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An Agent-Based System for the Design of New Products Using a Fuzzy Multicriteria Approach

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Abstract The intense competition of global markets stimulates a significant change in the way products are designed, manufactured, and delivered. Such a situation is forcing companies to consider the use of new tools to support this decision process. This paper describes an agent-based system implementing a novel consumer-based fuzzy multicriteria methodology to support the design of new products. It argues that a combination of marketing decision support systems, multicriteria and multiobjective methodologies, fuzzy models, and agent technologies could be a valuable tool to assist marketing managers in new product design applications. In the multi-agent system architecture, software agents were classified into types and organized in teams. The first includes interface, task, and information agents. The second reflects Simon's decision-making process, including intelligence, design, and choice teams. The communication between agents is carried out using an ontology. An example of system operation attempting to get the design of new corn oil is presented using sequence diagrams.

Keywords Marketing · Decision support systems · Agent technology · New product design · Multiobjective evolutionary algorithms · Multicriteria decision analysis

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1 Introduction

The product design problem is a significant part of the new product development problem and one of the most crucial decisions for a company [1]. In modern companies, the new product development process is becoming a decentralized task. In this new environment, activities are distributed among several working groups, which are organized in distributed and hierarchical structures, where specialists are divided by disciplines. Thus, companies are facing new challenges:

1. Designing products in collaboration with other partners in a decentralized environment;
2. Designing products that meet customer needs and expectations, which sometimes conflict;
3. Reducing product development time and costs through simultaneous optimization [2].

In this scenario, marketing managers are forced to become more competitive through better decision-making that helps them to make or change the company's marketing strategy rapidly. It makes it necessary to develop efficient tools to aid the marketing managers to support their decisions and make informed decisions [3], and building a marketing decision support system (MDSS) becomes a logical way to do it.

In addition to the above, we found that the new product design literature has paid little attention to the situation where consumers provide fuzzy (imprecise and uncertain) preference information in the criteria, and in consumer preference modeling where good scores on other criteria cannot compensate a terrible score on a criterion. These features are appropriate for solving instances of the new product design problem. Allowing consumers to provide various types of preference information would increase the flexibility of the market survey procedure and reduce the cognitive burden on consumers. Also, the decision-maker gains in the expressiveness of the underlying consumer preference model and the robustness of the recommendation suggested by the consumer preference model are strengthened. In particular, fuzzy outranking relations can be employed to take into account the non-compensatory effects between criteria when consumers express their preferences. Fuzzy outranking relations can be constructed from the preference information provided by consumers, which is usually collected with the use of questionnaires during the conduction of a market survey.

This paper proposes a distributed agent-based framework for the implementation of a strategic MDSS that supports new product design. The product design process is collaborative, involving multi-disciplinary functions and different tools. The MDSS automates the use of a new product design fuzzy multicriteria methodology based on consumer preferences that were proposed by [4–6]. The prototype is composed of elements of marketing decision support systems, Multiobjective Evolutionary Algorithms (MOEA), fuzzy models, and Multicriteria Decision Analysis (MCDA). Here, consumer satisfaction is modeled using flexible fuzzy-multicriteria outranking approaches through a new aggregation/disaggregation preferences model, a market segmentation model, and a brand choice model. In this way, unlike other proposals in the literature, when a product is evaluated, fuzzy preference information in the criteria is used, the principle of noncompensatoriness does not lie, and the importance of each criterion in the evaluation is considered. It is believed that this approach will produce an appropriate representation of consumer preferences in the software.

Because in the implemented methodology for the design of new products, there is a variety of elements, characteristics, and relationships between them and a necessity for a system facilitating interaction among them, this motivated us the development of an agent-based system. The characteristics, which are present in the problem of new product design are:

a. The intrinsic distribution of problem-solving abilities (the software agents perform different data analysis, preference disaggregation, market segmentation, brand choice, evolutionary algorithms, and multicriteria analysis methods), data, and information;
b. The necessity of flexibility, modularity (software agents can appear and disappear in the system without disturbing its functionality), and reusability (customization of agents for new decision-makers); and
c. Problem-solving complexity involving coordination between actors expressing different points of view.

From a strategic marketing perspective, the proposed system is the first to introduce a multicriteria methodology application in the product design process based on the fuzzy outranking approach. The proposed methodology considers the market demand based on consumer preferences, also considers the decision-maker preferences based on his/her knowledge and experience with design issues and market issues, and the fuzzy uncertainty in assessing the performance of the criteria. The methodology considers the non-compensatory decision rules through our purchase modeling approach.

The aim of this paper is consequently to propose an agent-based system with particular features (e.g., a multicriteria methodology application based on the fuzzy outranking approach in the product design process) for marketing specialists and end-users concerned with the products design process (e.g., decision-makers from management and production departments, and other non-marketing expert people).

The rest of the paper is organized as follows: Sect. 2 reviews the relevant literature for DSSs in product development. Section 3 describes a new consumer-based multicriteria methodology for the design of new products. Section 4 introduces the MDSS Multi-agent architecture. Section 5 provides an example of system operation to test the MDSS for new product design (NPD). Conclusions and further work are presented in Sect. 6.

2 Related Work

The use of MDSS for NPD has been recognized as an essential factor for the development of new products at a company level because they impact on the quality of product development.

In recent years, researchers have proposed different MDSS to support NPD.

Lei and Moon [7] present a DSS for market-driven product positioning and design, based on market data and design parameters which determines market segments for new products using principal component analysis (PCA), K-means, and AdaBoost classification. The system combines a database, the unparalleled analytical capability of Matlab suite, and a graphical user interface to allow users to explore and evaluate alternative scenarios during product development. Yang et al. [8] develop a tool to design for remanufacturing and manufacturability assessment (DRRA) to be used at early product definition stage which adopts the Fuzzy TOPSIS method to facilitate product design for remanufacturing from four major design perspectives: material selection, material joining methods, structure design, and surface coating methods. García-Diéguez, Herva [9] presented an Ecodesign Index (EcoInd) which integrates complex information contained in various individual environmental indicators and a DSS to evaluate the environmental sustainability and safety of children's footwear. The EcoInd indicates the departure of a design or product from ideal conditions from an environmental point of view. Zhang et al. [10] presented a decision support-oriented ontological modeling approach for product knowledge. The paper first introduces a framework of knowledge-based decision support for new product development; then, the OWL ontology is used to appropriately capture and organize the knowledge generated at various stages of the product lifecycle. Finally, they integrate the ontology with rule systems to construct a decision support platform for facilitating knowledge-driven decision-making in new product development, and a case of knowledge-based decision support is used to demonstrate the effectiveness of the method. Yang, Li [11] proposed a product configuration system, namely configurator. It is a computer-supported decision support system (DSS) that assists a customer and engineers/salesmen in eliciting preference, capturing customer needs, representing product knowledge and rules, selecting alternative components and options, building mathematical models for deriving configurations, and recommending opportunities to customers during the configuration process in an interactively or automatically way. Kłos [12] proposed the development of a DSS for the selection of the best prototypes for manufacturing enterprises. The DSS is based on an analysis of technical and business factors of new products and enables the improvement of effectiveness and reduce decision time. To automate the process of decision-making, the data required for the DSS should be acquired from an ERP. The proposed DSS is based on the AHP method.

Chen [13] presented a system that can extract and consolidate the reviews expressed via social media and derive insights (product feature specification and feature importance) to help enterprises make decisions on developing next-generation products by analyzing the reviewers' knowledge and authority and their opinion sentiment toward the target products. The experimental results obtained show that the proposed mechanism is suitable for trend prediction and customer acceptance. Lin et al. [14] presented a consumer-oriented design approach to determine the optimal form design of personal toys that best match consumer's preferences. The consumer-oriented design approach is based on the process of Kansei engineering using neural networks and the technique for order preference by similarity to ideal solution (TOPSIS). The neural network model is used to build a design decision support database, and then a neural network-based TOPSIS decision support model is used to enable product designers to obtain the optimal design alternatives that best meet consumer's preferences for new characteristic toy design.

