LEDs offer many advantages over other forms of lighting, including their flexible emitted light color design and low energy consumption. Of significant value are their potential use in agriculture and versatility and robustness in terms of weather and geography. This study conducts a performance assessment of new product development in the LED-based lighting plant factory whose contributions are described below:

- (i) Discovering the exact objectives and criteria which meet environmental requirements
- (ii) Indicating the relationships between objectives and criteria in view of new product development in the LED-based lighting plant factory
- (iii) Evaluating the weights of potential critical factors and top priority factors to help enterprises' selection of trade-offs in new product development
- (iv) Constructing a novel performance assessment system for new product development in the LED-based lighting plant factory.

The remainder of this study is arranged as follows. Section 2 examines the literature on the subjects and methodologies adopted in this study. Section 3 establishes a hybrid MCDM performance evaluation model for NPD in an LED-based lighting plant factory. A case study of an LED-based plant lighting factory in Taiwan is carried out to verify the practicality of the proposed model in the next section. The final section sums up this research and offers conclusions.

2. Literature Review

As noted above, in order to eliminate as much financial risk as possible in new product development, this study aims to develop an integrated MCDM evaluation model for new product development in LED-based lighting plant factories. This section will discuss previous studies in new product development (NPD), plant factory and related light-emitting diode (LED) lighting system, fuzzy Delphi method (FDM), fuzzy decision-making trial and evaluation laboratory (FDEMATEL), fuzzy analytic network process (FANP), and composite priority vector (CPV).

New product development (NPD) is a specific process which has a lifecycle with a high level of diversity from creativity in the concept stage to logistics actions in the commercialization stage. NPD is not a single act of invention but often described interchangeably with innovation or creativity, and NPD has a distinct purpose, characteristics, and applications. In addition, NPD encompasses the entire process with numerous critical success factors bringing a new product or service to the marketplace [6] where this process identifies consumers' wants and needs and transforms them into a commercialized product. In other words, new product development (NPD) is considered the most powerful weapon against competitors and also one of the most important MCDM issues for evaluating the sustainable development of enterprises [7]. NPD is one of the core operational management processes in enterprises and requires the capabilities of creation, innovation, enforcement, technology, teamwork, and integration. Each step during the development procedure has a significant impact on NPD, including customers' needs, competitors' intimidation, technical risk, cross-department cooperation, and resource allocation. Some environmental factors of NPD process can be noted in four aspects: firstly, the effect of the market context on business performance generally has been neglected; secondly, most of the NPD projects only focused on "main effects" relationships without

concerning the their environments, especially the external environment; thirdly, further research on the interaction between product design and market uncertainty is required at last, numerous unanswered questions with respect to the effects of environmental uncertainty on NPD still exist [8]. As new product development (NPD) is also a high-risk and costly process with significant failure rate, NPD success factors normally can be classified into firm internal environment, organizational capability, NPD process, level of new product's competitive advantage, and market environment; and among company-related factors, management commitment to NPD projects and managerial capabilities can be deemed two crucial factors [9]. Successful NPD is important in the survival and competitive advantage of enterprises [10]; it not only means sustainable development for a business, but also helps as a buffer in times of recession. NPD involves two highly related criteria, technology feasibility and market profitability, whereas effectiveness and efficiency are the main criteria for NPD performance. Enterprises may employ different methods to assess performance in light of their features, strategies, and designs. These methods include performance measurement balance matrix, performance measurement questionnaires, the Cambridge performance measurement design process, performance criteria systems, or performance measurement integration models. This study integrates FDM, FDEMATEL, and FANP with composite priority vector (CPV) to create a performance assessment model for NPD utilized in a Taiwanese LED lighting plant factory.

Plant factories are so-called artificially controlled environment systems which control the environmental factors such as lighting, temperature, humidity, water, and the concentration of carbon dioxide and can stably produce high-quality crops in an indoor space. In Asia, plant factory systems are able to cultivate high-profit fruits, vegetables, seedlings, and herbs with outstanding merits of high output, being pollution-free, safety, no pesticides, chemicals, and eco-friendliness [11, 12]. Normally, the configuration of plant factories is a closed plant production system which consists of six principal structural elements: thermally well-insulated and nearly airtight warehouse, multitier system equipped with lighting devices, air conditioners, and fans, a CO₂ delivery unit, a nutrient solution delivery unit, and an environmental control unit including EC (electric conductivity) and pH controllers for the nutrient solution [13]. Previously, the conventional light sources such as fluorescent lamp, metal halide lamp, and high pressured sodium (HPS) lamp were generally used to promote plant growth, in which some unnecessary light that mismatches with photosynthesis action spectrum (PAS) is included. To enhance the photosynthetic efficiency of the plants, it is vital to generate artificial lighting sources with coincided spectra with PAS. It is worth mentioning that the light qualities including peak position and intensity are able to be adjusted using wavelength tunable LEDs.

LEDs, typical energy saving, high efficiency, long-life-time, and environmental-friendly illuminating sources, have come to play a significant role in plant lighting. LED lighting systems have many advantages over lamps currently used in plant growth. LEDs can control the spectral output of

a lighting system for specific crops and even be modified over the course in view of a photoperiod or growth cycle. Special lighting modes can also be used to solve plant disease or injury problems [14]. Additionally, LED lighting systems can be configured to produce very high light levels, have a very long operating life, and can be turned on and turned off instantly without warm-up time. Moreover, LEDs have the potential for significant cost savings, do not contain mercury, which needs to be safely disposed of, do not have glass envelopes or high surface temperatures that can cause injury, and do not produce damaging ultraviolet wavelengths. As LEDs replace existing lamp technologies in lighting applications, significant cost decreases will be driven by economies of scale. These advantages mean that LEDs meet the standards of environmentally friendly energy. LEDs present a different technology from lamps currently used in plant lighting. LED technology is considered one of the most valuable advances in plant lighting because of the capabilities mentioned above. Many previous studies have shown the development and benefits of LED lighting systems for plant production. In the late 1980s and early 1990s, testing of LEDs for plant growth was conducted with lettuce, potato, spinach, and wheat. LEDs began to be explored for tissue culture systems in Japan [15]. LEDs were discovered to be particularly effective in germinating seeds and rooting cuttings in the Netherlands [16] and later in other researches [17, 18]. These early developments quickly led to the development of LED-based systems for plant physiology experimentation, since blue LED technology did not offer sufficient levels of blue irradiance. Researchers worked with NASA at the Kennedy Space Center (KSC) on plant-based regenerative life-support systems for future Moon and Mars bases and investigated the effect of LED-based light systems on several crop plants such as wheat, radish, spinach, lettuce, and peppers [19–21].

