Article

Intelligent Task Planning System Based on Methods of Fuzzy Natural Logic

Bogdan Walek 1,* and Vilém Novák 2

1 Department of Informatics and Computers, University of Ostrava, 30. dubna 22, 701 03 Ostrava, Czech Republic
2 Institute for Research and Applications of Fuzzy Modeling, University of Ostrava, 30. dubna 22, 701 03 Ostrava, Czech Republic; vilem.novak@osu.cz
* Correspondence: bogdan.walek@osu.cz

Abstract: In this paper, we present a novel approach to task planning based on an intelligent expert system that makes it possible to obtain a conclusion based on linguistically characterized knowledge. The main goal of the proposed task planning system is to arrange and display tasks for the solver in an effective way. Therefore, the system shows the most important tasks first and then the less important ones (in a determined ordering). The solver has a list of tasks arranged according to their importance at each time the task list is displayed. Another goal of the system is to show the effectiveness of all subordinate workers (solvers) for the manager. The expert knowledge contained in the system is characterized by three linguistic descriptions: determination of the task importance, determination of the final task importance, and determination of the efficiency of the task solvers. The system shows the ordered task list in real time. Evaluation of the relative and final importance of the tasks is performed periodically. The system has been implemented as a WEB application and verified on real data set. We also present experimental results of our system.

Keywords: intelligent task planning system; fuzzy expert system; linguistic description; evaluative linguistic expression; task planning; task solver

MSC: 68T27; 68T35; 68T50

1. Introduction

Every company or organization needs to maximize the efficiency of work of its employees. The company, obviously, considers an employee to be efficient, if the assigned tasks are performed well and in time. Therefore, the employees should have actual information about the state of their tasks and deal primarily with those being most important and urgent. For these purposes, the term work efficiency time management training program has been introduced. Its main goal is to establish high-quality employee time management as a path to higher work efficiency. A number of studies have been published in this area, for example [1–7]. The study [8] is an attempt to answer the question if time management training can work successfully.

1.1. Time Management

Efficient time management is one of the keys to increase the efficiency of the company. The authors in [7] divided the company’s employees into two groups: the first group attended a 3-day time management training program while the second group did not participate in it. The first group rated their management significantly higher after passing the program than the group not attending the training program. The authors have thus demonstrated the impact of the time management training program on employees’ efficiency. In [9], the authors carried out several experiments on groups of teachers who were presented different types of time management training program. Four groups of
teachers were randomly assigned to one of three conditions to test the effectiveness of brief training in time-management techniques. The three conditions were: time management, time management in combination with supervised practice, or a control condition in which the participants attended a seminar discussing the broad concerns of beginning teachers. Dependent variables were: meeting an intermediate and a long-term deadline; the number of completed reports; promptness in returning of a questionnaire; self-reports of time management; and a supervisor evaluation of performance.

The results showed that in the combined conditions, more reports were finished, the questionnaires were returned more promptly, and the self-reports of time management were higher. However, compared with the control condition, even the primary training conditions affected promptness in meeting the intermediate deadline and returning the questionnaire. The long-term timeline and the supervisory ratings were not altered in either training condition. The significant result in the primary conditions suggests that time management training may reduce procrastination on intermediate deadlines. The study provided support for the effectiveness of the training (cf. [10]). An overview study [11] then describes various approaches to time management.

1.2. Task Planning

Currently, there are several approaches and proposed systems in the area of task planning. The study [12] presents an intelligent information system that allows, on the basis of various problem-oriented optimization methods, to automate the planning process and form optimal production schedules for flexible multi-assortment productions. The study [13] presents a framework for intelligent Supply chain decision support to plan the harvest and supply of mango fruit according to consumer demand. The aim of the proposed system is to co-create supply chain with consumer input. The research published in [14] proposes methods for planning, monitoring, and displaying tasks based on user-defined criteria. Patent [15] describes an intelligent planning and calendaring system for planning daily tasks. This system is mainly usable for creating daily calendar of tasks and to-do lists for common user needs. The study [16] describes various expert systems for planning and scheduling manufacturing systems. The SWOT-analysis system important in the field of strategic planning is described in [17]. The research published [18] in proposes hierarchical decision support system for production planning which enables production planners to utilize complex and structured planning algorithms interactively with no difficulty. This decision support is focused on area of production planning, not on area of task planning of workers (employees) in company. Ref. [19] presents a system to support decision-making of the production manager when scheduling the manufacturing orders. The system is also focused on production planning in factory, not on area of task planning of workers in company.

1.3. Decision Support in Advanced Planning Systems

The area of task planning is also related to production control in factories and companies. The category of systems for advanced planning and scheduling tasks for production in factories is called Advanced Planning and Scheduling (APS) systems (see [20]). There are several approaches and proposed systems in the area of APS-systems. The study [21] presents a hybrid Decision Support System for automating decision making in the event of defects in the era of Zero Defect Manufacturing. The study [22] presents a decision support system (DSS) for sourcing and inventory management, with the aims of helping SMEs compile and exploit data, and supporting their decisions under business ambiguities. The research published in [23] describes how standardized APS-systems can be used for solving planning problems on tactical and strategic levels. Ref. [24] proposes a methodology for hierarchical production planning systems in an enterprise integration context. The study [25] describes decision support system for planning, scheduling, and dispatching tasks in a specific factory. The proposed system consists of three modules: planning module, scheduling module, dispatching module to optimize the production process.
1.4. Task Management Tools