Zhou [15] presented a multi-agent DSS for new product development composed of eight modules: data collection, data management, statistical analysis, breakeven analysis, risk prediction analysis, resource optimization scheduling, expert system, and information exchange. Guillard, Buche [16] presented a new multicriteria DSS as a web application for designing biodegradable packaging for fresh produce; they describe the functional specification, the software architecture, the implementation of the developed tool and its operational functioning through a real-life case study to determine the most satisfactory materials for apricots packaging. Starostka-Patyk [17] presented an analysis of usage of the SimaPro 8 software as a tool supporting the new product design decision-making process on the base of inferior product management. In general, the paper implies the useful role of SimaPro 8 (as an IT solution example) in the processes of decision-making for the companies dealing with the design of new products and defective products that have to be managed properly.

Morales and Ortega [18] presented a distributed intelligent system to determine tendencies in customer's preferences from the application of surveys to clients; Guo et al. [19] developed a DSS based on the methodology of Kansei engineering composed of a friendly human–computer interface, a database management module and a model management section. The reader can review other MDSS to support NPD in the literature review by Figueroa-Perez, Leyva-Lopez [20].

Based on this review, new product design is facing demands such as

1. Designing products that meet customer needs;
2. Designing products in a collaborative distributed environment; and
3. Reducing product development time and costs [2].

Thus, two new essential challenges to carry out this activity in modern companies are to consider consumer satisfaction (CS) for decision support (DS) and the distributed decision-making support (DDMS).

Several of the systems, found in the literature, consider consumer satisfaction for decision support or distributed decision-making support; others do not. Decision support includes fuzzy systems, knowledge-based systems, expert systems, hybrid systems, multicriteria methods, or others.

Distributed decision-making support includes layered, software agents, or other architectures. The use of these elements in the implementation of the systems varies between them.

Among the systems that do not support consumer satisfaction for decision support or distributed decision-making support are those presented by Lei and Moon [7], Yang et al. [8], García-Diéguez et al. [9], Zhang et al. [10], Yang et al. [11] and Kłos [12]. Several of the reviewed systems support only consumer satisfaction for decision support, but they do not consider distributed decision-making support. Such is the case of those developed by Li, Chen [13], and Lin, Chen [14].

On the other hand, some of the revised systems support only distributed decision-making, but they do not consider consumer satisfaction for decision support in their models. Such is the case of those presented by Yu et al. [15], Guillard et al. [16], and Starostka-Patyk [17].

Only a few of the reviewed systems consider both consumer satisfaction for decision support and distributed decision-making support. Still, they have the disadvantage that methods implemented to model consumer satisfaction do not consider the parameter of importance that is assigned by a customer to each criterion to evaluate a product, ignoring with it valuable information to model consumer preferences accurately. Such is the case of those presented by Morales and Ortega [18] and Guo et al. [19]. We consider this an important finding to highlight an area of opportunity for new developments.

3 Consumer-Based Fuzzy Multicriteria Methodology for the Design of New Products

To support the product design process, [4–6] proposed an original consumer-based fuzzy multicriteria methodology for the design of new products (CBFMMDNP) (Fig. 1). It is based on the application of different fuzzy models for multiobjective and multicriteria analysis and brand personal choice.

The first step of this methodology aims to acquire an overall frame of the particular survey. During the market survey, each consumer expresses his/her evaluations on a set of reference products involved in the research based on a group of criteria. Finally, he/she is requested to rank the products per the order of preference. The collection of this kind of data entails a specific questionnaire. We call it the *market survey* task. Fuzzy outranking relations are constructed from the preference information provided by consumers. After that, in the second step, a new multicriteria preference disaggregation method [21] is applied to the multicriteria consumer preferences to determine the criteria explaining each of the consumer's choices.

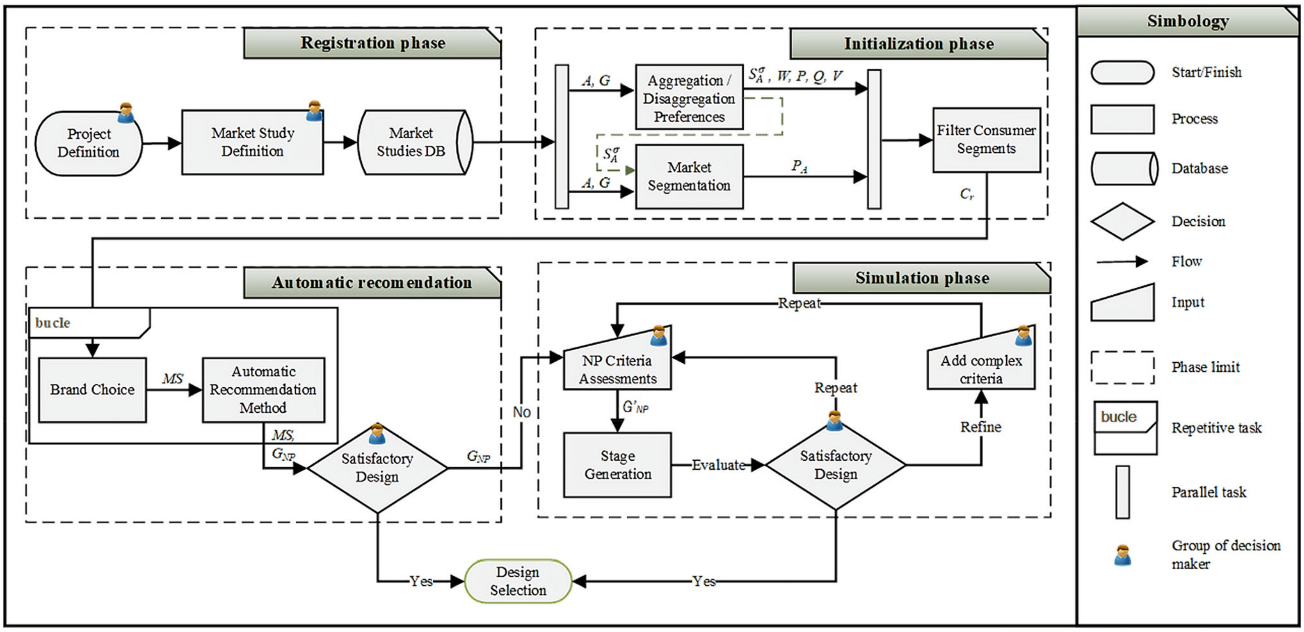
A preference disaggregation analysis (PDA) with the ELECTRE III method is used to support consumers to construct an aggregation preference model. Due to the original data, it can be fuzzy (imprecise and uncertain); the proposed technique seems appropriate as a part of the multicriteria decision analysis approach for the consumer preference to the products of the market. The presented method corresponds to a genetic algorithm developed as a disaggregation approach, which may produce a representative compatible set of preference parameters for ELECTRE III. The fuzzy outranking relation containing the preferential model is derived from the inferred parameters and should be as consistent as possible with the ranking reference of consumers. The objective is to infer the parameters of the ELECTRE III model that minimize the inconsistencies between the ranking of the ELECTRE III model and the ranking of the products provided by the consumer.

Thus, we obtain a plurality of set of parameters, for the construction of an ELECTRE III fuzzy outranking model that best restore the reference ranking.

The preference disaggregation method estimates the fuzzy outranking relation for each consumer one by one which is as consistent as possible with the rank order of the products used, the relative importance of the criteria is then obtained from this fuzzy outranking model. We call this preference disaggregation analysis as *Criteria Analysis*.