The Delphi method was developed in 1960 to combat some shortcomings of traditional prediction methods such as theoretical or quantitative models or trend extrapolation. However, ambiguity and uncertainty problems persisted in survey questions and responses [22]. In order to address these problems, fuzzy set theory was first incorporated with the Delphi method in 1985. The Delphi method was originally proposed by Dalkey and Helmer in 1963 and has been used in a wide range of research applications. The Delphi method systematically shows that group judgments are more valid than individual ones. In general, the standard procedure requires experts in the relevant field to answer questionnaires in two or more rounds. The researcher then provides an anonymous comment on the experts' forecasts from the previous round after each round of the survey. The experts are encouraged to revise their earlier answers according to the responses of other members of their panel. It is believed that the group will converge towards the correct answer, since the range of the answers will decrease during this process. Eventually, the process is repeated several times until a consensus emerges and the mean scores of the final round determine the result. Although the conventional Delphi method offers much scaffolding, the method still includes ambiguity and uncertainty problems in survey questions and responses

[22–24]. The incorporation of fuzzy set theory with the traditional Delphi method is one of the approaches to solving these problems [25–27]. Murray et al. [28] first applied fuzzy theory to the traditional Delphi method in 1985. Ishikawa et al. [29] utilized the cumulative frequency distribution function and fuzzy integration to convert the expert judgments into fuzzy numbers and employed the “gray zone,” the overlap section of the triangular fuzzy numbers, to develop the maximum membership degree and the FDM. FDM has been applied in many different fields of study. Chang et al. [24] established the key successful factors (KSFs) of knowledge management for university students using e-portfolio by using FDM and FAHP. Mohammad [30] developed educational system strategies in university student applications by using a hybrid fuzzy Delphi AHP. The research identifies elements which affect the admission and application of students in an Iranian University.

The decision-making trial and evaluation laboratory (DEMATEL) was proposed by Fontela and Gabus [31] for the application of solving complex problems. DEMATEL aims to yield casual dimensions and intensity of impact by using matrix computation through direct comparison of the interrelation between criteria. These structure and casualty matrices are used to express the relationship between properties in order to find the core issues of an evaluation system [32]. These methods thus benefit the decision-maker in terms of execution. DEMATEL is frequently applied to multiple criteria decision-making (MCDM) to understand the core problems and construct evaluation performance models using the mutual impact between factors and the cause-and-effect diagram drawn based on their significance. J.-K. Chen and I.-S. Chen [33] discussed the innovative performance of Taiwan's advanced education institutes in academic research and used DEMATEL, FANP, and TOPSIS to determine the relative weight of each measurement criterion and were thereby able to evaluate how to form the ideal solution and technology that will support the system through development innovation. Büyüközkan and Çifçi [34] noted that enterprises responded to increased public awareness following environmental impacts, while at the same time environmental (green) criteria and strategies became more important. The environmental performance of enterprises is not only related to the internal efforts of enterprises, but also subject to impact from the environmental performance and image of suppliers. Nonetheless, the choice of suppliers is a complex and multiple criteria decision-making problem. Therefore, green supply chain management and the capacity for green supply chain management should be employed as a basis to combine MCDM with DEMATEL in order to find the core factors to building a green supplier evaluation model for automobile companies using ANP and TOPSIS.

The Analytic Hierarchy Process (AHP), proposed by Saaty in 1971, assumes that criteria (effecting factors) in the same level are mutually independent. However, because this assumption does not reflect reality, Saaty and Takizawa [35] indicated dependence and independence from linear hierarchies to nonlinear networks using the composite vector of priorities (or composite priority vector, CPV),

which illustrated how to generate priorities for decisions in view of the dependence of criteria on criteria, criteria on alternatives, and alternatives on alternatives, based on the hierarchical feedback system framework. They distinguish two types of dependence: either functional, semantic, or qualitative dependence or structural or quantitative dependence. Moreover, they represented two kinds of dependence (outer dependence: dependence between components; inner dependence: interdependence within a component combined with feedback between components) in a nonlinear network diagram. Saaty [36] proposed the analytic network process (ANP) to extend AHP by gathering dependency and feedback with AHP. The purpose of the ANP method is to improve the traditional AHP structure in which the criteria in the same level are not interactive and dependent. In the real world, the factors influencing decision-making are no longer limited by a linear top-down structure. In other words, factors interact more like a network than a linear relationship, as one hierarchy may dominate or be dominated by other hierarchies, namely, the feedback effects. ANP tolerates criteria with feedback in the same cluster (inner dependence) and allows criteria feedback in different clusters (outer dependence). Researchers can identify the relationship among criteria in a cluster and the relationship among the clusters and then infer the priority of the alternatives.

Many previous studies have used FANP to solve complex problems in decision-making models, choosing the best alternative or strategy by fuzzy weights. Mikhailov and Singh [37] published an extended ANP approach that includes personal preference, transfers fuzzy evaluation values to range values by α -cut method, and obtains the weights in light of the range value to design a decision-making system. Promentilla et al. [38] applied the ANP technique to analyze polluted yards and assess improvement strategies. The procedure of their methodology is to apply the α -cut method, interval arithmetic, and fuzzy optimism index to the definite matrix and then find the priority weights by calculating the eigenvalues. Each value in the pairwise comparison matrix represents the subjective opinions of a decision-maker. Associating ANP with fuzzy theory can demonstrate the fuzzy consensus from the group evaluators' point of view on the importance between any two criteria. Büyükoçkan et al. [39] introduced a fuzzy number to the supermatrix using linguistic assessment and a fuzzy algorithm to solve the fuzzy problems arising from the criteria selection and judgment process. Mohanty et al. [40] employed the FANP method to analyze the risks and uncertainty for investments, calculating the weights based on scope analysis and selecting the best R&D project by fuzzy cost analysis. An FANP method provided enriched insights into strategic management in the Turkish airline industry [41]. Chen and Chang [42] employed ISM (Interpretative Structural Modeling) to obtain the dimension-dimension and criterion-criterion dependence relationship and used the fuzzy analytic network process (Fuzzy ANP) to determine the top priority weight for assessment improvement in new product development solutions. Song et al. [43] depended on an integrated AHP and ISM method to make an exploration of the vulnerability factors.

3. Proposed Methodologies and Procedures

This study employs the fuzzy Delphi method (FDM), fuzzy decision-making trial and evaluation laboratory (FDEMATEL), fuzzy analytic network process (FANP), and composite priority vector (CPV) to make better decisions in new product investments in LED plant lighting industries. The procedure consists of two stages. In the first stage, major perspectives and all performance criteria affecting new product design will be collected from previous studies and analyzed. Experts from different LED plant lighting industry areas are then selected and invited to take part in the study, according to problems identified in the analysis. The experts are also asked to complete a questionnaire. After determining the indicators for the hierarchical structure by literature review and expert interviews, an FDM is applied to screening those perspectives and criteria for the performance assessment model. In the second stage, FDEMATEL is used to obtain the relationships among the perspectives (outer dependence) and among the performance criteria (inner dependence). A supermatrix is created by using an FANP, and the weights of perspectives and all criteria are computed. A determination of the ranking weights shows the importance of investments in a new product project. The complete MCDM research flowchart is presented in Figure 2.

Step 1 (explore and define research questions). The first thing to be done is to collect data pertaining to the LED plant lighting industry through literature reviews in order to identify the problems encountered during new product development. Other LED applications including product development, manufacturing, marketing, and recycling will also be discussed.

