Chapter 4

# Implementing Complex Fuzzy Analysis for Business Planning Systems

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Additional information is available at the end of the chapter

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**Abstract**

The chapter deals with implementing fuzzy logic for transition of descriptions in natural language to formal fuzzy and stochastic models and their further optimization in terms of effectiveness and efficiency of information modeling and prediction systems. The theoretical methods are implemented in lifelong learning business for development-specific virtual trainings for adult students.

**Keywords:** fuzzy, fuzzy set, fuzzy risk, lifelong learning, virtual learning, training method prediction, fuzzy analysis, complex definition area

## 1. Introduction

In the first part of the chapter the author examines challenges in transforming subject description in a natural language to a formal model. Establishing collaboration between specialists in different knowledge areas (technology, information, business, etc.) is usually a very complicated problem. In the process of common work there is a strong need to estimate model clearness, effectiveness, and efficiency for specialists in different knowledge areas. We consider effectiveness as correct interpretation of a subject in a real world by a model. And efficiency is calculated based on the share of the service states of the model.

In the second part, the author shows the implementation of the approach in virtual training design. Developing specific training methods for adult lifelong students is a very complicated task. We implemented fuzzy-based analysis to determine the best learning methods for different student groups and course types.

The special section is devoted to adapting and implementing virtual training for hard of hearing people.

## 2. Extension for fuzzy model definition area

### 2.1. Introduction

Information systems are widely spread in our daily life: offices, industry, and home. Each system represents or controls an extra object, such as household appliances or industrial control devices. Efficiency of those information and control systems depends on a wide range of factors. Wide-known methods for control systems' synthesis demand the formal model represented in analytical format [1]. The main problem of the discrete automate models is the strong necessity of formalization at the beginning of the process. It is a rather difficult task for complicated technological and information processes. Moreover, it is more appropriate to set a task of the adaptive control system with parametric adaptation features synthesis.

Let us consider the control system for an informational object as a "black box" with two sets of inputs and outputs [3]. Two main inputs are a math (or analytical) model, and data. One of the important features is a number and percentage of internal states of an information system/control device. Internal states are always necessary to control stability of work, prevent user's mistakes, etc. These internal states and their properties require additional computing resources. The author examines an approach aimed at balancing advantages and resource usage of internal states [2].

Meanwhile these both inputs are (or can be) cross-dependent. Creating an analytical model as the first step of the system synthesis is based on intrinsic and semantic analysis of input data. Establishment of collaboration between specialists in different knowledge areas (technology, information, business, or others) is usually one of the main problems and challenges almost in all practice-based projects [3]. Factor analysis or lingual models may provide partial decision of the problem. Lingual models combine a system description in both formal and descriptive terms. A restriction of linguistic models is in their insufficient formalization and a high level of dependence on subjective expert appraisals.

Fuzzy models implementation ensures an analysis of processes in technical and information-based systems with nonlinear and/or multifactor-based behavior [1, 5]. The author presents the approach that combines model analysis based on natural language with strict formal systems by implementing fuzzy logic approaches.

### 2.2. General approach based on lingual models

We consider a process of analytical model synthesis as a first phase of a control model synthesis. The first important step at this phase is transition of a description based on natural language to a formal model. We should consider an interaction between specialists in different knowledge areas while creating such models as they may use different terms. Another important task is establishing back coupling between input data and information/control system. It is quite necessary for creating information and control systems with adaptive features. We implement fuzzy logic to solve the task of information system synthesis for complicated technological objects.

Implementing fuzzy logic ensures the opportunity of a semantic analysis of the object description made on natural-based language due to partial entrance of an element in one or several sets. The conceptual structure of the research area is represented as a set of abstract entities relying on concepts and terms of both a natural language and fuzzy sets. Next, we need to extend the existing fuzzy sets' model as an analytical model contains features, appropriate to elements of analyzable object, and own properties of the model, that provide its integrity.

Second step should be to deal with input data analysis to adapt the model and control system to environment changes. We do not need to change our model but make it adaptive. We need to establish clear borders for research object and its analytical model. To resolve this task, we need also to extend current fuzzy sets and models' methods and features. In this work, we present an extension range of definition of fuzzy sets and its elements' logical division to two sets: corresponding to object properties and internal properties of a system itself.