In the third step of this methodology, we propose a new MCDA approach for market segmentation that integrates the analysis of consumer preferences and the implementation of segmentation decisions within a unified framework. Since any set of parameters of ELECTRE III generates a fuzzy outranking relation and an associate ranking of products, the preferences of each consumer could be further represented by the distribution of possible rankings of products, each of which is associated with a support degree defined as the portion of corresponding sets of parameters. Then, based on the distribution of possible rankings of products and associated support degrees, we use a new metric to measure the similarity between the preferences of different consumers. This metric reflects the degree of coincidence of consumer's attitudes and preferences about product characteristics. With the measurement of similarity between the preferences of different consumers, we form groups of consumers (market segments), and each segment of consumers are addressed with targeted marketing policies and appropriate products.

Consequently, we develop a hierarchical clustering algorithm to group consumers into clusters, and generated clusters are considered as segments of consumers. This task is called *Market Segmentation*. Market trends are identified through this approach.



Notation:

$A = \{a_1, a_2, ..., a_m\}$ = set of products available to the customers

$G = \{g_1, g_2, ..., g_n\}$ = Family of criteria

S_A^σ = Fuzzy outranking relation

$P = \{p_1, p_2, ..., p_n\}$ = set of preference thresholds

$Q = \{q_1, q_2, ..., q_n\}$ = set of indifference thresholds

$V = \{v_1, v_2, ..., v_n\}$ = set of veto thresholds

P_A = set of segments of the market

C_r = *r-th* market segment, $C_r \in P_A$

MS = Market Share

G_{NP} = Optimal configuration of the new product

$G_{NP}^{'}$ = Configuration for the new product given by the decision-maker

Fig. 1 Consumer-based fuzzy multicriteria methodology for the design of new products

In the fourth step, we apply a new model of personal consumer choice based on the fuzzy outranking approach for handling in algorithms that solve the optimal product design problem, using the share of preference frequency criterion [6]. In this criterion, the new product is determined to maximize the relative preference frequency at which customers choose the new product. Choice models are calibrated for each consumer, through the calculation of best-fitting individual weights, allowing for the model to adequately represent the consumer heterogeneity. Modeling consumer heterogeneity in choice behavior is implemented through an aggregation of individual preference model, represented by a fuzzy outranking relation, estimated for each consumer separately. This process is implemented through a genetic algorithm, which permits the (near) optimization of the weights in tractable time. The procedure aims at the determination of the most suitable choice model, as close as possible to the real market shares (this is the *Brand Choice* Task). The use of models of personal consumer choice allows for the market simulation and the computation of the market shares of the products taking part in the research.

Since the practical point of view of the methodology, this step involves using fuzzy outranking relations and determining a brand choice model that best fits the consumer choice, per their preferences in the fuzzy outranking relation, and find out their estimated market share for the current market (estimation the purchasing decisions of consumers). Those market shares need to be validated with current market shares so that the potential new products evaluated are as consistent as possible with current preferences of consumers, and later, we can feel confident with their estimated market shares.

The fifth step involves preference simulation, which can be used to determine the market share of new products or changes to existing products. The output of the simulation is an estimated market share for products that are not yet on the market or for novel combinations like new products for an existing brand.

The sixth step is, in the same way of the previous step but a more elaborated process, a *new product design* task. Here the decision-maker can input a new product design manually or could use an optimization algorithm that uses the fuzzy outranking relations to find those products that provide the best market share within the boundaries selected by the decision-maker. Those market shares are converted to sales, and based on costs for the development and introduction of the product, we can simulate the design and presentation of different potential products. For example, there could be a budget limitation on the kind of product to design, or a technology limitation, which could have several iterations, until the decision-maker, decides the best product. This procedure could be highly iterative, given the nature of the problem, particularly from the fourth step to the sixth.

Given the time-consuming nature of the algorithms and features in this last step, it should only be used with the design of those products that are being seriously considered (it has been revised thoroughly in the previous steps). At the end of these iterations, the decision-maker decides which products to launch based on the information of consumers, the estimated demand and production, and logistical information that can better inform him/her of the best course of action.

4 Multi-agent Architecture of the System

Current characteristics of new product design decision problems show that their solutions involve the reception of information from different sources, the decomposition of a task into different subtasks, the gradual resolution of these subtasks, and the integration of each subtask's solution to get the complete solution [15]. Software agent technologies offer one of the highest levels of abstraction in computer science [22]. The characteristics of multi-agent systems (MAS) architectures include the close cooperation between each software agent, which provides a condition for the task's decomposing, distribution, and result integration.

By analyzing those mentioned above, the feasibility of building an MDSS as a MAS [23] is shown. Each part of the decision support system can be constructed as an agent with autonomy and communication ability, which allows confirming a multi-agent MDSS with capabilities of getting information from different sources, task distribution, and solution integration. Thus, details of agents' types, organization, and communication of the proposed MDSS's Multi-agent Architecture are shown below.

4.1 Agents' Types and Functionalities

MDSS's software agents are classified based on the well-known Sycara, Pannu [24] proposal. In this work, we consider three types of agents, which are listed below accompanied by their functionalities:

1. *Interface agents* Interact with the user by receiving user specifications and delivering results. Their main functions include collecting relevant information from the user to initiate a task, presenting relevant information, including results and explanations, asking the user for additional information during problem-solving, and asking for user confirmation when necessary.
2. *Task agents* They support decision-making by formulating problem-solving plans and carrying them out through querying and exchanging information with other software agents. The functionalities of task agents are receiving user-delegated task specifications from an interface agent, interprets the specifications and extracts problem-solving goals, forms plan to satisfy these goals, decomposes the plans, and coordinates with appropriate agents for plan execution, monitoring, and result composition.
3. *Information agents* Provide quick access to information sources. Their goal is to provide information by drawing on relevant information from the system's global database, other information agents, or interface agents.

4.2 Agent Organization

The organization of MDSS's software agents is based in Vahidov and Fazlollahi [22] component integration proposal. We organize the agents in teams that reflect the phases of Simon's decision-making process (SDMP) that the corresponding group of agents aim to support. Our adaptation is as follows:

1. *Intelligence team* Group of agents to obtain relevant information related to the problem.
2. *Design team* Group of agents to develop alternative and attribute suggestions.
3. *Choice team* Group of agents to analyze and select available choices.

4.3 Agent Ontology Communication

MDSS's ontology models the CBFMMDNP and support agent's communication, giving meaning to the contents of messages sent between agents. It represents the concepts that agents use in their internal operations or tasks, providing a foundation for interoperability among them.

For this study, the ontology of CBFMMDNP was defined in Protégé, as shown in Fig. 2.

The structure of agents' ontology shows:

1. new product design fuzzy multicriteria methodology;
2. Project: NPD description;
3. Market study: target market description;
4. Aggregation/disaggregation preferences: a group of consumers to obtain consumer behavior;