Step 2 (establish an expert committee). Since the field of this study is the LED plant lighting industry, the challenges in designing renewable energy-related new products will be addressed through related data collection, expert interviews, and questionnaires.

Step 3 (analyze the responses of the surveys). A fuzzy Delphi method (FDM) is used to obtain a reasoned consensus and consolidate individual judgments systematically. First, the questionnaire is completed by the selected experts for their suggestions and then reframed by those experts until a consensus is reached. This study uses the FDM proposed by Ishikawa et al. [29] and Lee et al. [44], and the process of the FDM is briefly explained as follows.

Step 4 (collect the possible evaluation criteria). $U = \{u_i \mid i = 1, 2, 3, \dots, n\}$, where u_i is criterion i . Once the initial perspectives and criteria are established through literature review, this study obtains critical criteria for new product development. A 0–10 point evaluation scale is designed in the questionnaires and sent to the experts. Each expert is asked to give a value $S^i = \{(C_k^i, O_k^i)\}$, where S^i should be an integer; C_k^i and O_k^i are the lowest value and the highest value for the criterion u_i scored by the expert k . These two values also, respectively, indicate the quantitative scores of

FIGURE 2: The proposed complete MCDM research flowchart.

the criteria for each expert's most conservative value and most optimistic value. The lowest level C_k^i and the highest level O_k^i of all expert judgments for each criterion u_i are then statistically calculated, and any extreme values greater than twice the standard deviation will be removed from

the criteria U [22]. The triangular values (the minimum C_L^i , the geometric mean C_M^i , and the maximum C_U^i) of the remaining most conservative value C_k^i and the triangular values (the minimum O_L^i , the geometric mean O_M^i , and the maximum O_U^i) of the qualified most optimistic

FIGURE 3: Gray zone in two triangular fuzzy numbers.

value O_k^i are then processed, resulting in a triangular fuzzy number.

As indicated above, this study creates two triangular fuzzy numbers, $C^i = (C_L^i, C_M^i, C_U^i)$ and $O^i = (O_L^i, O_M^i, O_U^i)$, for each criterion u_i with triangular values of the remaining most conservative value C_k^i and the qualified most optimistic value O_k^i . If they overlap, the area of the overlap is the “gray zone” [22, 45] shown in Figure 3.

According to the gray zone of each criterion u_i , operate the importance of consensus value G^i , and examine the expert opinions to see if they arrive at a valid consensus. The consensus value G^i expresses how important a criterion u_i is. The higher the G^i value, the more important the criterion u_i . Once C_U^i and O_L^i are obtained from Step 4, the consensus value G^i can be met as the following formula.

(1) If the two triangles do not overlap ($C_U^i \leq O_L^i$), the criterion u_i achieves consensus among the experts. The consensus importance value G^i will be the average of C_M^i and O_M^i .

(2) If the two triangles overlap ($C_U^i > O_L^i$), there is a gray zone Z^i in the criterion u_i and $Z^i = C_U^i - O_L^i$. The value ranging between the geometric mean of the most optimistic value and the geometric mean of the most conservative value can be shown as $M^i = O_M^i - C_M^i$. The relationship between $M^i = O_M^i - C_M^i$ and $Z^i = C_U^i - O_L^i$, meanwhile, ought to be identified as follows:

(a) If $Z^i < M^i$, it seems that there is no consensus among the experts, but the extreme opinions attributed by the experts are considered not far from other opinions given by the rest. For this reason, let the consensus on the importance G^i of the criterion u_i be the fuzzy relationship in order to find the fuzzy sets, and then obtain the maximum membership degree [44]. $\mu_F(x_j)$ represented below is the membership function of the fuzzy triangular numbers C^i and O^i :

$$F^i(x_j) = \left\{ \int_x \{ \min [C^i(x_j), O^i(x_j)] \} dx \right\}, \quad j \in U, \quad (1)$$

$$G^i = \{x_j \mid \max \mu_{F^i}(x_j)\}, \quad j \in U.$$

(b) If $Z^i > M^i$, it is certain that there is no consensus among the experts, and the extreme opinions

attributed by the experts are considered far from other opinions given by the rest. Thus, the criterion u_i which is not converged will provide the experts with the ranging value M^i for the next questionnaire. All criteria are expected to reach a convergence until the consensus value G^i is generated.

As G^i above indicates, a threshold S is set to estimate whether a criterion u_i is qualified or not. That is, compare a consensus value G^i with S ; a criterion u_i will be selected if $G^i > S$; otherwise, it will be eliminated [46]. In general, a threshold S is suggested from 6.0 to 7.0, according to literature review; however, this is subject to change in order to make a better choice [46, 47].

To sum up, the FDM procedure described above can be organized into three main phases as follows.

Phase 1. Calculate twice the standard deviation ($2 * SD$).

Phase 2. Identify the gray zone (yes or no).

Phase 3. Set the threshold.

Step 5. Identify the relationships among the perspectives and among the criteria by utilizing a fuzzy decision-making trial and evaluation laboratory (FDEMATEL) method, and build a network relationship map.

Step 6. Derive the weights of the perspectives and criteria in new product design by using a fuzzy analytic network process (FANP). This study employs a 9-point scale of relative importance, proposed by Saaty, to design the FANP questionnaire. Experts are then asked to represent decision-makers in LED plant lighting industries for the purposes of the survey. The FANP is processed as follows.

(1) Form the network structure in which the goal, the perspectives and criteria are well defined, and the exterior relationship among the perspectives and the interior relationship among criteria are determined.

(2) Form pairwise comparison matrices with the 1 to 9 scores received from the expert responses in the questionnaires. Analyze consistency. The priority of the elements can be compared by the computation of eigenvalues and eigenvectors:

$$A \times w = \lambda_{\max} \times w, \quad (2)$$

where w is the eigenvector, the weight vector, of matrix A , and $\lambda_{\max}$ is the largest eigenvalue of matrix A .

(3) Check the consistency of pairwise matrices with consistency index (CI) and consistency ratio (CR). The consistency property of the matrix is then checked to ensure the consistency of judgments in the pairwise comparison.

As suggested by Saaty [48], the upper threshold CR values are 0.05 for a 3×3 matrix, 0.08 for a 4×4 matrix, and 0.10 for larger matrices. If the consistency test is not passed, the original values in the pairwise comparison matrix must be revised by the decision-maker.

(4) Construct fuzzy positive matrices. The pairwise comparison scores are transformed into linguistic variables, which are represented by positive triangular fuzzy numbers. According to Buckley [49], the fuzzy positive reciprocal matrix can be defined as

$$\tilde{R}^k = [\tilde{r}_{ij}]^k, \quad (3)$$

where $\tilde{R}^k$ is a positive reciprocal matrix; k is the number of decision-makers; $\tilde{r}_{ij}$ is relative importance between elements i and j ;

$$\begin{aligned} \tilde{r}_{ij} &= 1, \quad \forall i = j, \\ \tilde{r}_{ij} &= \frac{1}{\tilde{r}_{ji}}, \quad \forall i, j = 1, 2, \dots, n. \end{aligned} \quad (4)$$

(5) Calculate fuzzy weights. Based on the Lambda-Max method proposed by Csutora and Buckley in 2001, calculate the fuzzy weights of decision elements. The procedures are as follows.