Task planning is also related to task management tools and personal task management (PTM). This category of tools helps users to manage their common daily or important tasks. The study [26] conducted a survey with users to obtain how people recorded and remembered their tasks and how they maintained their task lists. The main goal of the study was to investigate how and why personal task management behaviors differ across individuals. Based on survey results, the authors recommended PTM tools which should be personalizable, relatively effortless to use and integrate well with other systems in use to satisfy make-do tendencies. A lot of studies have investigated the use of email for task management ([27–32]). These studies have identified a variety of problems of using email for PTM. As a result, several solutions such as TaskMaster ([33]), TeleNotes ([34]) and ContactMap ([35]) have been developed to enhance email support for managing tasks that involve other people ([36]). In a similar way, for instance, Gmail Inbox is centered on task management and it has the action of marking an email as “done”.

1.5. Intelligent Personal Assistants, Personalized Task List, Personalized Calendar Scheduling

Task planning and task management is also related to personalized task lists and personalized calendar scheduling. The main goal of these approaches is to organize and manage user tasks based on user preferences and behavior. The study [37] presents Artificially Developed Intelligent Assistant (ADINA) which fulfill the basic requirements of its users and based on the usage of the user to predict its behavior. The basic requirement of this user that this application covers include making web-based as well as Wikipedia searches, event scheduling of users (calendar and planner), exploring real time news headlines throughout the globe as well as exploring new places. The study [38] presents an empirical study of various intelligent assistants. Data were collected from users of intelligent assistants through a survey. Another research work [39] presents analysis of 111 published articles in the area of intelligent assistants. Ref. [40] proposes a BDI-based framework for a cognitive agent that acts as an assistant to a human user by performing tasks on her behalf. The framework is based on BDI model [41]. The proposed framework is a part of an intelligent personal assistant called CAI (Cognitive Assistant that Learns and Organizes) [42]. CAI assists its user with six high-level functions: Organizing and Prioritizing Information, Preparing Information Artifacts, Mediating Human Communications, Task Management and Scheduling and Reasoning in Time. Another tool for task management and personalized task list is Towel (see [43]). Towel is a task management application that couples a user’s to-do list with a software personal assistant. This to-do list provides a unified environment for managing personal tasks, delegating tasks to the software personal assistant, and collaborating with other users. The authors use to-do list and instant messaging metaphors to enable the user to initiate, manage, and modify complex agent-executed tasks. Next, study [44] presents the Personalized Time Manager (PTIME) system, a persistent assistant. Important part of this system is a module for learning user preferences in area of task and reminders of tasks. Another tool is a Personalized Calendar Assistant [45]. The main goal of this paper is to develop personalized calendar for organizing meetings and managing constant changes and adjustments with daily tasks based on user wishes and preferences. Another system is a fuzzy logic-based personalized task recommendation system for recommending suitable working tasks based on history of solved tasks, structure of tasks and user preferences [46].

In the area of task planning, there are a lot of approaches and implemented applications. Many of them focus on time management and organization of daily tasks of users. Other approaches focus on personalized task lists and personalized calendars for managing and organizing meetings and daily schedules of users. However, these systems are primarily focused on the area of daily tasks, not the area of working tasks and projects at work. One of the presented systems was a fuzzy logic-based task recommendation system, but this system works mainly with the history of user tasks.
1.6. Motivation of this Paper

The system described in this paper works with other properties of tasks, namely, task completion status, a deadline for completion of the task, remaining time of the task completion, etc. The main problem is that we deal with concepts such as “importance of the task”, etc., that is vague and so, it cannot be specified precisely. Moreover, the available information is almost entirely specified in natural language. Therefore, the expert system for the task planning must be able to manipulate with such kind of information and capable to derive conclusion based on it. Such a system does exist and is described in this paper.

The novelty of the proposed system is a connection of task planning system with an expert system for calculating the importance of tasks. The system shows the most important tasks first and the importance is calculated in real time using various inputs. The expert system consists of three linguistic descriptions which were designed and implemented based on real problems which occur in task planning area.

The core concept is that of a linguistic description of a given situation. By this, we mean a description in natural language that is formed using the so-called, evaluative linguistic expressions. The considered linguistic description is then used in the special inference mechanism called perception-based logical deduction (PbLD).

The main characteristics of the proposed approach are the following:

(a) The system enables to create new tasks for subordinates or people on the same level in the hierarchy of the company. The tasks are ordered according to importance (on the basis of various parameters), enabling the worker to see the most important tasks on the top of the list.

(b) Regular evaluation of the tasks ordered due to (a) based on fixed parameters, for example, importance of the task, the role of the manager (assigner in the hierarchy of the organization), and also on the dynamic parameters, for example, time remaining to accomplish the task, the level of fulfillment of the task by the solver, and other ones.

(c) In addition, it is possible to modify the knowledge base (i.e., the linguistic descriptions) of the expert system and thereby modify the final ordering of tasks.

(d) From the point of view of the head of the company (CEO, owner of the company), it is important to be able to view information on the number of completed/unfulfilled tasks within the specified deadline for each employee, and also to display statistics on the effectiveness of the individual employees (solvers) of the company.