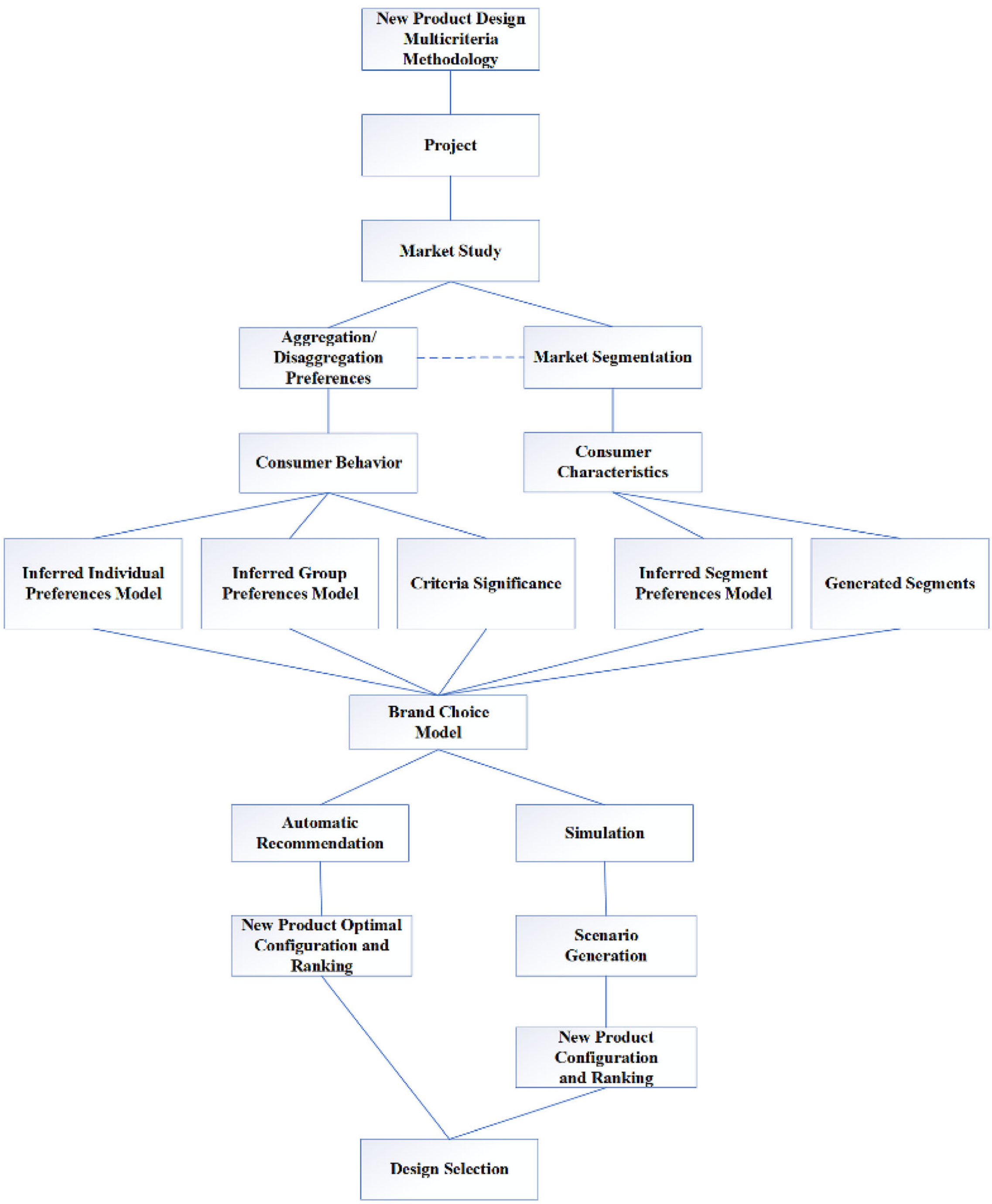


Fig. 2 CBFMMDNP's agents ontology for the MDSS

5. Market segmentation: group of consumers to obtain consumer characteristics;
6. Consumer behavior: preferences of each consumer represented with a ranking of the evaluated products;
7. Consumer characteristics: consumer groups who have similar characteristics;
8. Inferred individual preferences model: valued matrix of preferences of each consumer;
9. Inferred group preferences model: fuzzy matrix of preferences of all consumers;
10. Criteria significance: relative weights of each criterion and intercriteria parameters;
11. Inferred segment preferences model: groups of consumers with similar preferences;
12. Generated segments: a set of generated segments;
13. Brand choice model: a model of brand choice to use;
14. Automatic recommendation: automatic recommendation of optimum configuration for the new product;
15. Optimal configuration and ranking: new product optimal configuration and products ranking in the segment including the position in which it would be positioned the new one;
16. Simulation: new product configuration and products ranking in the segment including the position in which it would be positioned the new one;
17. Scenario generation: generating different simulation scenarios;
18. Design selection: selected configuration of the new product.

Figure 3 shows MDSS's multi-agent architecture. The design reflects the combination and adaptation of some agent types, component integration, and the proposed communication ontology.

The intelligence team has one information agent: Project (PRJ). Its responsibilities include defining the decision problem, identifying criteria to evaluate new products, and the alternatives of an existing product in the market. The design team incorporates fuzzy information and task agents: Initialization Manager (IM), Aggregation/Disaggregation Preferences (ADP), and Market Segmentation (MS). Its primary responsibilities include the initialization of the environment for the NPD.

It obtains consumer behavior through a multiobjective evolutionary algorithm (MOEA) based on ELECTRE III fuzzy multicriteria method incorporated in the ADP agent. A second MOEA obtains consumer characteristics based on the non-dominated sorting genetic algorithm II (NSGA II). The output of both elements is used as input for the Brand Choice (BC) agent. The choice team also consists of information and task agents: Choice Manager (CM), Automatic Recommendation (AR), Simulation Manager (SM), Scenario Generation (SG), and BC. Its primary responsibility is to generate an optimal recommendation of the new product or coordinate the simulation process. The output of this team is the configuration of the new product and its position in a particular market segment concerning its competitors. The recommendation and simulation output is coordinated and generated from an evolutionary algorithm. It is an iterative process accompanied by a what-if analysis.

Decision-Maker (DM), Facilitator (F), IM, and Monitor (MON) are independent interface and information agents. They provide user interaction, communication with other agents, and access to the system's global database.

5 An Example of the System Operation

The system is operating as a Web Site in a Remote Apache Web Server and can be accessed from any mobile device or PC with internet access at the URL (http://midss.net). The interface was developed in Laravel PHP Framework, and it provides interaction between the user and the MDSS's MAS architecture. MAS architecture was developed using the JADE agent's framework and Java programming language. Data are stored in a relational Microsoft SQL Server database.

To improve the MDSS's chances for success, a menu-driven user-interface with standard easy-of-use features such as grid formats, navigators for grids and pop-up menus, has been chosen. Short cuts are used to act quickly. Tools provide an easy to understand an obvious way to present options to the user. It is assumed that the end-users are familiar with using the Web environment. No specialized knowledge about the underlying models is required to use the system. The end-users must input the necessary data, and the results of the models appear in an easy to understand form. There are many benefits to be gained by the selected user-interface, such as the facilitation of learning, and reduced error rates.

According to Eriksson, Penker [25], UML notation for sequence diagrams can be used adequately to present the inter-agent interactions that take place during the execution of the system. Thus, the agent's interactions are represented in this way with agents' types showed as classes and inter-agent messages as methods.

In this example, a DM attempts to get the design of a new product using the MDSS. A new Corn Oil example is used. The example is not based on a real application. Before the user interacts with the MDSS, we suppose that:

- The good or service to be designed has been identified.
- A representative set of products in the market has been identified.