### 2.3. Model analysis in a partially defined environment based on fuzzy sets

Any analytical model has several internal features that ensure its internal integrity and reliability of a control system to controlled object. One may implement internal model states for internal data integrity control, exchange, additional logic control, etc.

Let's name a set of objects to be synthesized as $S = \{a[i]\}$. Each noun in a lingual model compares to an object $a[i]$ with value (weight) $a(i)$ and functionality $H(a[i])$. Lets' define an expansion of a definition range values for fuzzy attributes to imaginary area:

$$\begin{cases} \mathrm{j}{*}a\,(i), & \text{if an object exists only in a formal model} \\ a\,(i) = a\,(i) & \text{if an object compares to a modelling subject} \end{cases} \tag{1}$$

Based on the above, it is obvious that model S always consists of objects with both rational and imaginary features and functionality weights. $H+$ and $H-$[4, 6, 7]. In this case, total number of object $a[i]$ features is h(n).

1. Number of features compared to lingual model is h+.
2. Total number of object features in fuzzy model– S.
3. Weights of each feature is $s(i)$.
4. A functional as a summary (vector) weight of features divided into rational and imaginary parts $a[i]$ -> $H$.

A model functional parameter may be represented as the following complex number:

$$H = H + +jH - \tag{2}$$

### 2.4. Extending fuzzy logic procedures for analysis and synthesis of information systems

Below, we show the extension is correct and does not break the fuzzy logic postulates. The definition area would be the following:

$$H\ (A|B) \in\ [0;\infty[+\mathrm{j}([0,\infty[) \tag{3}$$

Lemmas:

If A is the element of a real object and B is the internal element:

$$H\ (A|B) \in\ [0;\infty[ \tag{4}$$

If both A, B are internal elements:

$$H\ (A|B) \in j([0;\infty[) \tag{5}$$

$$H(U) = \infty \tag{6}$$

U is a universal set.

We provided a transformation of the traditional fuzzy sets axioms and features to a specific fuzzy model for using complex-based definition area to specify features of models for synthesis of control automation systems.

#### *2.4.1. Fuzzy model synthesis based on lingual model analysis for technological and information objects*

First, we need to transform a lingual model based on subject area terms and definitions to a metalanguage-based model. This model still may include some terms from its predecessor—the certain lingual model. Let us mark sets of keywords, and consider them as fuzzy model objects. At the first step, we may consider all nouns as fuzzy model objects [1–3].

Next let's define a transition between fuzzy objects:

$$\begin{cases} \quad\ \ \mathrm{fi} \\ a[i] \rightarrow\ a[i{+}1], \mathrm{fi\ is\ an}\ a[i]\ \mathrm{object's\ method} \end{cases} \tag{7}$$

If weight $a(i)$ is an imaginary one, then the object $a[i]$ does not match any object in a lingual model, and only meta model contains it.

Then, based on $\delta$-operation, as it is defined in common fuzzy logic, we provide the following transformation between logically tied objects:

$$\begin{cases} a[i]\ \ \delta i a[i{+}1]\ \ \Rightarrow\ a[i{+}1] \\ \qquad\quad \mathrm{fi}+1 \\ a[i]\ \delta i+1\ [i{+}1]\ \Rightarrow\ a[i]\quad \rightarrow\quad a[i{+}2] \end{cases} \tag{8}$$

So, we can formalize an object's method based on a 2-step $\delta$-operation.

Let's introduce a weight of a fuzzy object $H\ (M){=}A$. We consider $\sum H(a[i])>=H(P))$, as the model contains both objects and their methods $f(i)$, that define a consequence of transitions between objects in a model. $f(i)$ methods are described by $\gamma$ and $\delta$ operations. $\delta$ -operation defines a consequence of operations, events, and nodes of a model, and $\gamma$-operation defines weights (for example, possibility, availability, resilience, etc.) for nodes, events, operations. If we take into consideration both types and an optimization factor $H(M)=A\rightarrow$max, then the following equality is true:

$$H(P) = H(a[1]\gamma H(a[2]\gamma\ \gamma H(a[i]\gamma\ \gamma H(a[n] \tag{9}$$

The following set of conditions provides model and based on it control system integrity:

$$\begin{cases} \mathrm{H(M)} \quad \rightarrow \max; \\ \mathrm{H(M)} = \Gamma a[i]\ \Delta a[i]; \\ \nabla a[i], \mathrm{H}(a[i] \neq 0; \\ \nabla a[i], \mathrm{H}(a[i]) \rightarrow \max; \\ \gamma\mathrm{i} \in a[i],\ \delta\mathrm{i} \in\ a[i]; \\ \mathrm{f(i)} = \gamma\mathrm{i} \cup \delta\mathrm{i} \end{cases} \tag{10}$$