The paper is organized as follows. Section 2, ‘Methodology’, describes the model of the proposed system for task planning. Section 3 ‘Fuzzy Expert System for Task Planning’ describes the main parts of the proposed fuzzy expert system, which evaluates tasks in the system. The proposed expert system consists of three linguistic descriptions: determination of the task importance, determination of the final task importance, and determination of the efficiency of the task solvers. This section also describes the validation process of the proposed expert system. In Section 4, ‘Implementation and Experimental Results of the Expert System’, the implementation of the proposed fuzzy expert system is described, and the experimental results of the task planning system are shown. Section 5 provides a discussion of the obtained results, and finally, in ‘Conclusion’, we summarize the proposed approach and the task planning system and outline the goals of further research.

2. Methodology

In this section, we describe the model of the system for task planning. First, we introduce the main concepts used in the system.

The person who creates tasks for solvers and monitors their completion is called a manager. This person also monitors the overall effectiveness of each solver, how many tasks the solver has accomplished within the deadline, and how many tasks he accomplished after the deadline. The person who solves the assigned tasks and regularly fills in the status of each task is a solver. The main task of the solver is to solve the assigned tasks within the given deadline and to fill in the real status of the unfinished tasks.
The main goal of the proposed task planning system is to order and display tasks for the solver in an effective way. Therefore, the system shows the most important tasks first and then the less important ones (in a determined ordering). The ordering is updated periodically. It is essential for the solver to have a list of tasks ordered according to their importance at each time the task list is displayed. Another goal of the system is to show the effectiveness of all subordinate workers (solvers) for the manager. Then, the manager has an overview of the most and also the least efficient workers. This is valuable information for further decision making (rewards of effective workers, sanctions of inefficient ones, etc.).

In accordance with the description above, the proposed system consists of three data modules: managers, solvers, and tasks.

- The managers module contains personal information and a position of the manager in the company hierarchy.
- The solvers module contains information on superior person.
- The tasks module contains information about creator — a person from the Managers module who created the task, solver, priority and task completion status measure by numbers from \([0, 1]\), deadline and remaining time to the task completion.

The scheme of the proposed system is in Figure 1.

![Figure 1. Scheme of the proposed system.](image)

3. Fuzzy Expert System for Task Planning

In this section, we will describe the expert system for task planning. Recall that the main problem is the correct determination of the importance of similar tasks and their comparison. Consequently, the solver can focus first on the most important tasks and then on less important ones. Since importance is a vague concept we can describe it more or less aptly using sentences of natural language only. This makes the development of any task planning system difficult.

We suggest to apply a special fuzzy logic-based expert system that is capable to work with description given in natural language and to derive conclusion based on it. The implementation consists of three modules: determination of the task importance, determination of the final task importance, and determination of the efficiency of the task solvers.

The expert system is realized on the basis of algorithms provided in the core of the special software system LFL Controller (Linguistic Fuzzy Logic Controller; LFLC) developed in the University of Ostrava. The detailed description and justification of the methods implemented in LFLC can be found in several papers (see, e.g., [47]), and in its most succinct form in the book [48].

3.1. Perception-Based Logical Deduction (PbLD)

3.1.1. Introduction to PbLD

This method stems from the assumption that knowledge, on the basis of which a conclusion is to be drawn, is expressed in natural language. The algorithm just mimics the
human thinking. In practice, however, we need only relevant parts of the language, and so, the knowledge has the form of a linguistic description, which is a set of fuzzy/linguistic IF-THEN rules

\[
\text{IF } X_1 \text{ is } A_1 \text{ AND } \cdots \text{ AND } X_n \text{ is } A_n \text{ THEN } Y \text{ is } B_1
\]  

(1)

where \(X_1, \ldots, X_n\) are antecedent variables and \(Y\) is a consequent variable. The \(A_i, B\) are special expressions of natural language called evaluative linguistic expressions, for example small, very small, medium, extremely important, roughly medium important, etc. It is necessary to emphasize that expressions from Equation (1) are formulated and interpreted as conditional clauses of natural language.

3.1.2. Evaluative Linguistic Expressions

The general form of linguistic expressions in Equation (1) is

\[
\langle \text{linguistic hedge} \rangle \langle \text{TE-adjective} \rangle
\]

where \(\langle \text{TE-adjective} \rangle\) is a class of special adjectives that include gradable adjectives (big, cold, deep, fast, friendly, happy, high, hot, important, long, popular, rich, strong, tall, warm, weak, young), evaluative adjectives (good, bad, clever, stupid, ugly, etc.), but also adjectives such as left, middle, medium. The expressions small, medium, big are canonical and in a concrete situation, can be replaced by specific ones, such as “important, tall, deep, short, long,” etc.

Recall from the theory of evaluative (linguistic) expressions that their semantics is defined with respect to a linguistic context that is a triple of numbers \(\langle v_L, v_S, v_R \rangle\) using which the range of values of the given variable is divided into two parts: \([v_L, v_S] \cup [v_S, v_R]\) where \(v_L\) is the smallest possible value, \(v_R\) is the largest possible value and \(v_S\) is a typical medium value laying somewhere inside the interval \([v_L, v_R]\) (not necessarily in its middle). The interval \([v_L, v_S]\) contains all values that can be linguistically evaluated as small, and \([v_S, v_R]\) all values linguistically evaluated as big. The medium values are distributed around \(v_S\).

For example, heights of (adult people) can be characterized in the context \(\langle 140, 170, 220 \rangle\) (cm). Hence, we can speak about “very small” people being about 140 cm tall (and less), “medium tall” whose height is about 170 cm and “very tall” with a height of about 190 cm (and more).