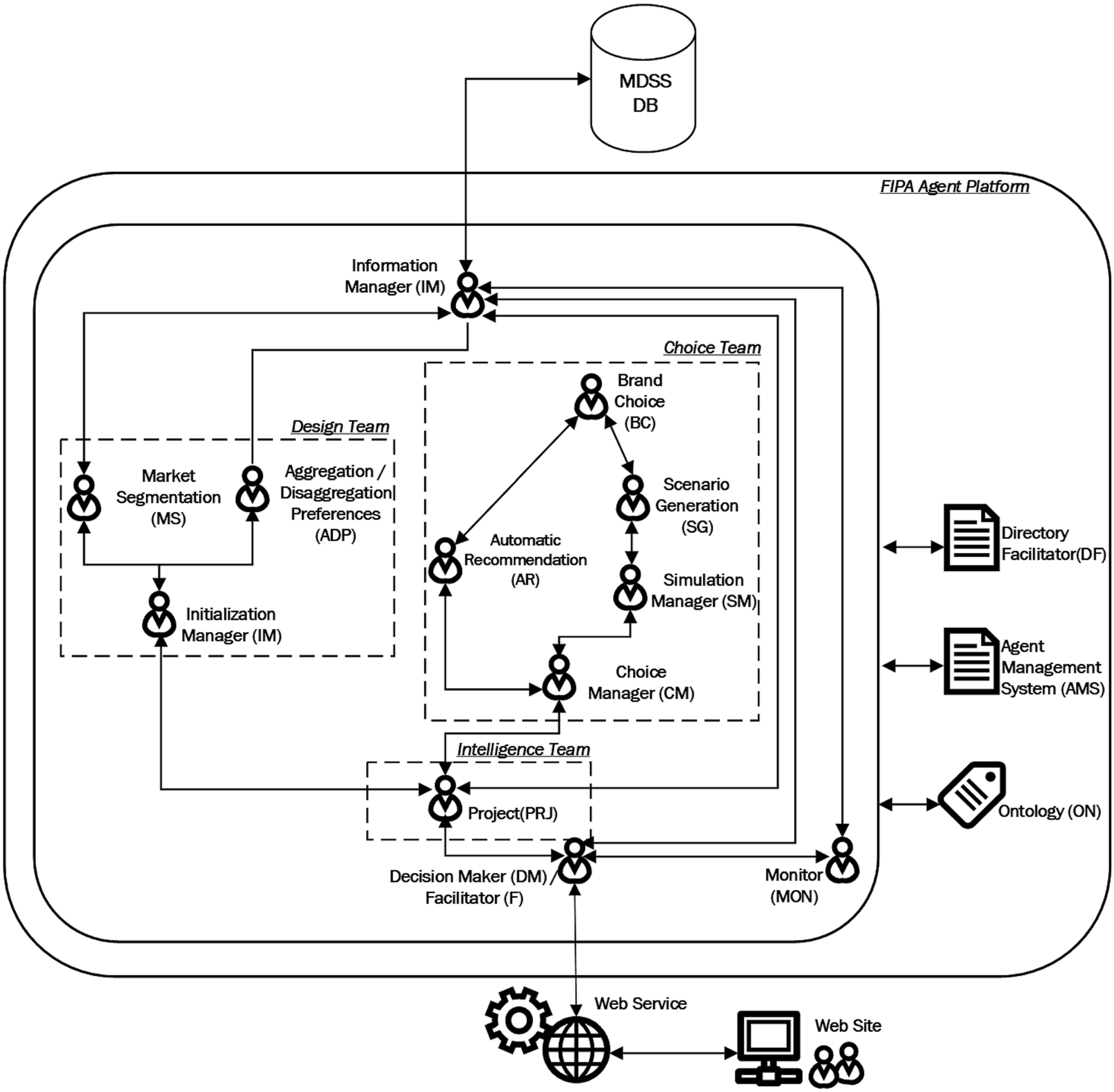


Fig. 3 MDSS's multi-agent architecture. *DM* decision-maker, *F* facilitator, *MON* monitor, *PRJ* project, *IM* initialization manager, *MS* market segmentation, *ADP* aggregation/disaggregation preferences, *CM* choice manager, *AR* automatic recommendation, *SM* simulation manager, *SG* scenario generation, *BC* brand choice, *ON* ontology, *AMS* agent management system, *DF* directory facilitator

- A representative family of criteria and the associated scales that adequately describe the good or service have been identified.
- Have been constructed an experimental design that is appropriate for those criteria and scales either from a design catalog or via a software program.
- Have been constructed and administered a survey to a sample of respondents via a web survey.
- The corresponding data of the survey have been stored in the database of the MDSS.

Figure 4 shows the definition of a new project for the NPD. As soon as the user contacts the system, an interface agent initiates a project and ask to define its details. Interface agent (DM or F) delegates job to PRJ Task Agent, which is responsible for coordinating and sending collaboration requests to an IM Information Agent to register the different elements of the project in the system database. These include registration of the problem description, product attributes, products to evaluate (alternatives), and market study.

The description of the problem is crucial for its good understanding. DM must know the problem details that are being solved so that this activity is not a trivial task. Product attributes are the elements that DM will use to evaluate a particular alternative by assigning specific values. The criteria list is formally specified $G = \{g_1, g_2, \ldots, g_n\}$. Alternatives are the set of options in the market to be evaluated, formally specified $A = \{a_1, a_2, \ldots, a_m\}$. In this case, the alternatives are the products that DM should consider as a competition of the product he/she is trying to design and against which the design of the new product will be compared. System database takes as its main entry a survey related to a market study of the new product to design, which includes a market description and the assessment of consumers to the attributes of each one of the alternatives. With the information collected, the performance matrix $\left[g_j(a_i)\right]_{\substack{i=1,2,\ldots,m \\ j=1,2,\ldots,n}}$ is obtained for each consumer who answered the survey, where $g_j(a_i)$ represents the evaluation of the product a_i by criterion g_j. This performance matrix is used by the methodology with the support of evolutionary algorithms to determine the preferences that consumers have towards specific products and discover which attributes are the most important.

In the sequence diagram in Fig. 4, once the user enters the system, a dashboard is presented, showing a list of