Apply α -cut. Let $\alpha = 1$ to obtain the positive matrix of decision-maker k , $\tilde{R}_b^k = [\tilde{r}_{ij}]_b^k$, $\tilde{R}_a^k = [\tilde{r}_{ij}]_a^k$, and let $\alpha = 0$ to obtain the lower and upper bound positive matrices of decision-maker k , and $\tilde{R}_c^k = [\tilde{r}_{ij}]_c^k$. Based on the weight calculation procedure proposed in ANP, calculate weight matrices $W_b^k = [w_i]_b^k$, $W_a^k = [w_i]_a^k$, and $W_c^k = [w_i]_c^k$, $i = 1, 2, \dots, n$.

In order to minimize the fuzziness of the weight, two constants, M_a^k and M_c^k , are chosen as follows:

$$\begin{aligned} M_a^k &= \min \left\{ \frac{W_{ib}^k}{W_{ia}^k}, 1 \leq i \leq n \right\}, \\ M_c^k &= \max \left\{ \frac{W_{ib}^k}{W_{ic}^k}, 1 \leq i \leq n \right\}. \end{aligned} \quad (5)$$

The upper and lower bounds of the weight are defined as

$$\begin{aligned} W_{ia}^{*k} &= M_a^k W_{ia}^k, \\ W_{ic}^{*k} &= M_c^k W_{ic}^k. \end{aligned} \quad (6)$$

The upper and lower bound weight matrices are

$$\begin{aligned} W_a^{*k} &= [W_{ia}^{*k}]^k, \\ W_c^{*k} &= [W_{ic}^{*k}]^k, \\ i &= 1, 2, \dots, n. \end{aligned} \quad (7)$$

By combining W_a^{*k} , W_b^k , and W_c^{*k} , the fuzzy weight matrix for decision-maker k can be obtained and is defined as $\tilde{W}_i^k = (W_{ia}^{*k}, W_{ib}^k, W_{ic}^{*k})$, $i = 1, 2, \dots, n$.

(6) Integrate the opinions of decision-makers. Geometric average is applied to combine the fuzzy weights of decision-maker opinions:

$$\overline{\tilde{W}}_i = \left[\prod_{k=1}^K \tilde{W}_i^k \right]^{1/K}, \quad \forall k = 1, 2, \dots, K, \quad (8)$$

where $\overline{\tilde{W}}_i$ is the combined fuzzy weight of decision element i of K decision-makers, $\tilde{W}_i^k$ is the fuzzy weight of decision element i of decision-maker k , and K is the number of decision-makers.

(7) Defuzzify the synthetic triangular fuzzy numbers into crisp numbers by centroid method.

Form pairwise comparison matrices using the defuzzification values, and combine each submatrix with priority vectors to be an initial supermatrix. As they may not fit the column stochastic rule, normalize each column matrix to make a weighted supermatrix. Calculate a limited supermatrix by taking the weighted supermatrix to $2k + 1$ powers so that the supermatrix converges into a stable supermatrix.

Step 7. The weight values acquired from FANP with CPV are ranked, and the best alternative is selected. Moreover, the significant elements (factors) that LED-based lighting plant factories try to use in developing a new product will be indicated and will provide decision-makers with important guidance.

Step 8. Conclusions and recommendations will be summarized.

4. Case Study

This study aims to construct an investment decision-making model using the fuzzy Delphi method (FDM), Fuzzy DEMATEL (FDEMATEL), and the fuzzy analytic network process (FANP) for new product development (NPD). An empirical case study from the LED-based lighting plant industry is presented as follows: (1) integrating crucial objectives and criteria of new product development obtained by literature review and expert interviews; (2) exploiting the FDM to screen the elements of objectives and criteria and identifying the cause-and-effect relationships among them; (3) determining the weights of priority vectors of objectives and criteria using FANP, which can facilitate the decision-making quality and enhance the NPD investment benefits in the LED-based lighting plant factory.

As this study is primarily concerned with decision-making in new product development in the LED-based lighting plant factory, it invites industrial and academic experts experienced in electromechanics, agriculture, and venture capital. Relevant literature surveys and repeated discussions between experts and scholars allow the study to identify crucial elements of potential objectives and criteria of new product development in an LED-based lighting plant factory,

TABLE 1: FDM participants' backgrounds and qualifications.

Expertise areas	The number of people
Academia	7
Plant industry	7 (including photoelectric 3 & agriculture 4)
Machinery industry	2
Investment consultancy	1

TABLE 2: The definition of objectives in the FDM process.

Objectives	Definitions
O1: management team	NPD team members of LED lighting plant project
O2: financial fund	Required investment and cost for LED lighting plant project
O3: product & technology	Required technical support and R&D capabilities
O4: marketing	Market successfully accepted by consumers
O5: external environment	Natural environment or man-made force majeure

and the proposed evaluation model can be further utilized in the future development of new products.

In the first phase, the expert questionnaires for the fuzzy Delphi method (FDM) are implemented to select the critically affected elements of objectives and criteria in new product development. The expert questionnaire for the fuzzy decision-making trial and evaluation laboratory (FDEMATEL) is next employed to determine the degree and direction of impact from each performance index and to draw the network structure of each index via causality relationships in the second phase. In addition, a fuzzy analytic network process (FANP) is applied to analyze the objective and criteria weights and to determine the priorities of critical impact factors in the third phase. Through the above process, the critical priority factors are identified in this research, which will affect investment in new product development in an LED-based lighting plant factory.

In addition to the literature survey and expert interviews, this study arranges five objectives and twenty-two criteria as FDM factor-screened samples. This is sufficient to obtain the cumulative frequency distribution function and the fuzzy integration to turn the experts' judgments into fuzzy numbers using 10 to 15 participants. Using more than 10 participants in the FDM process effectively reduces the error among them [50]. A total of 17 experts from different professional and academic fields take part in this study, including the photovoltaic industry, agricultural industry, machinery industry, and academia. The various FDM participants' backgrounds and qualifications are listed in Table 1.

In recent years, a plant factory-related research has received significant attention as an emerging industry. This study focuses on an LED-based lighting plant factory in view of the current market situation and limited human resources, with the aim of meeting potential consumers' NPD demands. Based on the research methodology of the previous section, the study allows experts and scholars to proceed to the related FDM questionnaires and identify the objectives and criteria using brainstorming discussions, which are described in Tables 2 and 3.

By integrating the results of comparing extreme values with their threshold values, the trimmed new product development decision-making model for an LED-based lighting plant factory can be generated by using the Fuzzy Delphi method (FDM) and represents 4 objectives and 11 criteria, as shown in Table 4. Moreover, the decision-making hierarchy schematic model for an LED-based lighting plant factory is depicted in Figure 4.