After specification of the context, we construct fuzzy sets of elements that model the meaning of the expressions in concern. These fuzzy sets are called extensions and their typical shapes are depicted in Figure 2. The shapes are derived on the basis of logical analysis of the meaning of evaluative expressions. Note that, e.g., small values are values greater than \(v_L\) but smaller than \(v_S\). Furthermore, very small values form a part of small ones and similarly extremely small ones. Clearly, each very small value is also small but there are small values that are not very small. Analogous reasoning holds also big or medium values. The linguistic hedges very, extremely have narrowing effect and roughly, more or less, etc., have a widening effect. Note also that there are no hedges with narrowing effect for medium values.
Figure 2. Extensions of evaluative linguistic expressions and their model using fuzzy sets. They are determined w.r.t. the context $\langle v_L, v_S, v_R \rangle$.

3.1.3. The Difference Between PbLD and Simple Fuzzy Inference

The differences between PbLD method and “simple fuzzy inference” (i.e., essentially the Mamdani–Assilian method) can be summarized as follows:

(a) The PbLD is, in principle, the logical deduction based on the rule of modus ponens while MA method is a technique based on composition of fuzzy relations that provides approximation of a function known imprecisely.

(b) The PbLD method works locally. This means that the meaning of rules is vague (fuzzy) but still, the information contained in the given rule is distinguished from the information contained in the other ones. For example, recall the above-mentioned obstacle avoidance problem, what to do if we have the information that “IF the obstacle is near THEN turn left” and “IF the obstacle is very near THEN turn right”. Using the MA method we strike the obstacle because it interpolates between both rules. The PbLD method, however, can distinguish between them. First, it evaluates whether the obstacle is near or very near and, then, the appropriate rule is fired which results in bypassing the obstacle.

(c) The MA method works well with fuzzy sets of triangular (trapezoidal) shape. Such fuzzy sets, however, cannot be considered as extensions of evaluative expressions since the latter require the shapes depicted in Figure 2 (for the detailed justification, see [49]). Since they essentially overlap, the MA method cannot cope with genuine linguistic descriptions.

(d) The MA method is convenient for fuzzy control when the engineer thinks mainly in terms of a proper control function and thus, the shapes of the membership functions are modified to obtain the best result. The linguistic character of the expert knowledge on the basis of which the control strategy is derived is unimportant (Let us notice that PbLD can be used also for control (we speak about linguistic control). It effectively utilizes expert knowledge specified in natural language and, because of that, it can be reconsidered for various kinds of modification even after years because the engineer can easily capture meaning of the used linguistic description).

(e) Because of (c) and (d), the MA method is not convenient for the main goal of this paper, which is design of the task-planning system.

For the extensive description of the above differences, many details and demonstrations on examples, see [48].

Extensions of evaluative expressions from Figure 2 are implemented in LFL Controller and so, the user does not specify them. Actually, the user even needs not know about them and should specify only the context. The linguistic description is specified directly in
natural language. The final output is obtained using a special method called Defuzzification of Linguistic Expressions (DEE). For the details, see [48].

3.2. Linguistic Description for Task Importance
3.2.1. Specification of Variables

First, we must specify variables used in the linguistic description and the linguistic context for them. Referring to the main modules of the system presented in Section 2, we can specify the used variables as follows:

Input variables:

• Task priority ($X$). This variable essentially attains only two values 1, 2 that are in LFLC replaced by fuzzy categories \{low, high\} (priority) interpreted using triangular fuzzy sets (see Figure 3).

• Task completion status ($Y$). This variable attains values from $[0, 100] \%$ where the value 0 means that the task is completely unfinished, the value 100 means that the task is completed. The linguistic context of this variable is defined as $c = (0, 50, 100)$. So, using canonical evaluative expressions, “small $Y$” are values of $Y$ around 5–15 (and smaller), “medium $Y$” are values around 40–60 and “big $Y$” around 85–95 (and bigger). Instead of the canonical expressions, we can use specific expressions such as “a little unfinished”, “half completed”, “more or less completed”, “almost completed”, etc.

• Remaining time to the task completion ($Z$) that can attain values from $[0, 180]$ (h). The maximum value $v_R = 180$ (hours) was chosen by experts on the basis of experience that tasks older than 7.5 working days are treated similarly as tasks with 7.5 days remaining. Higher values are then converted to 180 h (= 7.5 days). In this case, the terms such as “enough time”, “a lot of time”, “quite a lot of time”, “a little time”, “a very little time”, etc., are used to describe the remaining time until the task is completed. Hence, the linguistic context of this linguistic variable is defined as: $c = (0, 60, 180)$. Thus, “small $Z$” are (in the given context) values of $Z$ around 6–18 and smaller, “medium $Z$” are values around 50–80 and “big $Z$” are values around 155–170 and bigger. This context was chosen because the experts required higher sensitivity to lower values of the remaining time.

Output variable is relative importance of the task $D$ with the context $\langle 0, 0.4, 1 \rangle$. This importance is for the manager expressed using evaluative linguistic expressions, e.g., “very high”, “high”, “medium”, “low”, “very low”, and other ones provided by the software.

3.2.2. The Form of Linguistic Description

This linguistic description enables to characterize importance of the considered tasks. Evaluative expressions are well suitable for this purpose. For example, an unimportant task is characterized using the following rule:

IF the task priority $X$ is low AND the task $Y$ is nearly complete AND the remaining time for completion $Z$ is very small THEN the task importance is very low.