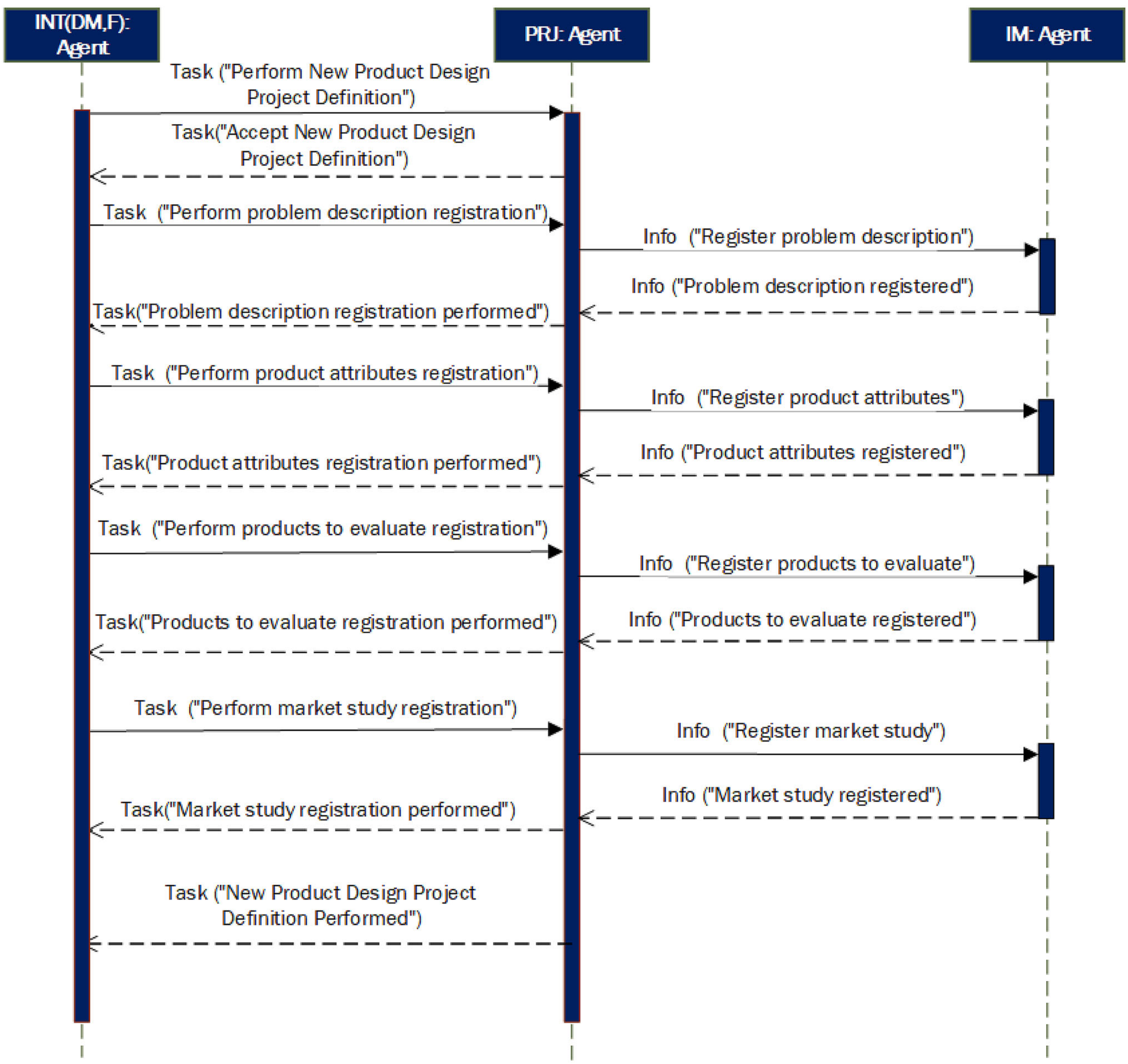


Fig. 4 Example agents interactions: new project definition

projects in which the user participates. Here it is possible to create a new project or manage an existing one.

The problem description registration task is the simplest in the definition of the project. Here user inputs in the system NPD project's code, name, and description.

In the product attributes registration task, the user must enter the set of attributes. In our Corn Oil example, they consist of the characteristics Color, Odor, Packaging, Taste, Image, and Price. Something to highlight is that some attributes can be easily measured through an integer or decimal number, for example, the amount in milliliters of a Corn Oil, but others cannot be measured with a single number, for this, a qualitative scale that allows the consumer to express his/her evaluation for a said attribute is required. For example, the taste, this window allows the user to select an existing scale for an attribute or create a new one according to the needs.

In Table 1, we present the scales that were defined for each attribute. In the case of the Price attribute, since it can be measured directly, the numeric type that can contain decimal values was used; for the Image and Package attributes, a 4-point Liker scale was used indicating the value of the relative importance for each option.

The user must enter the set of products, to be evaluated by consumers; its operation is like the prior one in which the attributes are registered. In our example, we considered similar Mexican Corn Oil products as Mazola, Maceite, Cristal, La Gloria, Great Value, and Patron.

It must be considered that the consumer will evaluate m number of alternatives by n number of criteria. As these values increase, it may be more difficult for the consumer to give a more precise assessment.

The marketing study registration task loads the primary data set of the NPD problem. Here, a survey to obtain consumer's preferences is designed, administered, and registered in the MDSS's database through a web-based external subsystem.

Figure 5 shows the steps to carry out the initialization process of NPD. In this phase of the methodology, the information obtained through the performance matrices of each consumer is exploited. To do this, when the user contacts the system, an interface agent delegates job to an IM Task Agent, which is responsible for coordinating and send collaboration requests to ADP and MS Task Agents. These include the execution of the tasks of Aggregation/Disaggregation Preferences and Market Segmentation.

In the ADP task, the preferences of each consumer are disaggregated; thus, a fuzzy outranking relation associated with each one is obtained. The objectives of this task are [1] to determine the behavior of the consumers by generating a ranking of the products evaluated; [2] determine the significance of the criteria, obtaining relative weights w_j of each criterion, and the intra-criteria parameters of preference threshold (p_j), indifference threshold (q_j), and veto threshold (v_j). Once the parameters w_j, q_j, p_j, and v_j have been obtained, the DM must review the values to make the adjustments he/she deems necessary. All data generated by these tasks are stored in the system database for later use as input in the market segmentation, the automatic recommendation, and the simulation processes.

Table 1 Definition of a unit of measure for each attribute

Attribute	Type	Values
Image	Scale Likert 4	1 = bad (0.05),
Package		2 = regular (0.40)
		3 = good (0.25)
		4 = very good (0.30)
Color	Scale Likert 3	1 = artificial (0.20)
		2 = natural (0.70)
		3 = expressive (0.10)
Odor	Scale Likert 3	1 = artificial (0.30)
		2 = natural (0.50)
		3 = pleasant (0.20)
Taste	Scale Likert 3	1 = artificial (0.15)
		2 = natural (0.55)
		3 = exquisite (0.30)
Price	Numeric	Real numbers

In the ADP task, the system invokes a genetic algorithm of preference disaggregation as an indirect approach to determine the preference parameters, which are required by the ELECTRE III method to construct a fuzzy outranking relation that represents the consumer's preferences (Alvarez et al. 2018). The method disaggregates overall preferences of the consumer from a preorder (complete or partial) in a set of intra- and inter-criteria parameters: the weight vector $W = (w_1, w_2, \ldots, w_n)$, $w_i \geq 0$, $\sum_{i=1}^{n} w_i = 1$; and the vector of veto thresholds $v = (v_1, v_2, \ldots, v_n)$.

In the MS task, groups of consumers that have similar characteristics are generated. Groups can be generated based on (1) socio-economic data, creating groups with similar socioeconomic characteristics that help DM to determine what type of market he/she wishes to focus on his/her NPD considering the socioeconomic level of his potential clients; (2) consumer preferences, generating groups of consumers who have specific preferences in common; and (3) a mix of both type of data. In the MS task, the system invokes an evolutionary algorithm that corresponds to a method based on the fuzzy multicriteria outranking approach ELECTRE III and an MOEA for the market segmentation problem [4].