The impact interactions of the above 11 key indicators (i.e., A to K) can be identified through the Fuzzy DEMATEL survey, which invited six domestic industrial experts and scholars in the plant factory field to take part in the questionnaires. They were asked to identify, based on their expertise, the direct effects exerted by each element on other elements, using a scale ranging from 0 to 4, where "0," "1," "2," "3," and "4," respectively, mean "no influence," "low influence," "medium influence," "high influence," and "very high influence." The larger the value of impact indicators, the greater the influence of the factor on another factor! After completing the above questionnaires, each expert evaluates the direct impact effects and places them in direct-relation matrices, and the corresponding triangle fuzzy number can be seen in Table 5.

The direct-relation matrix is developed by summing all vectors and taking the sum of maximum vectors as the benchmark of form. The initial direct-relation matrix D is shown in (9). The normalized direct-relation matrix (X) can be obtained by calculating (10) and (11).

$$D = \begin{bmatrix} 0 & D_{12} & \cdots & D_{1j} \\ D_{21} & 0 & \cdots & D_{2j} \\ \vdots & \vdots & \ddots & \vdots \\ D_{i1} & D_{ij} & \cdots & 0 \end{bmatrix}, \quad (9)$$

$$\lambda = \frac{1}{\max_{1 \leq i \leq n} \left(\sum_{j=1}^n D_{ij} \right)}, \quad (10)$$

$$X = \lambda \times D. \quad (11)$$

TABLE 3: The definition of criteria in the FDM process.

Criteria	Definitions
C1-1: expertise and management skills	The background of the team members should allow them to communicate and coordinate
C1-2: business management philosophy	Whether the management concept of board members is consistent
C1-3: top management approval	Department heads are actively involved in product development plan
C2-1: investment preparation in funding	Required project (customer satisfaction) investment funds
C2-2: cost of investment opportunities for government grants	The government provides the relevant laws and regulations, subsidies or tax cuts, and other measures
C2-3: return on investment	The economy scale of the investment is the percentage ratio between the income and the cost
C3-1: technical personnel and R&D capability	R&D efficiency and technical support capability
C3-2: effective manufacturing processes	The manufacturing process of the product must be comprehensive and flexible and effectively enhance the production capacity
C3-3: technical resources management	Promoting the maintenance and management capabilities of optoelectronics, agriculture, and machinery fields
C3-4: product added value	Not only food but also architectural design and ornament can be further developed
C3-5: patents and intellectual property rights	Intellectual property rights and patents for the LED plant growth box portfolio
C4-1: potential market demands	Total demands for LED plant growth boxes in target markets
C4-2: product differentiation of the market competitive advantage	Differences in the products and services provided by the company and its competitors
C4-3: new product marketing strategy	Hybrid innovative marketing model for LED plant growth box
C4-4: market status survey	Current LED plant growth box in the target market vendor survey
C4-5: consumer acceptance	The perception of target consumers, which benefits from the LED plant growth box
C4-6: channel profit	The profits from assisting before LED plant growth box products given to the consumers
C4-7: integrity of after-sales service	Providing after-sales service and support after the product enters the market
C5-1: imitation by competitors	Product portfolio can be copied by existing competitors or potential competitors
C5-2: government decrees and patents	Changes in government regulations or patent factors leading to product supply chain or promotion affected
C5-3: research report unfavorable to this industry	Research report will affect the promotion of products in the market
C5-4: geography, climate, and other extreme environmental constraints	Force majeure of natural and environmental factors for LED plant growth box products

TABLE 4: The trimmed NPD decision-making model.

Objectives	Definitions	Criteria
O1: management team	NPD team members of LED lighting plant project	A: expertise and management skills B: business management philosophy
O2: financial funding	Required investment and cost for LED lighting plant project	C: investment preparation in funding D: return on investment E: technical personnel and R&D capability
O3: product & technology	Required technical support and R&D capabilities	F: effective manufacturing processes G: technical resources management H: potential market demands
O4: marketing	Market successfully accepted by consumers	I: new product marketing strategy J: market status survey K: consumer acceptance

FIGURE 4: The decision-making hierarchy schematic diagram of an NPD project.

TABLE 5: Triangle fuzzy number of identified direct effect and scale range.

Direct effect	Scale	Triangle fuzzy number
No influence	0	(0, 0, 0)
Low influence	1	(0, 0.25, 0.5)
Medium influence	2	(0.25, 0.5, 0.75)
High influence	3	(0.5, 0.75, 1)
Very high influence	4	(0.75, 1, 1)

Substitute the direct-relation matrix X into (12) to calculate the total-relation matrix (T), while the direct-relation matrix can also be addressed as the total-relation matrix. Particularly, the unit matrix I is defined in (13), and all criteria

direct-relation matrices are combined to become the total-relation matrix:

$$T = \lim_{k \rightarrow \infty} (X^1 + X^2 + \dots + X^k) = X(I - X)^{-1}, \quad (12)$$

$$I = \begin{bmatrix} 1 & 0 & 0 & \dots & 0 \\ 0 & 1 & 0 & \dots & \vdots \\ 0 & 0 & 1 & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \dots & 1 \end{bmatrix}. \quad (13)$$

At the outset of constructing the experts' questionnaires, the elements of objectives such as management team, financial funding, product and technology, and marketing are used

TABLE 6: Relevance and level of impact among objectives after integration.

Objectives	D_i	R_j	$D_i + R_j$	$D_i - R_j$
O1: management team	92.1266	92.1266	183.2259	-1.027280765
O2: financial fund	89.8125	89.8125	179.6254	0.000492328
O3: product & technology	93.0257	93.0257	183.9982	-2.053063573
O4: marketing	87.8109	87.8109	178.7017	3.07985201
Average			181.3878	(0.00)

to obtain the relevance and level of impact through direct-relation analyses, as shown in Table 6. The sum of D_i on each column and the sum of R_j on each row, respectively, are then calculated, as shown in (14), where D_i denotes the level of impact directly and affects other criteria; R_j denotes the level; and criterion j is directly affected by other criteria. $D_i + R_j$ denotes relevance, signifying the intensity of the relationship between criteria. $D_i - R_j$ denotes level of impact, also known as the intensity with which criteria have effect or are affected.

$$D_i = \sum_{j=1}^n x_{ij}, \quad i = 1, 2, 3, \dots, n, \quad (14)$$

$$R_j = \sum_{i=1}^n x_{ij}, \quad j = 1, 2, 3, \dots, n.$$

Using two-dimensional coordinates as the base of a causal diagram and taking $D_i + R_j$ as the x -axis and $D_i - R_j$ as the y -axis, the relevance and level of impact of each criterion are marked on the coordinates. The causality between criteria is drawn according to the threshold, in addition to analysis. In particular, if $D_i - R_j$ is a positive value, it suggests that i affects criterion j ; conversely, if $D_i - R_j$ is a negative value, it suggests that j affects criterion i . In order to obtain the relevance and level of impact among objectives, the matrix values are substituted into (14) to yield D_i and R_j , which, in addition to a summary, are found in Table 16. In particular, $D_i + R_j$ represents the relevance value between objectives, whereas $D_i - R_j$ denotes the level of impact or impact value.