Another example is a rule that describes a very important task:
IF the task priority $X$ is high AND the task $Y$ is very poorly completed AND the remaining time for completion $Z$ is very small THEN the task importance is very high.

Let us emphasize that the LFL Controller system enables us to concentrate on faithful characterization of the problem using expressions of natural language. After specification of the linguistic context, the expert is free to use natural language expressions directly without thinking about their mathematical model. Furthermore, the expert should not be even aware of their existence.

The initial linguistic description consists of 50 fuzzy/linguistic IF-THEN rules. A few examples of them are listed in Table 1. Fuzzy IF-THEN rules were created in cooperation with an expert for task planning area and they describe real life scenarios and situations in task planning.

Table 1. Example of fuzzy/linguistic IF-THEN rules from the initial linguistic description

<table>
<thead>
<tr>
<th>Rule No.</th>
<th>IF X Is</th>
<th>AND Y Is</th>
<th>AND Z Is</th>
<th>THEN Importance $D$ Is</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Low</td>
<td>Very small</td>
<td>Very small</td>
<td>Very big</td>
</tr>
<tr>
<td>4</td>
<td>Low</td>
<td>Very small</td>
<td>Big</td>
<td>More or less medium</td>
</tr>
<tr>
<td>9</td>
<td>Low</td>
<td>Small</td>
<td>Big</td>
<td>Very very roughly small</td>
</tr>
<tr>
<td>13</td>
<td>Low</td>
<td>Medium</td>
<td>Medium</td>
<td>More or less medium</td>
</tr>
<tr>
<td>25</td>
<td>Low</td>
<td>Very big</td>
<td>Very big</td>
<td>Extremely small</td>
</tr>
<tr>
<td>26</td>
<td>High</td>
<td>Very small</td>
<td>Very small</td>
<td>Extremely big</td>
</tr>
<tr>
<td>31</td>
<td>High</td>
<td>Small</td>
<td>Very small</td>
<td>Very big</td>
</tr>
<tr>
<td>42</td>
<td>High</td>
<td>Big</td>
<td>Small</td>
<td>Roughly big</td>
</tr>
<tr>
<td>50</td>
<td>High</td>
<td>Very big</td>
<td>Very big</td>
<td>Very small</td>
</tr>
</tbody>
</table>

3.2.3. Validation of the Linguistic Description

Validation of the designed linguistic description is performed using the test module of an LFL Controller. It is possible to enter real input values to the knowledge base of the expert system and to calculate the value of the output variable. For example, let us consider the following values of the input variables: $X = 2$ (high priority of the task), $Y = 5$ (task execution status 5%) and $Z = 5$ (5 hours remaining to the task completion). On the basis of these values, the first the following rule is fired:

IF $X$ is High AND $Y$ is Very small AND $Z$ is Very small THEN $D$ is Extremely big

The output crisp value $D = 0.99$ of Importance is obtained after defuzzification. The validation process is presented in Figure 4.

![Figure 4. Validation of the first linguistic description in LFL Controller.](image-url)
Table 2. Validation process of the first linguistic description

<table>
<thead>
<tr>
<th>X</th>
<th>Y</th>
<th>Z</th>
<th>D (Importance)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>15</td>
<td>5</td>
<td>0.82</td>
</tr>
<tr>
<td>1</td>
<td>25</td>
<td>5</td>
<td>0.70</td>
</tr>
<tr>
<td>1</td>
<td>46</td>
<td>62</td>
<td>0.43</td>
</tr>
<tr>
<td>1</td>
<td>61</td>
<td>151</td>
<td>0.27</td>
</tr>
</tbody>
</table>

3.3. Linguistic Description for Evaluation of Importance of the Final Task

3.3.1. Specification of Variables

The final importance of the given task is calculated on the basis of the following variables: \( D \) (Importance) and \( E \) (Level), characterized the manager’s (task creator) position in the organizational structure of the company. The output is the second linguistic description \( F \) (Final importance of the task).

Input variables:
- \( E \) (Level) characterizes the manager’s position in the organizational structure. Its context is \( ⟨0, 0.4, 1⟩ \).
- \( D \) (Task importance) is the output variable from the first linguistic description. The output variable is \( F \) (final-importance) that indicates the final importance of the task. Its context is \( ⟨0, 0.4, 1⟩ \).

3.3.2. The Form of Linguistic Description

Several fuzzy/linguistic IF THEN rules from the second linguistic description are in Table 3.

Table 3. Selected fuzzy/linguistic IF-THEN rules from the second linguistic description

<table>
<thead>
<tr>
<th>Rule No.</th>
<th>IF ( E ) ls</th>
<th>AND ( D ) Is</th>
<th>THEN Final-Importance ( F ) ls</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Small</td>
<td>Small</td>
<td>Very small</td>
</tr>
<tr>
<td>2</td>
<td>Small</td>
<td>Medium</td>
<td>Small</td>
</tr>
<tr>
<td>3</td>
<td>Small</td>
<td>Big</td>
<td>Medium</td>
</tr>
<tr>
<td>4</td>
<td>Medium</td>
<td>Small</td>
<td>Small</td>
</tr>
<tr>
<td>5</td>
<td>Medium</td>
<td>Medium</td>
<td>More or less big</td>
</tr>
<tr>
<td>6</td>
<td>Medium</td>
<td>Big</td>
<td>Big</td>
</tr>
<tr>
<td>7</td>
<td>Big</td>
<td>Medium</td>
<td>Big</td>
</tr>
<tr>
<td>8</td>
<td>Big</td>
<td>Big</td>
<td>Extremely big</td>
</tr>
</tbody>
</table>

We can conclude from them that the highest manager’s position in the organizational structure has a significant impact on the final importance of the task.