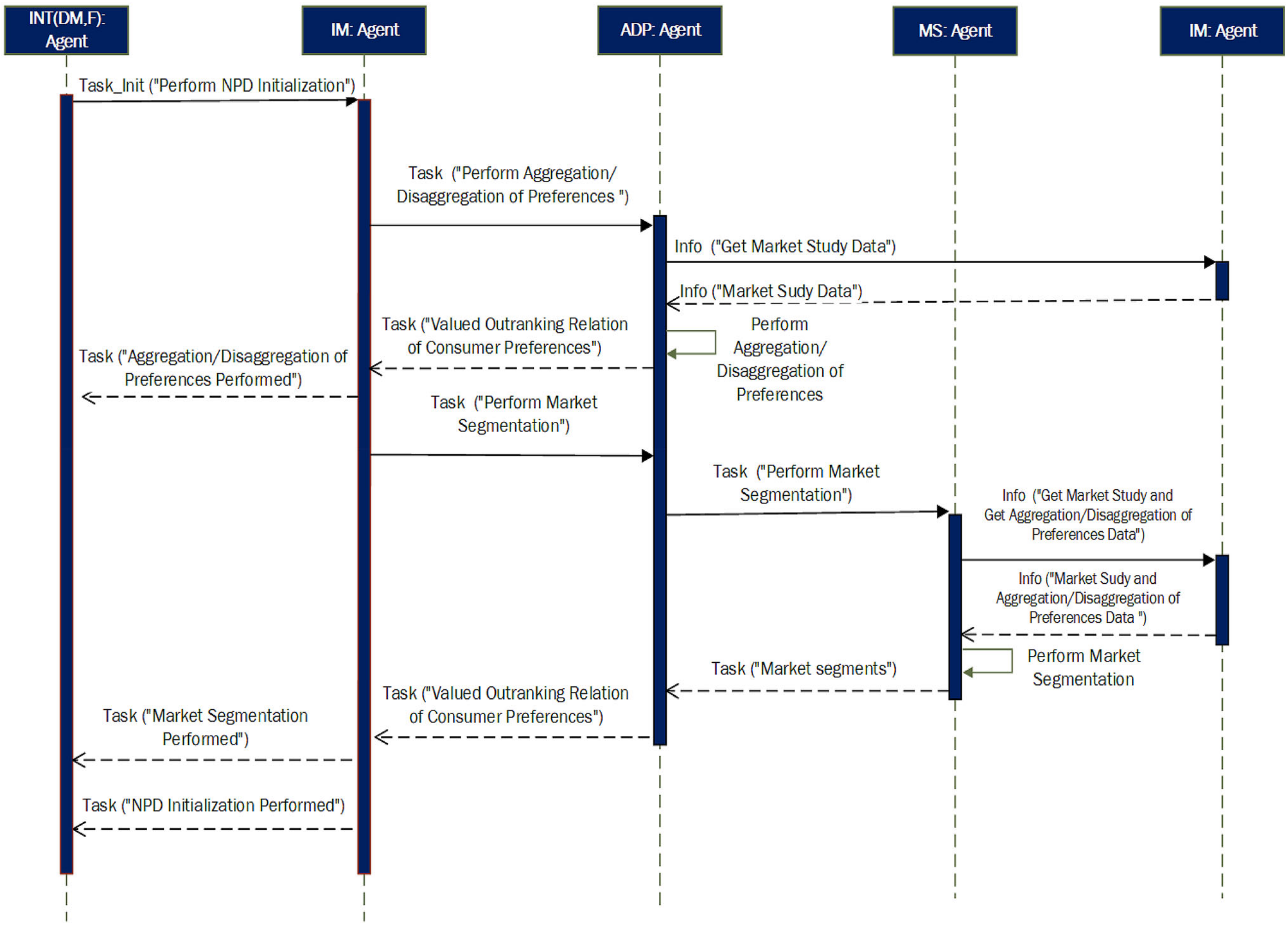


Fig. 5 Example agents interactions: initialization

Figure 6 shows the steps to carry out the automatic recommendation process of NPD configuration. In this phase of the methodology, the design recommendation for the new product is generated and presented to the decision-maker. To do this, when the user contacts the system, an interface agent delegates the job to a CM Task Agent. CM Agent is responsible for coordinating and send collaboration requests to AR Task Agent, which generates Automatic NDP Recommendation obtaining first the brand choice model from the BC agent.

During the automatic recommendation task, values of the attributes of the new product are generated automatically using combinations with the possible values that each of the attributes defined for the new product can have by selecting the best possible combination.

The various possible combinations are made considering both DM preferences and consumer preferences. Once the optimal recommendation is presented to DM, he or she evaluates it and, if the DM accepts the recommendation, the methodology process is terminated, else, if the DM may decide that it is not the best combination either because it is the most expensive or the most difficult to implement technically speaking, he or she can adjust and thus continue with the next phase of the methodology in the process of simulation.

As an example, we present in Tables 2 and 3 the output of the automatic recommendation task for the design of new corn oil. They display a) the set of optimal automatic values for each NPD attribute (design settings) b) the ranking with the market share that would obtain the new product in the current market segment with those attribute values regarding their competitors' products evaluated by consumers in the market study (expected market share).

Figure 7 shows the steps to carry out an interactive and iterative simulation process of NPD configuration. This phase of the methodology is carried out if the DM is not satisfied with the automatic recommendation. To do this, when the user contacts the system, an interface agent delegates the job to a CM Task Agent. CM Agent sends collaboration requests to SM Task Agent, which creates SG Task Agent. SG Task Agents are responsible for generating different simulation scenarios obtaining first the brand choice model from the BC agent.

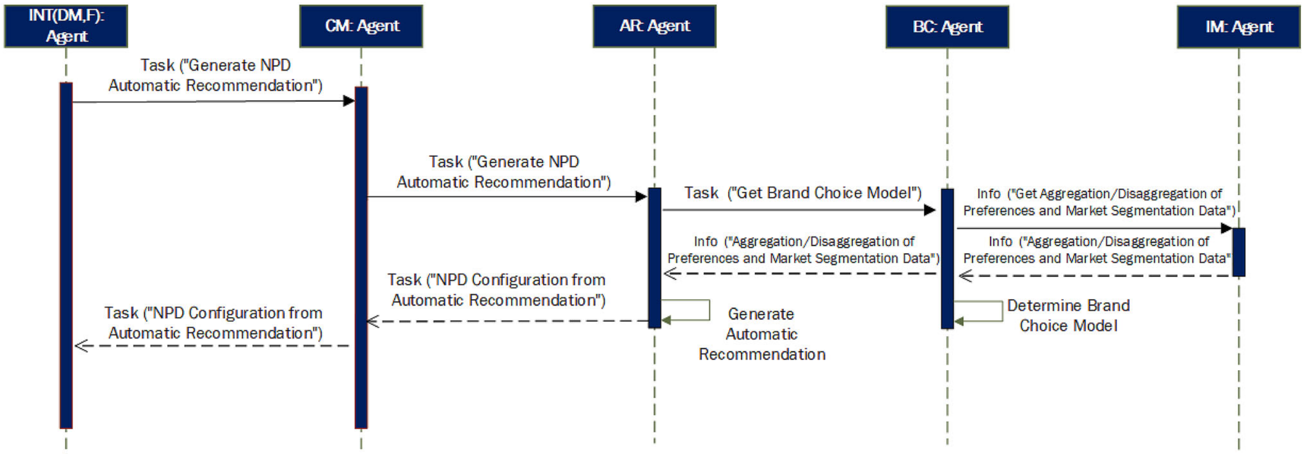


Fig. 6 Example of agent interactions: automatic recommendation

Table 2 New corn oil design settings

Id	Name	Weight	Value
001	Color	0.10	Unaware
002	Odor	0.20	Natural
003	Image	0.10	Unaware
004	Taste	0.25	Natural
005	Packaging	0.15	Fair
006	Price	0.20	$35

Table 3 New corn oil expected market share

Position	Product	Market share (%)
1	Mazola	0.20
2	New corn oil	0.18
3	Maceite	0.16
4	La Gloria	0.13
5	Patrona	0.12
6	Cristal	0.12
7	Great Value	0.09

This last phase of the methodology consists in a series of steps that help DM to generate simulation scenarios through which he/she can adjust the values of attributes established for NPD and thereby determine the market share that would possibly have a new product launched into the market according to consumer preferences in the selected market segment.

For this, it is necessary to perform the following steps:

1. Evaluation of the design of the new product: DM must evaluate the values of each of the criteria that were generated in the automatic recommendation for NPD;
2. Simulation scenario generation: consists of a series of repetitive steps through which the DM adjust the values of each of the criteria to try to determine the best possible combination for the NPD;
3. Incorporate the new product into the market: simulates introduction of new product in the market as if it had been presented in the market from the beginning and were evaluated by consumer along with the others;
4. ADP: This step is identical to that described before in Fig. 5, the difference is that on this phase it is simulated that the new product is part of the set of products in the market;
5. Market share calculation: with the information obtained in ADP, market share by-product is calculated;
6. Generation ranking by-product: generating a ranking of the evaluated products to show where the new product would be located concerning its competitors with the simulated configuration;
7. Evaluation of the new product: in this step, results obtained are evaluated, and if this evaluation meets the expectations of DM, he/she goes on to the next step; otherwise he/she returns to adjust he/she deems necessary and thus generates a new simulation scenario;
8. Selection of NPD: this is the last step of the methodology. It consists of selecting the NPD configuration that best suits the needs of the DM from the different generated simulation scenarios. The scenario may occur for some of the following reasons: DM has accepted the assessment of the attributes in any of the simulation scenarios generated since they have met their expectations, or DM has decided to stop the simulation process since he does not find a scenario that meets its expectations.