The relevance value and impact value are set up in two-dimensional coordinates, where relevance value ($D_i + R_j$) is filled in the x -axis, and impact value ($D_i - R_j$) is filled in the y -axis. This study configures a threshold to highlight the causality. In particular, the threshold value is 1.073, which is the maximum value of diagonal elements within the total-relation matrix (T). Through the configuration of the threshold, a number smaller than the threshold will be deleted, while a number greater than or equal to the threshold will be drawn on the coordinates to form the direct-relation causal diagram for objectives. The causal diagram for objectives is shown in Figure 5.

The relevance and level of impact of management team, financial funding, product and technology, and marketing are shown in Tables 7–10, and causal diagrams for management team, financial funding, product and technology, and marketing are shown in Figures 6–9.

In addition to the above, a fuzzy analytic network process (FANP) is used to calculate the relative weights of relationships between objectives and criteria, so that enterprises or

◆ $d-r$

FIGURE 5: Causal diagram for objectives.

◆ $d-r$

FIGURE 6: Causal diagram for management team.

R&D departments can select the most important elements in the new product development decision-making scheme. This study constructed dependency relationships between hierarchical relationships of the key elements of objectives and criteria in new product development of an LED-based lighting plant factory using Fuzzy DEMATEL. Moreover, the study composes pairwise relative weights of the FANP architecture, while the questionnaire responses of 10 experts are assessed with the fuzzy semantic variables integrated by

TABLE 7: The relevance and level of impact (6 experts) for management team.

Items	Elements	D_i	R_j	$D_i + R_j$ (relevance)	$D_i - R_j$ (level of impact)
A	Expertise and management skills	12.95	13.55	26.50	-0.60
B	Business management philosophy	13.23	13.49	26.71	-0.26
C	Investment preparation in funding	13.23	13.50	26.73	-0.26
D	Return on investment	13.36	12.83	26.19	0.53
E	Technical personnel and R&D capability	13.23	13.32	26.55	-0.09
F	Effective manufacturing processes	12.88	13.02	25.90	-0.13
G	Technical resources management	12.95	12.98	25.93	-0.03
H	Potential market demands	13.44	12.85	26.29	0.59
I	New product marketing strategy	13.01	13.04	26.05	-0.03
J	Market status survey	12.46	12.68	25.14	-0.22
K	Consumer acceptance	12.96	12.46	25.41	0.50
	Average			26.13	(0.00)

TABLE 8: The relevance and level of impact (6 experts) for financial fund.

Items	Elements	D_i	R_j	$D_i + R_j$ (relevance)	$D_i - R_j$ (level of impact)
A	Expertise and management skills	15.93	16.35	32.28	-0.42
B	Business management philosophy	15.52	15.78	31.30	-0.27
C	Investment preparation in funding	15.66	16.10	31.76	-0.45
D	Return on investment	15.56	15.79	31.35	-0.22
E	Technical personnel and R&D capability	15.99	15.53	31.52	0.45
F	Effective manufacturing processes	15.31	15.25	30.57	0.06
G	Technical resources management	15.79	15.38	31.16	0.41
H	Potential market demands	15.52	15.45	30.97	0.07
I	New product marketing strategy	15.72	15.90	31.62	-0.17
J	Market status survey	15.12	15.08	30.21	0.04
K	Consumer acceptance	15.77	15.29	31.06	0.49
	Average			31.25	(0.00)

TABLE 9: The relevance and level of impact (6 experts) for product and technology.

Items	Elements	D_i	R_j	$D_i + R_j$ (relevance)	$D_i - R_j$ (level of impact)
A	Expertise and management skills	18.56	18.28	36.83	0.28
B	Business management philosophy	18.38	18.58	36.96	-0.21
C	Investment preparation in funding	18.68	18.50	37.19	0.18
D	Return on investment	18.50	18.03	36.53	0.47
E	Technical personnel and R&D capability	18.42	18.21	36.62	0.21
F	Effective manufacturing processes	17.96	17.88	35.85	0.08
G	Technical resources management	18.42	18.84	37.26	-0.42
H	Potential market demands	17.97	18.27	36.23	-0.30
I	New product marketing strategy	18.23	18.40	36.63	-0.18
J	Market status survey	17.87	17.98	35.85	-0.11
K	Consumer acceptance	18.31	18.32	36.63	-0.01
	Average			36.60	0.00

TABLE 10: The relevance and level of impact (6 experts) for marketing.

Items	Elements	D_i	R_j	$D_i + R_j$ (relevance)	$D_i - R_j$ (level of impact)
A	Expertise and management skills	16.29	16.40	32.70	-0.11
B	Business management philosophy	16.17	15.81	31.98	0.36
C	Investment preparation in funding	16.07	16.15	32.22	-0.08
D	Return on investment	15.86	16.04	31.91	-0.18
E	Technical personnel and R&D capability	16.19	15.82	32.01	0.36
F	Effective manufacturing processes	15.47	15.86	31.33	-0.40
G	Technical resources management	16.22	15.71	31.93	0.52
H	Potential market demands	15.95	15.77	31.72	0.18
I	New product marketing strategy	16.27	16.47	32.73	-0.20
J	Market status survey	14.97	15.63	30.60	-0.66
K	Consumer acceptance	15.59	15.39	30.98	0.20
Average				31.83	0.00

◆ $d-r$

FIGURE 7: Causal diagram for financial funding.

◆ $d-r$

FIGURE 8: Causal diagram for product and technology.

geometric mean, and the holistic process of the FANP is illustrated as follows.

FIGURE 9: Causal diagram for marketing.

Step 1 (establish the network structure). An analytics network process structure consisting of the business goal and objectives and criteria well defined in the first step of this case study is established. This structure includes the exterior relationship among criteria and the interior relationship among criteria under each objective, as shown in Figure 10.

Step 2 (form pairwise comparison matrices). Based on the (1–9) scores from the expert responses to the FANP questionnaires, the pairwise comparison matrices for the objective and criteria are formed. Meanwhile, the entries in each column are normalized and the eigenvectors are obtained. The fuzzy and defuzzy pairwise comparison matrices from 10 experts' answers to the four objectives are shown in Tables 11 and 12.

Step 3 (examine the consistency). Once the eigenvectors are obtained, the largest eigenvalue for each matrix can be computed. Then, the consistency index (CI), random index (RI), and the consistency ratio (CR) are calculated. According to Saaty's suggestion, the consistency is satisfied if the CR is smaller than 0.1. Thus, the expert responses are

TABLE 11: The fuzzy pairwise comparison matrix (10 experts) for objectives.