3.4. Linguistic Description for Efficiency of the Task Solvers

On the basis of the results of the first two linguistic descriptions, we can also measure the efficiency of the task solvers. The main reason for the measurement of solver efficiency is to monitor how many tasks are solved by solvers before a deadline, after a deadline, and how many tasks remain unsolved. For the calculation of the main efficiency of the solver, we used the number of finished tasks and the number of solved tasks before the deadline. The efficiency is then calculated simply as the ratio of solved tasks before the deadline with finished tasks. For instance, if the number of finished tasks is 10 and the number of solved tasks before is 10, then the efficiency is 100%. If the number of finished tasks is 10 and the number of solved tasks before deadline is 5, then the efficiency is 50%.

Specification of variables
- Input variable: \( G \) (The number of solved tasks after deadline). Its linguistic context is \( ⟨0, 20, 50⟩ \).
• Input variable: $H$ (Time of task completion after deadline). Its values represent the number of hours after the task deadline. The context is $\langle 0, 80, 180 \rangle$.

• Output variable: $K$ (Coefficient of completion after deadline). Its context is $\langle 0, 0.4, 1 \rangle$. Highest values indicate that the effectiveness of the solver is low, because a solver has lots of tasks solved after the deadline and with a long time of completion after deadline.

Example of this linguistic description is in Table 4.

Table 4. Selected fuzzy/linguistic IF-THEN rules from the third linguistic description

<table>
<thead>
<tr>
<th>Rule No.</th>
<th>IF $G$ Is</th>
<th>AND $H$ Is</th>
<th>THEN $K$ Is</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Small</td>
<td>Small</td>
<td>Very small</td>
</tr>
<tr>
<td>2</td>
<td>Small</td>
<td>Medium</td>
<td>Small</td>
</tr>
<tr>
<td>3</td>
<td>Small</td>
<td>Big</td>
<td>Medium</td>
</tr>
<tr>
<td>4</td>
<td>Medium</td>
<td>Small</td>
<td>Small</td>
</tr>
<tr>
<td>5</td>
<td>Medium</td>
<td>Medium</td>
<td>More or less big</td>
</tr>
<tr>
<td>6</td>
<td>Medium</td>
<td>Big</td>
<td>Big</td>
</tr>
<tr>
<td>7</td>
<td>Big</td>
<td>Small</td>
<td>Medium</td>
</tr>
<tr>
<td>8</td>
<td>Big</td>
<td>Medium</td>
<td>Big</td>
</tr>
<tr>
<td>9</td>
<td>Big</td>
<td>Big</td>
<td>Extremely big</td>
</tr>
</tbody>
</table>

From the above, we can conclude that a small number of solved tasks after deadline with a short time of task completion of these tasks indicates that the coefficient of completion after deadline is very low. On the other hand, a large number of solved tasks after the deadline with a long time of task completion of these tasks indicates that the coefficient of completion after deadline is very high.

If the solver has 0 tasks solved after deadline, the coefficient of completion after the deadline is automatically 0. Examples of the calculated efficiency of solvers are shown in Table 5.

Table 5. Examples of calculated efficiency of solvers

<table>
<thead>
<tr>
<th>Solver</th>
<th>Finished Tasks</th>
<th>Solved Tasks</th>
<th>Unsolved Tasks</th>
<th>$G$</th>
<th>$H$</th>
<th>$K$</th>
<th>Efficiency</th>
</tr>
</thead>
<tbody>
<tr>
<td>S1</td>
<td>30</td>
<td>30</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>100%</td>
</tr>
<tr>
<td>S2</td>
<td>12</td>
<td>9</td>
<td>3</td>
<td>5</td>
<td>20</td>
<td>0.10</td>
<td>75%</td>
</tr>
<tr>
<td>S3</td>
<td>25</td>
<td>20</td>
<td>5</td>
<td>15</td>
<td>60</td>
<td>0.72</td>
<td>80%</td>
</tr>
<tr>
<td>S4</td>
<td>60</td>
<td>52</td>
<td>8</td>
<td>40</td>
<td>140</td>
<td>0.91</td>
<td>87%</td>
</tr>
</tbody>
</table>

We may conclude from Table 5 that the main efficiency stores information only about solved tasks due to finished tasks. The main role of the this linguistic description and the calculated value $K$ is to signal the efficiency the ratio of tasks solved after the deadline and the time of their completion.

4. Implementation and Experimental Results of the Expert System

The proposed task planning system has been implemented as a web application. It is responsive and can be applied on different types of devices (PC, tablet, smartphone). The expert system is realized in the core of the special software system LFL Controller (Linguistic Fuzzy Logic Controller; LFLC) developed in the University of Ostrava. The web system contains the following main modules:

• management of the organizational structure of the company (for the administrator);
• management of solvers and managers (for administrator);
• management of tasks (for managers);
management of solver with their efficiency (for managers);
• task evaluation module using FES (for solvers);
• editing tasks (for solvers).

The most important module is the *task evaluation* module. The diagram of the main processes of this module is in Figure 5.