The following operations provide structuration of fuzzy sets in A:

1. Establish relations between sets:

1.1. Relation of entrance Ai ∈ Aj

1.2. Relation of inheritance. Ai inherits Aj if a(i) ∈ Ai has the fixed set of values, and methods no less than a(j) ∈ A(j).

2. Let's introduce meta-set M, which describes a set of sets:

$$\mathrm{Ai}:\ \mathrm{M} = \cup(\mathrm{n(i)}, \cup \mathrm{h(i,j)}), \tag{11}$$

And a system of their internal relationships, where $n(i)$, Ai's unique identifier (usually string name); $h(i,j)$, a weight of relation between Ai and Aj sets.

An optimization of model parameters provides by consequent iterations. A rate, which weights reliability between fuzzy meta-model and preceding lingual model, is one of the most important optimization criteria. It is based on a feature $\nabla a[i] \in M$, that indicates a belongingness of a set element to a real or imaginary areas.

*2.4.2. Fuzzy model synthesis algorithm based on a preceding lingual model*

**1.** Allocate described essences based on the linguistic analysis. Create a set S of subessences.

**2.** Allocate a set of described attributes of essences. Based on it create a set T of fuzzy model attributes as mentioned in [2, 3].

**3.** Create a set K of basic knowledge sources, including experts, knowledgebase, and experimental data.

**4.** Create set C as a united set of weight criteria of each element. Primary weight is proportional to number of its occurrences into subsets $C(i)$.

5. Create subsets $S(i)$ as based on the S set. $S(i)$ elements are united into a certain subset according to $C(i)$ criteria.

6. Create sets H(j) containing experts', knowledgebase articles and other data sources' weights: $Ci \to Hj(Ci)$.

7. Create sets $A(i)$ including attributes $a(i)$, as Ai ∇ S,t(i)A1, An, where

$$n >= 1, \nabla h(j)(Ai) = f(h(j), A(i), Hj, [Ai] \setminus Ci).$$

8. Establish fuzzy model M $(Ai,\ H[a(j)]$.

Synthesis of a control system for technical and/or information object is based on the defined fuzzy set M.

### 2.5. Scope definition for fuzzy sets usage in control and simulation systems for technical and information systems

While designing formal model (including fuzzy one), it is necessary to estimate the following items:

- Possibility of implementing a certain formalization method to a certain object;

- Degree of model compliance to an object. Consider fuzzy set A, containing $a[i]$ elements. Each $a[i]$ is compliant with an object feature or internal feature of a model. We consider a method of compliance between model and object based on research of mutual consistency of elements. The method is based on a ∪-operation, and indicates subsets, which can describe an object behavior if used in common [2, 3]:

$$M = A \cup B \cup C \cup \ \cup N \tag{12}$$

#### *2.5.1. Internal consistency criteria*

1. Redundancy property:

$$\forall H(a[i]\beta a[j] > 0$$

2. Compliance property:

$$\forall H(a[i]|a[j] \neq \infty$$

3. Efficiency and resilience balance:

$$\begin{cases} \sum a[i](h+) > 0 \\ \sum a[i](h-) > 0 \\ \sum a[i](h) > 0 \end{cases} \tag{13}$$

*2.5.2. Compliance to modeling object criteria*

(1) Compliance between M - model transformations results, and an object fact features: implementing of any possible track of operations of M model cannot lead an object to a prohibited state.

$$\forall \mathrm{H}(Xi(Ai)) > 0, \tag{14}$$

or

Implementing of any possible track in M, model can transform the controlled system or object R into a possible state or common null state

$$\forall H(Xi(Ai)) >= 0 \tag{15}$$

Thus, we consider a fuzzy model is applicable in case that its real functional is positive and there is at least one set of allowed methods that transform a control system from its initial to final state.