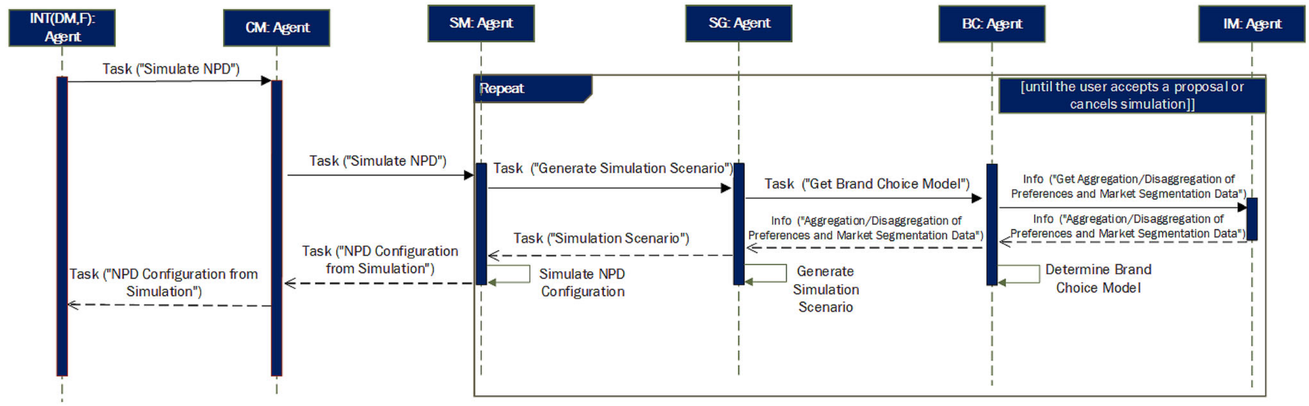


Fig. 7 Example of agents' interactions: simulation

Table 4 New corn oil design settings

Id	Name	Weight	Value
001	Color	0.15	Natural
002	Odor	0.15	Natural
003	Image	0.10	Unaware
004	Taste	0.30	Natural
005	Packaging	0.10	Fair
006	Price	0.20	$35

Table 5 New corn oil expected market share

Rank	Product	Market Share (%)e
1	Mazola	0.23
2	Maceite	0.17
3	New Corn Oil	0.16
4	La Gloria	0.14
5	Cristal	0.12
6	Patrona	0.10
7	Great Value	0.08

As an example, we present in Tables 4 and 5 the output of one iteration of simulation's task for the design of new corn oil. They display: [1] the value that the DM gives to each NPD attribute in current simulation iteration (design settings); [2] the ranking along with the market share that would obtain the new product in the current market segment with those attribute values regarding their competitors' products evaluated by consumers in the market study (expected market share).

6 Analysis of the Results

The proposed system has advanced functions to build and issue new product design recommendations and uses advanced techniques of information manipulation to do it. It stores procedures and uses input data from the consumers and users. We think that these operational characteristics are the most consistent with the current nature of this decision-making process.

The proposed MDSS uses what-if and optimization analysis. Another impressive result is that the proposed MDSS is cooperative, that is, allow the user to modify their recommendations and adapt them to their needs. We think that this is an essential characteristic in this type of MDSS since, in this way, the users could refine the recommendations issued by the system to adjust them to their particular needs.

The MDSS supports distributed decision-making. It is based on software agents. It is consistent with the characteristics of the new product design's current decision process, whose solution is carried out by receiving information from different sources, then decomposing it into separate tasks, gradually solving these tasks and integrating each task's result to get the complete solution.

On the side of decision-making support, the proposed MDSS considers and models consumer satisfaction to issue their recommendations, and it is based on fuzzy multicriteria methods to model it.

Fuzzy Multicriteria Decision-Making has been an active area of research since the 1970s, and different methods for solving fuzzy multicriteria problems have been published. In this sense, many papers report the satisfactory their application in various disciplines such as sustainable and renewable energy, transportation systems, service quality, energy management e-learning, tourism, and hospitality, among others. However, in the reviewed papers, its use and application for new product designs are scarce.

Table 6 Reviewed MDSS which use multicriteria methods to model consumer satisfaction

No.	Year	Authors	Operational classification	Analytical Models Classification	User-Relationship Classification	Technical Classification	Decision Making Support: Modeling Consumer Satisfaction	Distribution Support
1	1998	(Nikos Matsatsinis et al.)	MD	W-I	C	EWD	*UTASTAR*	*SA*
2	1999	(N. F. Matsatsinis & Siskos)	MD	W-I	C	DD	UTASTAR	NS
3	2003	(N. Matsatsinis et al.)	MD	W-I	C	EWD	*UTASTAR*	*SA*
4	2005	(Byun & Lee)	MD	W-I	A	DD	TOPSIS	MN
5	2010	(Morales & Ortega)	MD	OA	P	EWD	*AHP*ss	*SA*
6	2011	(Chan & Ip)	MD	OA	P	DD	AHP	MN
7	2013	(Behzadian et al.)	MD	W-I	A	DD	*PROMETHEE*	*MN*
8	2014	(Lin et al.)	MD	W-I	A	DD	TOPSIS	MN
9	2014	(E. Liu et al.)	MD	OA	A	DD	*AHP*	*MN*
PROPOSED MDSS			MD	W-I	C	EWD	ELECTRE III	SA

MD Model-driven, *W-I* What If analysis, *OA* Optimization analysis, *P* Passive, *A* Active, *C* Cooperative, *DD* Desktop DSS, *EWD* Enterprise Wide DSS. *SA* Software Agents, *MN* Monolithic, *NS* not specified

Characteristics of MDSS for new product design developed to date showed that most of these are model-driven, using what-if analysis, have active user-relationships, and are desktop DSS. Their implementation of decision-making support principally includes knowledge-based systems or expert systems, and consumer satisfaction is used to a lesser extent. Distributed decision-making environments are moderately considered through layer-based or software agent architectures, and most systems are monolithic.

In this way, Table 6 shows the papers found in the literature that describe MDSS using a multicriteria model. The objective of the table is to visualize different characteristics of what has been developed to date and compare it with our proposal.

As shown in the table, MDSS that uses multicriteria methods to model consumer satisfaction had employed UTASTAR, TOPSIS, AHP, and PROMETHEE. The use of any other multicriteria method is not reported. Thereby, our proposal makes use of ELECTRE III to model consumer satisfaction, which is a multicriteria method not considered to date in the literature of the new product design problem. With this, unlike other approaches, consumer preferences are modeled using a more flexible approach, which allows considering the importance assigned by a customer to each criterion to evaluate a product with what is intended to model more appropriately consumer preferences. Also, our MDSS is a cooperative, enterprise-wide DSS with what-if analytical models. It is built using a generic reusable multi-agent architecture that allows having distributed decision-making support. We believe that in this way, our proposal is more consistent with the current nature of this decision problem considering consumer satisfaction and a distributed work environment and will be able to provide more effective support.

7 Conclusions and Further Work

This paper presented an agent-based decision support system to assist the design of new products in a real-world distributed context with the use of a fuzzy multicriteria methodology based on the outranking approach. The proposed system attempts to approach the problem of new product design based on the analysis of consumer's behavior. The methodology implemented by the system has as one of its main characteristics that it models consumer preferences using a more flexible approach than others used currently in the literature and consider the importance assigned by a consumer to each criterion to evaluate a product.

The multi-agent system architecture was designed per the current characteristics of new product development decision problems. For it, software agents were classified into types and organized in teams. The first includes interface, task, and information agents. The second reflects Simon's decision-making process, including intelligence, design, and choice teams. The communication between agents is carried out using an ontology-based on the implemented methodology for new product design, providing a foundation for interoperability among them. An example of system operation attempting to get the design of new corn oil is presented using UML sequence diagrams. It shows the feasibility of using the system to carry out the design of a new product.

In the future, we intend to use an empirical approach to test the methodological basis of the MDSS to highlight the efficiency of the proposed methodology. Validation tests will be conducted on both artificial and real data sets. It will also be essential to explore the limits of this approach by finding the top size of products within instances that can be solved with acceptable performance. Furthermore, future work will be to test the functionality of the system with real case studies to verify and contrast the results obtained in this environment.

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