![Diagram of the task evaluation module.](image)

Verification of the system was provided in cooperation with a real company, which has a branched company hierarchy (the organizational structure of the company contains five levels). The verification was performed on 105 assignments and 15 users (solvers and managers with different status of the contracting entity in the organizational structure of the company).
The system contains a section called My Tasks, which contains an ordered list of the assigned tasks using the expert system. The task list in this section for a specific solver called Solver 1 is shown in Figure 6.

![Figure 6](image)

Table 6 shows values of input variables along with the output value of the Importance \( D \) and the Final importance \( F \). The following data correspond to the values shown in Figure 6.

Table 6. Input values and calculated importance for ordered task list of specific solver

<table>
<thead>
<tr>
<th>Task</th>
<th>X</th>
<th>Y</th>
<th>Z</th>
<th>( D ) (Importance)</th>
<th>( E ) (Level)</th>
<th>( F ) (Final Importance)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Task11</td>
<td>1</td>
<td>0</td>
<td>10</td>
<td>0.91</td>
<td>1</td>
<td>0.99</td>
</tr>
<tr>
<td>Task12</td>
<td>2</td>
<td>0</td>
<td>21</td>
<td>0.91</td>
<td>1</td>
<td>0.99</td>
</tr>
<tr>
<td>Task13</td>
<td>1</td>
<td>0</td>
<td>10</td>
<td>0.91</td>
<td>0.8</td>
<td>0.99</td>
</tr>
<tr>
<td>Task16</td>
<td>1</td>
<td>0</td>
<td>8</td>
<td>0.92</td>
<td>1</td>
<td>0.99</td>
</tr>
<tr>
<td>Task17</td>
<td>2</td>
<td>20</td>
<td>7</td>
<td>0.90</td>
<td>1</td>
<td>0.99</td>
</tr>
<tr>
<td>Task14</td>
<td>1</td>
<td>50</td>
<td>3</td>
<td>0.87</td>
<td>1</td>
<td>0.97</td>
</tr>
<tr>
<td>Task10</td>
<td>1</td>
<td>0</td>
<td>20</td>
<td>0.85</td>
<td>1</td>
<td>0.96</td>
</tr>
<tr>
<td>Task3</td>
<td>2</td>
<td>90</td>
<td>9</td>
<td>0.86</td>
<td>0.6</td>
<td>0.81</td>
</tr>
<tr>
<td>Task4</td>
<td>1</td>
<td>90</td>
<td>8</td>
<td>0.95</td>
<td>0.6</td>
<td>0.81</td>
</tr>
<tr>
<td>Task6</td>
<td>2</td>
<td>20</td>
<td>12</td>
<td>0.90</td>
<td>0.6</td>
<td>0.81</td>
</tr>
<tr>
<td>Task7</td>
<td>1</td>
<td>90</td>
<td>10</td>
<td>0.84</td>
<td>0.6</td>
<td>0.81</td>
</tr>
<tr>
<td>Task8</td>
<td>2</td>
<td>90</td>
<td>4</td>
<td>0.87</td>
<td>0.6</td>
<td>0.81</td>
</tr>
<tr>
<td>Task15</td>
<td>1</td>
<td>0</td>
<td>20</td>
<td>0.85</td>
<td>0.6</td>
<td>0.81</td>
</tr>
<tr>
<td>Task19</td>
<td>1</td>
<td>0</td>
<td>23</td>
<td>0.84</td>
<td>0.6</td>
<td>0.81</td>
</tr>
<tr>
<td>Task1</td>
<td>2</td>
<td>40</td>
<td>30</td>
<td>0.71</td>
<td>0.4</td>
<td>0.76</td>
</tr>
<tr>
<td>Task5</td>
<td>2</td>
<td>70</td>
<td>30</td>
<td>0.71</td>
<td>0.6</td>
<td>0.76</td>
</tr>
<tr>
<td>Task18</td>
<td>1</td>
<td>0</td>
<td>95</td>
<td>0.69</td>
<td>1</td>
<td>0.71</td>
</tr>
<tr>
<td>Task9</td>
<td>1</td>
<td>0</td>
<td>28</td>
<td>0.83</td>
<td>0.2</td>
<td>0.43</td>
</tr>
</tbody>
</table>

As we can see in Table 6, there are 18 tasks shown to the Solver 1. At the first position in the task list is Task 11, because this task has only 10 hours to the task completion deadline, its relative importance is very high, and the manager’s position is very high. Task 14 has only 3 hours to the task completion deadline, but the completion status is 50%, and so, the relative and final importance is evaluated with a lower value. Hence, the task is in the sixth position. Task 3 and Task 4 are in the middle of the task list because they are almost fulfilled, and the manager’s position is medium. However, they have high final importance because there are few hours to the task completion deadline. Task 9 is the last in the task list because the relative importance is not too high, and the manager’s position is very low.
We conclude from Table 6 that, besides the importance $D$, also the position of task creator (Level $E$) is essential in the organizational structure of the company because it has an impact on the final importance $F$. According to this value, the list of all tasks for the solver is sorted in descending order; see Figure 6. The first column represents the task name; the second column represents the task category; the third column indicates the priority of the task. The creator of the task is located in the fourth column, the fifth column contains the deadline of the task, and the sixth column contains the task completion status. The figure was created, and the evaluation was provided on 9.5.2019 at 13:00. The task list is ordered according to the final importance evaluated by the expert system. We can conclude from Figure 6 that most of the tasks that need to be accomplished in the near future have a high position in the ordered task list. It means that they are the most important for the solver and need his/her attention.

Table 7 shows the ordered task list for a Solver 2.