Objectives	Management team			Financial fund			Product & technology			Marketing		
O1: management team	1.000	1.000	1.000	0.480	0.567	0.687	0.344	0.457	0.692	0.394	0.459	0.549
O2: financial fund	1.455	1.764	2.083	1.000	1.000	1.000	0.443	0.521	0.641	0.404	0.492	0.634
O3: product & technology	1.446	2.187	2.906	1.560	1.918	2.259	1.000	1.000	1.000	0.497	0.575	0.679
O4: marketing	1.823	2.178	2.541	1.578	2.032	2.472	1.473	1.740	2.011	1.000	1.000	1.000

FIGURE 10: An analytics network process structure of the proposed MCDM model.

TABLE 12: The defuzzy pairwise comparison matrix (10 experts) for objectives.

Objectives	Management team	Financial fund	Product & technology	Marketing
O1: management team	1.0000	0.5780	0.4976	0.4671
O2: financial fund	1.7674	1.0000	0.5350	0.5100
O3: product & technology	2.1797	1.9123	1.0000	0.5836
O4: marketing	2.1804	2.0276	1.7413	1.0000

TABLE 13: The consistency assessment of fuzzy pairwise comparison matrix.

Objectives	Management team	Financial fund	Product & technology	Marketing	Weight
O1: management team	0.1403	0.1048	0.1319	0.1824	0.1398
O2: financial fund	0.2480	0.1812	0.1418	0.1992	0.1925
O3: product & technology	0.3058	0.3466	0.2650	0.2279	0.2863
O4: marketing	0.3059	0.3675	0.4614	0.3905	0.3813

$\lambda_{\max} = 4.1092$; $CI = 0.0364$; $RI = 0.9$; $CR = 0.040$.

analyzed using the above process. The results show that all CR values are less than 0.1. This means that the questionnaires are validated. As an example, a consistency examination including CI, RI, and CR from the same experts' answers to the four objectives is shown in Table 13.

Step 4 (construct the supermatrix). Each matrix is defuzzified to obtain the weights of the matrix, and then the weights are brought into the supermatrix, and an iterative computing model is used to generate the limited matrix from

the supermatrix. Table 14 is an unweighted supermatrix, and a weighted supermatrix is shown in Table 15; after iterative computing, the limited supermatrix is generated, as shown in Table 16.

In addition, this study uses the expert questionnaire responses to obtain the positive reciprocal matrix required for AHP and FANP research and to obtain the priority weight of each objective and each criterion through the structure of composite priority vector of Figure 11.

TABLE 14: The unweighted supermatrix.

Assessed Items	Objectives											O4				
	O1	O2	O3	O4	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C11
O1: management team	0.3615	0.2203	0.5546	0.2245	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
O2: financial fund	0.1925	0.5150	0.1925	0.1925	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
O3: product & technology	0.6385	0.2647	0.4454	0.2948	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
O4: marketing	0.3813	0.3813	0.3813	0.4807	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
C1: expertise and management skills	0.0000	0.0000	0.0000	0.0000	0.0688	0.1252	0.1222	0.0630	0.0818	0.0790	0.1194	0.0994	0.1297	0.0909	0.1363	0.1363
C2: business management philosophy	0.0000	0.0000	0.0000	0.0000	0.0581	0.1147	0.0970	0.0548	0.0683	0.0674	0.0609	0.0968	0.1099	0.0909	0.0833	0.0833
C3: investment preparation in funding	0.0000	0.0000	0.0000	0.0000	0.1408	0.2443	0.3575	0.1565	0.2591	0.2765	0.2714	0.3448	0.3283	0.0909	0.2813	0.2813
C4: return on investment	0.0000	0.0000	0.0000	0.0000	0.0604	0.1876	0.1806	0.0770	0.1068	0.1110	0.1240	0.1421	0.1432	0.0909	0.1209	0.1209
C5: technical personnel and R&D capability	0.0000	0.0000	0.0000	0.0000	0.1222	0.0000	0.0000	0.0821	0.0994	0.0000	0.0000	0.0000	0.0000	0.0909	0.0000	0.0000
C6: effective manufacturing processes	0.0000	0.0000	0.0000	0.0000	0.0883	0.0000	0.0000	0.0694	0.0815	0.1022	0.0000	0.0000	0.0000	0.0909	0.0000	0.0000
C7: technical resources management	0.0000	0.0000	0.0000	0.0000	0.0913	0.0000	0.0000	0.0748	0.0793	0.0971	0.1539	0.1498	0.0000	0.0909	0.2229	0.2229
C8: potential market demands	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0950	0.0000	0.0000	0.0000	0.1671	0.0000	0.0909	0.1553	0.1553
C9: new product marketing strategy	0.0000	0.0000	0.0000	0.0000	0.1926	0.3281	0.2426	0.1528	0.2237	0.2668	0.2704	0.0000	0.2888	0.0909	0.0000	0.0000
C10: market status survey	0.0000	0.0000	0.0000	0.0000	0.0797	0.0000	0.0000	0.0918	0.0000	0.0000	0.0000	0.0000	0.0000	0.0909	0.0000	0.0000
C11: consumer acceptance	0.0000	0.0000	0.0000	0.0000	0.0979	0.0000	0.0000	0.0828	0.0000	0.0000	0.0000	0.0000	0.0000	0.0909	0.0000	0.0000

TABLE 16: The limited supermatrix.

[illegible]

FIGURE 11: The structure of composite priority vector.

- (1) The independent weights matrix under selected objectives is shown below:

$$W_{21} = \begin{matrix} O_1 \\ O_2 \\ O_3 \\ O_4 \end{matrix} \begin{bmatrix} 0.1398 \\ 0.1925 \\ 0.2863 \\ 0.3813 \end{bmatrix}. \quad (15)$$

- (2) The relational weight matrix between dependencies of objectives is then calculated, as shown below:

$$W_{22} = \begin{bmatrix} 0.2297 & 0.1595 & 0.3524 & 0.1883 \\ 0.1223 & 0.3728 & 0.1223 & 0.1614 \\ 0.4057 & 0.1916 & 0.2830 & 0.2472 \\ 0.2423 & 0.2761 & 0.2423 & 0.4031 \end{bmatrix}. \quad (16)$$

- (3) The independent weight matrix of the elements (criteria) under each objective is generated:

$$W_{32} = \begin{bmatrix} 0.0630 \\ 0.0548 \\ 0.1565 \\ 0.0770 \\ 0.0821 \\ 0.0694 \\ 0.0748 \\ 0.0950 \\ 0.1528 \\ 0.0918 \\ 0.0828 \end{bmatrix}. \quad (17)$$