### 2.6. Conclusion

Finally, we found that the synthesis of control systems based on descriptive models of natural language may be adequately implemented based on fuzzy sets. Logical separation of elements of fuzzy sets, in which the real domain includes the attributes and functional elements that describe the state of an object, but to the imaginary one—own internal state of the model and the management system that are required to make it operational. Based on this logical separation, we may estimate effectiveness and resilience of control system.

Finally, the authors resume that automated systems' synthesis is appropriately presented and formalized by fuzzy sets' models. Fuzzy logic definition area has been extended to an imaginary area. We established the logical division of model components to real and imaginary areas per their role. Internal objects of a model are presented in the imaginary area, and objects that describe the modeling system to the real area. We introduced necessary functional extensions for fuzzy logic to operate with logical extension.

Transformation algorithm is developed, and we recommend the certain implementation area for it.

## 3. Defining appropriate training methods for lifelong learning organization

### 3.1. Introduction

The author has developed a method and algorithms of fuzzy analysis for lingual models with complex digits' implementation. The author used the approach that differentiates native data, attributes of an object and internal model data, and attributes [2, 3]. Dividing these classes into real and imaginary leads to the decrease of dimensions in a model, and in this way to the decrease of computing capacity. This fact allows to decrease the risk of incorrect interpretation of results, and it provides also an opportunity to estimate costs of efficiency.

This article is devoted to implementing fuzzy analysis to define and implement various virtual training methods in a lifelong learning educational organization and reaches the highest possible satisfaction level by different categories of adult students as defined in Ref. [4].

### 3.2. Big challenges in lifelong learning

The lifelong professional learning training center offers short-term trainings and postdiploma programs to upgrade professional skills or gain a new specialization for adult professionals. A lot of students take multiple courses as bundles or periodically in accordance to new versions of software, technological equipment, or professional standards. It’s of great importance for the training organization to analyze big data interdependencies to find out trends, develop new courses, make targeted offers for students, and create specific training methods for certain client groups. Since 2009, the author has been deeply involved into developing and implementing various virtual—online, and blended—training methods. During this work, the author carried out a regular analysis of data from different sources to determine customer requirements, demands for courses, and ways of their representation, technical, and mythological opportunities [4, 5]. The goal of those continual research efforts was the development of strongly targeted training options for certain student groups and courses. The fuzzy-based modeling is considered as the most appropriate approach to the task, because students’, customers’, trainers’, and other staff’s feedback, requirements, as well as demand estimations, are mostly represented as a nonformal or mixed way. For example, rating A in a feedback means “more than I can expect.” It is obvious that the level of expectations differs among students, and customer representatives.

### 3.3. Opportunities and threats in lifelong learning

Based on M_o_R™ and Total Risk Management® concepts fundamental characteristics of any risk define organization behavior for it, for example: tolerance level, impact, mitigation and contingency strategies, management level, as well as level of financial reserves. While examining risk nature we often consider that a single risk belongs to different characteristic sets. For example, a risk of incorrect professional behavior can belong to human and organizational, and technical sets simultaneously. Therefore, we can create a fuzzy description of a risk:

$$r(i)\ \in O, r(i)\ \in\ T, \mathrm{r(i)}\ H \tag{16}$$

where ***O, T, H,*** fuzzy sets (organizational, technical, human features).

Implementing risk analysis in fuzzy terms ensures complex analysis for risk source, impact, mitigation, and contingency. The author examined complex risk analysis for portfolio (both projects and operational activities) of virtual learning methods in a lifelong adult training center. As a service-based and private user (a student) oriented business, its success depends dramatically on a subjective personalized opinion of students and partially of corporate HR managers. Their feedbacks are represented both in partially formalized manner, and comments in a natural language.

Another challenge concerns representing risk dependencies, or so-called domino effect. As it's a rather complicated task to formalize risks interdependencies, we can implement an approach, starting with an informal description in a natural language with further formalizing it by means of fuzzy-based algorithms.