<table>
<thead>
<tr>
<th>Task</th>
<th>$X$</th>
<th>$Y$</th>
<th>$Z$</th>
<th>$D$ Importance</th>
<th>$E$ Level</th>
<th>$F$ Final Importance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Task33</td>
<td>1</td>
<td>0</td>
<td>8</td>
<td>0.92</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Task40</td>
<td>1</td>
<td>0</td>
<td>5</td>
<td>0.90</td>
<td>0.8</td>
<td>0.99</td>
</tr>
<tr>
<td>Task38</td>
<td>1</td>
<td>40</td>
<td>22</td>
<td>0.86</td>
<td>1</td>
<td>0.97</td>
</tr>
<tr>
<td>Task31</td>
<td>1</td>
<td>40</td>
<td>12</td>
<td>0.85</td>
<td>1</td>
<td>0.97</td>
</tr>
<tr>
<td>Task37</td>
<td>2</td>
<td>90</td>
<td>14</td>
<td>0.85</td>
<td>1</td>
<td>0.97</td>
</tr>
<tr>
<td>Task32</td>
<td>1</td>
<td>90</td>
<td>27</td>
<td>0.85</td>
<td>1</td>
<td>0.96</td>
</tr>
<tr>
<td>Task34</td>
<td>1</td>
<td>30</td>
<td>5</td>
<td>0.83</td>
<td>0.8</td>
<td>0.95</td>
</tr>
<tr>
<td>Task36</td>
<td>2</td>
<td>80</td>
<td>15</td>
<td>0.83</td>
<td>1</td>
<td>0.95</td>
</tr>
<tr>
<td>Task39</td>
<td>1</td>
<td>0</td>
<td>24</td>
<td>0.93</td>
<td>0.4</td>
<td>0.82</td>
</tr>
<tr>
<td>Task35</td>
<td>2</td>
<td>0</td>
<td>9</td>
<td>0.90</td>
<td>0.6</td>
<td>0.82</td>
</tr>
</tbody>
</table>

We can see that there are two tasks that have only a few hours until the task completion deadline (Task 33 and Task 40), and so, they have the highest final importance. Therefore, they are at the top of the task list. Task 34 and Task 35 also have only a few hours to the task completion deadline, but the creators of these tasks have a lower manager’s position, and so, their final importance is less. Task 39 has 24 hours to the task completion deadline, but the manager’s position is low, and thus, its final importance is also low.

5. Discussion

The above-presented results and the practical verification reveal several findings. The proposed intelligent system was created using an expert system for the determination of task importance. The linguistic descriptions of the expert system are written in natural language (fuzzy/linguistic IF-THEN rules), and thus, they are easy to understand. Consequently, if necessary, all these descriptions can be easily updated and modified. The proposed system has no special algorithms or procedures that would affect the final task importance. The LFLC system also allows the user to change the context of all the variables. We conclude that the proposed expert system can be easily extended or updated.

The task planning system was implemented as a WEB application that shows the ordered task list for each solver. Based on this list, the solver can see the most important tasks (calculated by the expert system) at the top of the list and then less important tasks. The main idea is to provide a useful tool for solvers, which can better recognize the most important tasks and solve them first. In this case, the solvers can be more effective in their work and focus their attention on the critical tasks. The task planning system shows the ordered task list in a real time and the evaluation of the relative and final importance of the tasks is performed periodically. Hence, the solver still sees the current and evaluated list of the tasks.
The system also includes a module for the detection of the effectiveness of the individual solvers. This module provides information about solvers who complete their tasks before or after the deadline. It also evaluates which solvers solved their task with a long delay concerning the time completion deadline. The practical experiences demonstrate that such a system is a valuable tool for managers.

The results in Tables 6 and 7 show that the relative importance of each task is also essential because each task is evaluated based on task priority, task completion status, and remaining time to the task completion. Evaluation of the final importance is conducted on the basis of the relative importance and manager’s position and draws on experience with task planning. In general, this means that tasks created by a person with the highest manager’s position (for instance, CEO of the company) are more important for the solver than tasks created by a person with a lower position.

6. Conclusions

In this paper, we present a novel approach to task planning using an intelligent expert system that makes it possible to specify all the input information directly in natural language. The main goal is the correct determination of the importance of similar tasks and ordering of them in an effective way.

The expert system is developed using consistent application of the kernel of the software LFL Controller that can draw a conclusion based on a linguistic description provided in natural language (fuzzy/linguistic IF-THEN rules). Three main outputs are distinguished: the first output is the relative importance of the task that is evaluated based on the task priority, task completion status, and remaining time to the task completion. The second output is the final importance of the task, which is evaluated based on the level of manager’s (task creator) position in the organizational structure and the relative task importance (the output of the first linguistic description). The third output is the coefficient of the task completion after the deadline (this indicates the effectiveness of the solver) that is evaluated based on the number of solved tasks and the time of the task completion after the deadline. A brief description of the implementation and validation process is also provided.

In further research, we will focus on the development of new methods for the adaptive ordering of the tasks and a decision support system for a proposal of a suitable number and type of tasks for the solver.

Author Contributions: Conceptualization, B.W.; Methodology, B.W. and V.N.; Software, B.W.; Validation, B.W.; Formal analysis, V.N.; Data curation, V.N.; Writing – original draft, B.W. and V.N.; Supervision, B.W. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Conflicts of Interest: The authors declare no conflict of interest.

References

**Disclaimer/Publisher’s Note:** The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.