- (4) The relative weights between the dependency matrices of criteria are calculated:

$$W_{33} = \begin{bmatrix} 0.0688 & 0.1252 & 0.1222 & 0.0630 & 0.0818 & 0.0790 & 0.1194 & 0.0994 & 0.1297 & 0.0909 & 0.0909 \\ 0.0581 & 0.1147 & 0.0970 & 0.0548 & 0.0683 & 0.0674 & 0.0609 & 0.0968 & 0.1099 & 0.0909 & 0.0833 \\ 0.1408 & 0.2443 & 0.3575 & 0.1565 & 0.2591 & 0.2765 & 0.2714 & 0.3448 & 0.3283 & 0.0909 & 0.2813 \\ 0.0604 & 0.1876 & 0.1806 & 0.0770 & 0.1068 & 0.1110 & 0.1240 & 0.1421 & 0.1432 & 0.0909 & 0.1209 \\ 0.1222 & 0.0000 & 0.0000 & 0.0821 & 0.0994 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0909 & 0.0000 \\ 0.0883 & 0.0000 & 0.0000 & 0.0694 & 0.0815 & 0.1022 & 0.0000 & 0.0000 & 0.0000 & 0.0909 & 0.0000 \\ 0.0913 & 0.0000 & 0.0000 & 0.0748 & 0.0793 & 0.0971 & 0.1539 & 0.1498 & 0.0000 & 0.0909 & 0.2229 \\ 0.0000 & 0.0000 & 0.0000 & 0.0950 & 0.0000 & 0.0000 & 0.0000 & 0.1671 & 0.0000 & 0.0909 & 0.1553 \\ 0.1926 & 0.3281 & 0.2426 & 0.1528 & 0.2237 & 0.2668 & 0.2704 & 0.0000 & 0.2888 & 0.0909 & 0.0000 \\ 0.0797 & 0.0000 & 0.0000 & 0.0918 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0909 & 0.0000 \\ 0.0979 & 0.0000 & 0.0000 & 0.0828 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0909 & 0.0000 \end{bmatrix}. \quad (18)$$

(5) The actual weights among objectives are calculated:

$$W_{\text{goal-objectives}} = W_{22} \times W_{21} = \begin{bmatrix} 0.2355 \\ 0.1855 \\ 0.2689 \\ 0.3101 \end{bmatrix}. \quad (19)$$

$$W_{\text{objectives-criteria}} = W_{33} \times W_{32} = \begin{bmatrix} 0.1052 \\ 0.0854 \\ 0.2656 \\ 0.1278 \\ 0.0305 \\ 0.0330 \\ 0.0773 \\ 0.0444 \\ 0.1894 \\ 0.0204 \\ 0.0209 \end{bmatrix}. \quad (20)$$

(6) The actual weight of the criteria under each objective is calculated:

(7) The overall weight of each criterion for the goal is calculated:

$$W_{\text{goal-criteria}} = W_{32} \times W_{\text{goal-objectives}} = \begin{bmatrix} 0.0148 & 0.0129 & 0.0368 & 0.0181 & 0.0193 & 0.0163 & 0.0176 & 0.0224 & 0.0360 & 0.0216 & 0.0195 \\ 0.0117 & 0.0102 & 0.0290 & 0.0143 & 0.0152 & 0.0129 & 0.0139 & 0.0176 & 0.0283 & 0.0170 & 0.0154 \\ 0.0170 & 0.0147 & 0.0421 & 0.0207 & 0.0221 & 0.0187 & 0.0201 & 0.0255 & 0.0411 & 0.0247 & 0.0223 \\ 0.0195 & 0.0170 & 0.0485 & 0.0239 & 0.0255 & 0.0215 & 0.0232 & 0.0295 & 0.0474 & 0.0285 & 0.0257 \end{bmatrix}. \quad (21)$$

Normally, a decision-making model for NPD performance assessment includes a hierarchical structure with a variety of objectives and criteria, which is directly related to the processes of technology and management of different types of information (technological, economic, social, and environmental). Traditional single objective decision-making which is basically concerned with either maximization or minimization of a particular element or variable remains beneficial only in a study of small system. With the increase in the complexity and multiplicity in the problem, the single objective optimization/decision-making analysis is no longer a prevalent approach. Current multiple criteria decision-making (MCDM), considered as an evaluation structure to solve technical, socioeconomic, environmental, and institutional barriers, is a branch of operational research dealing with finding optimal weights of elements (factors) in complex scenarios including various indicators, conflicting objectives, and criteria [51]. The traditional evaluation methods, such as the macroeconomic and cost-benefit analysis indicators, are not sufficient to integrate all the elements (i.e., objectives or criteria) included in an LED-based light plant factory. On the contrary the MCDM methods provide more appropriate processes to evaluate a wide range of elements in different ways and thus offer valid decision support. This study provides evidence on the multicriteria decision-making approaches using FANP and CPV. The results of the data analytics and comparisons of FANP and the composite priority vector method for objectives and criteria are shown

in Table 17 and Figure 12. As the represented trend chart between FANP and CPV methods in Figure 12, the weight priority of both approaches reflects a consistent tendency. On the other hand, in light of the weights of objectives and criteria listed in Table 17, the most important objective is O4, marketing (FANP: 29.59%, CPV: 31.01%), followed by O3, product and technology (FANP: 28.55%, CPV: 26.89%), indicating the marketing for NPD priority of trade-offs is greater than product and technology in an LED-based light plant factories. Furthermore, the top three criteria are as follows: C3: investment preparation in funding (FANP: 27.36%, CPV: 26.56%); C9: new product marketing strategy (FANP: 22.98%, CPV: 18.94%); C4: return on investment (FANP: 13.519%, CPV: 12.78%).

5. Conclusion

This study first described objectives and performance criteria affecting new product design, collected and analyzed from previous studies and expert interviews and questionnaires. Experts were selected for their expertise and experience in various fields relating to LED plant lighting. Moreover, a reasoned consensus and consolidated individual judgments were systematically obtained by analyzing the responses of the surveys of a fuzzy Delphi method (FDM), and a fuzzy decision-making trial and evaluation laboratory (FDEMATEL) was managed to determine the relationships among the objectives and performance criteria. Secondly,

TABLE 17: Comparison of FANP and composite priority vector.

Assessed items	Weight for FANP	FANP rank	Weight for CPV	CPV rank
O1: management team	0.2399	3	0.2355	3
O2: financial fund	0.1787	4	0.1855	4
O3: product & technology	0.2855	2	0.2689	2
O4: marketing	0.2959	1	0.3101	1
C1: expertise and management skills	0.1072	4	0.1052	4
C2: business management philosophy	0.0881	5	0.0854	5
C3: investment preparation in funding	0.2736	1	0.2656	1
C4: return on investment	0.1351	3	0.1278	3
C5: technical personnel and R&D capability	0.0292	7	0.0305	9
C6: effective manufacturing processes	0.0260	8	0.0330	8
C7: technical resources management	0.0419	6	0.0773	6
C8: potential market demands	0.0224	11	0.0444	7
C9: new product marketing strategy	0.2298	2	0.1894	2
C10: market status survey	0.0230	10	0.0204	11
C11: consumer acceptance	0.0238	9	0.0209	10

FIGURE 12: Comparisons of weights of objectives and criteria between FANP and CPV.

environmental green standards can be met using the objectives and criteria obtained, which indicate the relationships among new product development objectives and criteria in the LED plant lighting industry. As a result, the weights of potential risk factors and top priority factors with FANP and the composite priority vector (CPV) can be generated to help enterprises establish an efficient decision-making assessment system, able to determine the most suitable alternatives for new product development in the LED-based lighting plant factories.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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