The fuzzy analysis is the very appropriate tool to transfer statements in a natural language into a formal model, and explore threats and opportunities. The fuzzy analysis is implemented as described by the author in Ref. [5]. Identifying and analyzing risks, and their interdependencies, we include both negative (threat) and positive (opportunity) parts of risk analysis with the primary aim for finding new opportunities for development and quality improvement.

Main threats for an adult professional training organization are in customer dissatisfaction, and on the opposite main opportunities are based on reaching continuous education of students personally, and corporate customers. Let's examine a simple example about modern technology-based virtual learning implementation, and consider online learning process. There are several main opportunities of online learning for an educational organization, which are:

1. Improve organization innovative brand.
2. Attracting more students from distant regions.
3. More students in a class in a certain group.

On the other side, there are threats:

1. Changing in teaching methods.
2. Decrease of teaching quality.
3. Student's and corporate customers' rejection of new training method.
4. Technical issues.

Those risks—both positive and negative—are well-known when we talk about them in a natural language, but training organization's decision-making process requires qualitative and quantitative estimates. As shown in reference [1] we can implement fuzzy analysis to transform natural language to a weak formalized fuzzy model, by placing model-internal risks into an imaginary area, and objective risks into a real area of the model.

### 3.4. Building current data analysis with fuzzy logic

We investigated our students, trainers, corporate clients, and internal administrative staff feedbacks to discover additional training opportunities.

In 2009 we started online webinar trainings, which are held as simultaneous trainings in groups consisting of online (webinar), and class-based students (named as "webinar-in-class™"). The example of feedbacks is given in a **Table 1**. Total number of feedbacks: 10,000+ student feedbacks, 700+ by trainers, 1000+ by training center administrative staff, and 500+ by corporate customers' representatives.

We compared and analyzed feedbacks of webinars with the excerpt feedbacks of traditional class-based trainings. As the "specialist computer training center (CCT)" has been operated since 1991, we extracted feedbacks for class trainings for previous 5 years, e.g., we included 25,000 students', 5000 trainers', 5000 administrative staff's, and 2000 customer representatives' feedbacks into comparative analysis against "webinar-in-class" feedbacks, which are presented in **Table 2**.

The "trapeze" form of a fuzzy interpretation, as shown at **Figure 1**, is used to represent fuzzy component, because rating values are subjective and personal oriented. For example, we use ratings from "1" or "E" (minimum value, means that a client is completely dissatisfied) to "5" or "A" (maximum value, indicates that a service exceeds customer's expectations). Rate "3" or "C" indicates customer's general satisfaction. These estimations are personally based and depend on a lot of factors, such as professional specialization, job function and rank, individual specialties. Only ratings "E" and "A" strongly indicate satisfactory level. For example, rating "3" or "C" at design or HR trainings is mainly considered as more dissatisfied than satisfied. On the other side a "C" rating at business or project management trainings is mainly considered as satisfied' and rating A" is very rare, because business managers are mostly not as emotional.

| Rate | Parameter (%) | | | |
|---|---|---|---|---|
| | Trainer | Technical facilities | Course | Willing for further training |
| A | 32 | 27 | 45 | 42 |
| B | 48 | 51 | 42 | 47 |
| C | 12 | 14 | 10 | 7 |
| D | 5 | 6 | 2 | 2 |
| E | 3 | 2 | 1 | 1 |

**Table 1.** An excerpt from webinar-N-class studies.

| Rate | Parameter (%) | | | |
|---|---|---|---|---|
| | Trainer | Technical facilities | Course | Willing for further training |
| A | 39 | 42 | 41 | 42 |
| B | 46 | 41 | 44 | 47 |
| C | 11 | 13 | 13 | 7 |
| D | 3 | 4 | 2 | 2 |
| E | 1 | 2 | 1 | 1 |

**Table 2.** An excerpt from traditional class-based studies.

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**Figure 1.** Trapeze interpretation of satisfaction level.

In fact, the total number of analyzed attributes is more than 100, and it changes regularly to follow customer, market demands, technical, and methodological facilities.

Below is a partial list of main attributes in the information system, which contain basic data and we consider them as a real area attributes in an analytical model:

- Student, Client/Customer, Learning format, Country/region, Course, Year/season/month, Vendor, Product Trainer, Trainer rating, Course rating, Training method rating, Number of courses taken by a student afterwards

The total number of real area attributes is more than 50.

Next I show an excerpt from a list of more than 25 additional (information model based) attributes. We consider these attributes in an imaginary area of our fuzzy model:

- Total rating of a training method, comparative rating to class-based training, comparative rating of webinars against class and self-learning combined method, views and filters across client types, regions, time, season, etc.

To build an integral customer satisfaction rating we use multidimensional fuzzy analysis of different partial (single-parameter) rankings as shown at **Figure 2**. Also, different filters and constraints are implemented to localize problems, challenges and find grow-points.

### 3.5. Investigating students' satisfaction against educational organization efficiency

We can investigate an integral satisfaction/dissatisfaction level of a training group based on the following attributes: trainer ratings, course ratings, willingness to continue training at a next course, and ratings of technical facilities. Each set is fuzzy and contains ranking values (ratings) by each student.

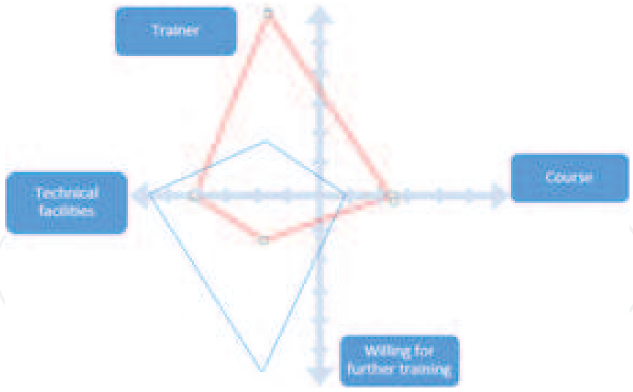


**Figure 2.** Determining the satisfaction area on an example of four parameter analysis.

In each case (for a student/group/trainer/course, etc.) we form a fuzzy area, in which we may consider that a course/study/trainer/class, etc. are satisfactory. According to company goals and statistical data we can also implement additional weights for attributes. For example, a trainer rank has coefficient "1, 5" and class ranking—"0, 8". Attribute "willing for further training" will have the maximum weight coefficient "2", as it's the most important factor for commercial adult learning company. This model shows a subjective satisfaction level as a set (family) of polygons. Each polygon draws by connecting points, which reflect partial ratings. For example, an area of subjective satisfaction is defined by the following partial ratings:

Trainer rating = 2 AND

Course rating = 4 AND

Technical facilities = 3 AND

Willing to continue education = 5.

In this case, we define that a group is partially satisfied/partially dissatisfied with a trainer, but if most of students of a certain group are ready to continue education at next courses, we can mark this group as "satisfied."

For complex estimation of job effectiveness of an adult life-long training organization we developed more complicated approaches, which include statistical data based on more than 70 attributes (both in real and imaginary areas) and collected them in multidimensional databases—OLAP cubes. This cube has the appropriate number (more than 70) of dimensions, and we need to build a set of fuzzy models, and optimize them for daily calculations and analysis. A real part of a model includes basic facts, and on the other side an imaginary part of a model includes filters, views, and additional states of a model or database. Due to this approach, we decrease number of dimensions to 50 in total, which leads to decrease in computing capacity requirements. Practical result: we have an opportunity to process analytical reports in a real-time mode, and postpone few complicated reports for nonworking hours (night time and Sundays).

Let us examine a comparatively simple set of fuzzy sets, which describes an integral satisfactory factor and training organization efficiency:

- By course, a certain trainer and/or trainer group, a company—customer, learning location, a certain period, a training method, a training branch (e.g., Management, ITSM, software development, HR, etc.).

The developed model contains both real area attributes, which reflect basic states, and imaginary area attributes, which reflect temporary, service states, filter conditions, identifiers, etc.

Below, I show an excerpt from a model. Attributes named in a lingual model terms to simplify understanding

$$\begin{cases} M1 = (CN + St + Tr + TM) + j(V + TP + ST), \\ M2 = (CN + Tr + CCF + TCF + WFT) + j(TP(i) + ACR(i) + ATR(i) + V), \\ M3 = (CN + TL + C + TM) + j(TP(i) + ACR(i) + AMR(i) + V), \end{cases} \tag{17}$$

where CN, Course name; St, Student identifier; Tr, trainer identifier; V, view name; TP(i), selected time period; St, threshold level of students' satisfaction for the certain model; TM, training method; CCF, course cash flow; TCF, cash flow on courses by a certain trainer; WFT, student's willing for continuous education; ACR, average course ranking for selected period; ATR, average trainer ranking for selected period; TL, training location; C, corporate customer name; and AMR, average ranking of a certain training method for selected period.

Set M1 reflects mean level of students' satisfaction for a certain course and a certain trainer for selected time period.

Set M2 reflects current level of economic efficiency of a certain trainer, based on dynamic trend of students' satisfaction across a number of time periods (for example, month to month or quarter to quarter).

Set M3 reflects dynamics of corporate customers' satisfaction for a certain training location, course, and a training method. This set gives a control how a certain training location provides quality for a certain course and a training method, for example, webinar, or blended, or self-paced, etc.

### 3.6. Defining training methods and models

Adult learning training organization should offer various training opportunities for its students, such as long- and short-term trainings, class-based, virtual, blended, synchronous, and asynchronous, etc. Based on the analysis model at our Specialist CCT we develop balanced cost-effective vs. "student satisfactory" training methods for precisely defined customer audience and course bundles.

While analyzing results of modeling, we find several maximums. Each of the maximums is characterized by a certain set of parameters, as shown in **Figure 3**.

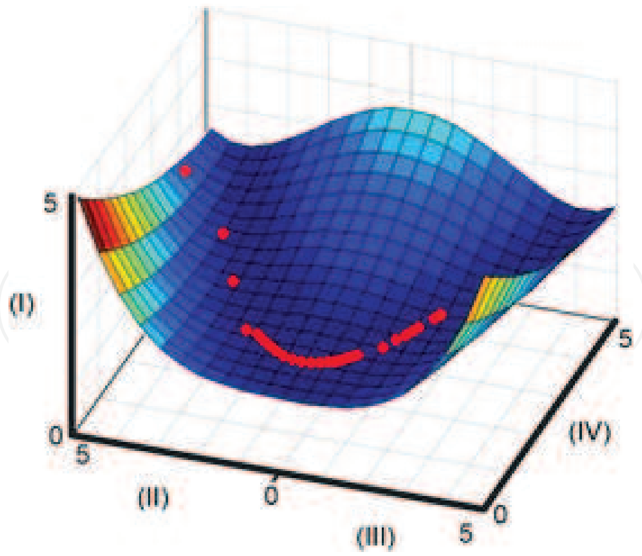


**Figure 3.** Multidimensional estimation, where I – Individual approach level; II – Trainer level; III – Technical facilities; IV – Training center economical effectiveness.

For example, the maximum satisfaction level which is found in an analytical cube is defined by the following attributes:

- student total expenses (minimal);

- high quality skills received;

- high qualified trainers;

- number of students in a class (maximal);

- collaboration facilities in the group (maximal);

- technical expenses are minimal.

The "webinar-in-class" training option is the best for mentioned attributes, because a webinar-based student has an opportunity to study anywhere, and has no travel or accommodation expenses. Simultaneously, he/she has an access to the best trainers, and can collaborate with classmates in a class and other webinar students, using a very simple software. The webinar students have an access to the same technical facilities such as labs. Thus, the webinar-in-class training method becomes very popular solution for students studying technical (Microsoft, Oracle, CISCO, etc.) courses, as well as project, and IT service management courses.

We worked further to analyze maximums, and another point is based on the following attributes:

- appropriate (frequent) course start date;

- individual approach;

- introvert students;

- students with high level of self-organization capabilities;

- full classes;

- low expenses on training organization by a training center.

In this example, we see more attributes, and it was a bit more difficult to create an appropriate training method. The result was a kind of blended learning, which we named an "open learning."

- blended "open learning" training method is the best solution for very specialized trainings, and self-organized students;

- unlimited webinar subscription is for students, who are unemployed or wish to change profession. Both categories need cheap training at a large number of courses.

To resume I want to stress that the estimating process is everlasting, as well as optimization of the research model. While preparing this article, one more training method was developed, which proves the efficiency of the described approach. The described methods won several professional awards [6, 7].

## 4. Identifying special tools for virtual training of hard of hearing people

### 4.1. Introduction

More than 10% of people on the Earth suffers from different hearing impairs as the World Health Organization data shows. Many of them are young people, or employees, which are involved into lifelong learning. They have difficulties with taking both class and virtual trainings, if they do not have or use special hearing aids. Meanwhile, many young people do not use special devices due to medical recommendations or having scruples.

Based on our research of students' with hearing impairs demands our research team deliver a special computer-based technology—named as Petralex©. It is implemented in mobile Apps and Windows driver, which works as a personal hearing assistant [6]. A student passes an "*in cito*" hearing test and the application creates a personal hearing profile for each place or environment (for example, public transport, café, car, room at home, classroom, and workplace). Mobile App acts as a hearing aid in a smartphone, so a student can easily attend classes. The Windows-based driver creates a Virtual audio device (VAD), which adapts streaming audio for both online and asynchronous virtual learning to an appropriate user's hearing profile.

Different virtual training methods—synchronous, asynchronous, blended—which are defined in Ref. [4], include online and/or off-line listening in videos, podcasts, as well as online training delivery, including real-time discussion with a trainer and classmates. So, students with hearing disabilities should have opportunities to be involved into the entire training process.

### 4.2. Synchronous learning methods

A student with partial hearing losses can feel uncomfortable while studying in class, or at online webinar. If a student studies in a class, he or she can implement the Petralex® mobile app as a hearing assistant, and involve in-depth into a learning process. In a synchronous learning training content is delivered in an online mode as shown in **Figure 4**. A student accesses it using the special audio driver, which ensures audio stream adjustment to personal hearing profile. As a result, a student can attend studies for a long time—up to 8 hours per day—due to improved hearing tolerance, reducing fatigue for long listening sessions, and attenuation of excessive sound pressure [6, 7].

#### *4.2.1. Typical learning cases for online trainings*

1. A trainer explains learning materials: a student studies at home. S/he connects to an online tool (for example, Skype®, Citrix GoTo®, WebEx, Adobe® Connect®, or any other), activates "My room" profile. Next, our driver transforms audio stream in a real-time mode with only 10–50 ms delay, so a student can hear a teacher clearly, have concentration on studying, and ask or answer questions; present his/her work, and discuss with other students in a real-time mode.

2. A business game: business games and other forms of group studies are very popular according to our model (Eq. (16)). An online student usually plays a role of a virtual team member or help desk agent. Implementing audio-driver provides both parties an opportunity to collaborate in a clear mode without delays.

### 4.3. Asynchronous learning methods

In this section let us consider different scenarios for asynchronous learning of students with partial hearing losses. The most popular tools for asynchronous learning are: learning management systems (LMS), stream and offline video, and audio services.

As shown in **Figure 5**, an external audio signal from a learning tool goes through the virtual audio driver, which transforms it according to an activated user hearing profile. Thanks to it, a student can study anywhere. At our training center, and with our partners, the following scenarios, as shown in **Figure 5**, were tested:

In a special class,

At home,

At a workplace, and

On a beach.

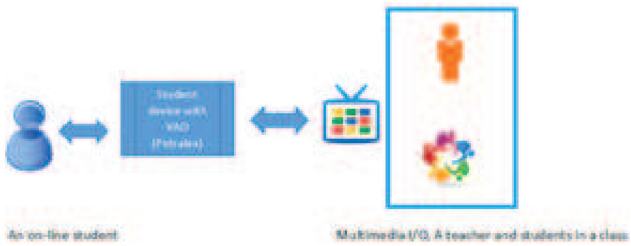


**Figure 4.** The learning schema for synchronous virtual learning.


**Figure 5.** Asynchronous learning scenarios.

One of the most impressive cases in our training practices is short-term learning for adult busy people. We defined lifelong business students as a separate category in our model. Lifelong learners often study during their vacations or weekends. Usually they are strongly motivated, so they can easily combine their rest and studies. As an example, a student creates a "beach" profile and can listen learning records on a comfortable manner for his/her hearing.

## 5. Resume

Implementing extended definition area for fuzzy set analysis provides vast opportunities for representation of control objects by information systems, their analysis and optimization. Based on implementation of fuzzy analysis the author succeeded in creating and launching various virtual training models for lifelong learning, including people suffering with partial hearing losses.

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