Intelligent Decision Support System for Selecting the University-Industry Cooperation Model Using Modified Antecedent-Consequent Method

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Abstract. This work is devoted to the analysis and selection of the most rational model of the university/IT-company cooperation (UIC) using intelligent decision support systems (DSSs) in the conditions of input information uncertainty. The modification of a two-cascade method for reconfiguration of the fuzzy DSS's rule bases is described in details for situations when the volume of input data can be changed. Authors propose an additional observer procedure for checking the fuzzy rule consequents before their final correction. The modified method provides (a) structural reduction of the rule antecedents, (b) correction of the corresponding consequents in an interactive mode and (c) avoiding the results' deformation in the decision making process with variable structure of input data. Special attention is paid to the hierarchically organized DSSs (with variable input vector and discrete logic output) and to design of the web-oriented instrumental tool (WOTFS-1). The simulation results confirm the efficiency and expediency of using (a) the software WOTFS-1 and (b) modified method of fuzzy rule base's antecedent-consequent reconfiguration for the efficient selection of the rational model of academia-industry cooperation.

Keywords: Fuzzy logic · Linguistic term · Rule base · Reconfiguration
Decision support system · University-industry cooperation

1 Introduction

To implement multidimensional fuzzy dependencies, it is expedient to use a hierarchical approach in the synthesis of DSS for automation of decision-making processes based on fuzzy logic output. In the process of developing fuzzy DSS there is a problem of the sharp increase in the rules bases (RBs) at increasing the dimension of the input vector and the number of corresponding linguistic terms (LTs). At present there is a sufficient number of publications [2, 3, 22] on the development and optimization of fuzzy DSSs, including for solving multi-criteria problems in conditions of uncertainty. However, a further solution is required for the methods and technologies of the

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synthesis of hierarchical DSSs based on fuzzy models with variable structure of the input vector, in particular, taking into account the input information from experts and a person, who is a decision maker (DM) and whose estimates are fuzzy [29–32]. It should be noted that the development of fuzzy DSSs to increase the efficiency of decision-making in the conditions of multi-criteria and a priori informational uncertainty, in particular, with the variable structure of the input coordinate's vector, is one of the perspective directions for the creation of intelligent information systems [27].

2 Related Works and Problem Statement

One of the problems of DSSs synthesis based on fuzzy logic output is the complexity of making decisions with variable structure of the input data of the system. This is due to the need to develop approaches to correcting fuzzy RBs in the decision-making process in a priori information uncertainty, in particular when a DM is not able to evaluate and insert specific input coordinates into the system [7, 25, 26, 34, 38].

In fuzzy modeling, Mamdani's algorithm is used most often, according to which the antecedents and the consequents of the rules of fuzzy RBs are given by fuzzy sets (linguistic terms) such as "Low", "Medium", "High", etc. [10, 11, 15–17, 21].

The process of determining the most important input coordinates and the experts' formation of their estimates significantly influences the structure of the hierarchically organized DSS, in particular on the dimensionality of the RBs [9, 14]. Previous studies [18–20, 33, 35–37] show that the decision-making results undergo significant deformation in the application of fuzzy DSSs (with a fixed structure of the knowledge base) under the conditions of the variable structure of the input vector. This is due to the fact that the values of the input coordinates, which do not participate in the simulation of DSSs and a consequent with zero value, due to the corresponding fuzzy rules negatively affect the result. Consequently, the change in the dimension of the input vector in the interactive modes of fuzzy DSSs requires the development of effective methods for the reconfiguration and correction of fuzzy RBs [23, 28].

Among the well-known approaches to correction of fuzzy RBs is the use of weighting coefficients for fuzzy rules [24, 29]. Changing the vector of weighting coefficients for the corresponding rules of fuzzy knowledge bases can reduce the influence of input parameters, which, by the choice of a DM in some situations may not participate in the decision making process, on the result of the system. In addition, there is an approach to the correction of RBs, which consists of identifying non-essential parameters of the model. The number of rules is significantly reduced, which allows to increase the sensitivity of the system to change the values of input signals.

The limited properties of the considered approaches and methods of correction of RBs do not allow them to be used directly to optimize the fuzzy hierarchical DSSs with variable structure of the input vector [9, 11, 33].

The purpose of this paper is to increase the efficiency of the processes of multi-criteria decision-making in fuzzy hierarchical DSSs with discrete logical output under the condition of the variable structure of the input vector and in the formation of incoming information with a high level of uncertainty (with the application of DSS for choosing a cooperation model within the "University – IT-company" consortium).

3 Structure of Fuzzy DSS for Choosing the UIC Model

The problem of choosing one of the models of cooperation between an IT-company and a department (faculty) of the university is relevant today, especially at the beginning of their cooperation and under conditions of a possible change in the direction of joint research. Previous studies and analysis of successful cooperation experience within different types of consortia [1, 4, 8, 9] show that the solution to the task of choosing a model of cooperation between the university and the IT-Company today is to select one of four alternatives ($m = 4$), such as alternative solution variants $d_i, (i = 1 \ldots m)$, where the solution variant d_1 corresponds the model A1; variant d_2 - model A2; variant d_3 - model B; variant d_4 - model C.

The authors developed a fuzzy DSS for choosing a model for cooperation between universities and IT-companies $y = d^*, (d^* \in d, d = \{d_1, d_2, d_3, d_4\})$ in terms of previously proposed and defined indicators (input coordinates). DSS includes 11 fuzzy subsystems and has 27 input coordinates $X = \{x_j\}, j = 1, \ldots, 27$ and one output y, which are interconnected by the fuzzy dependencies $y_k = f_k(x_1, x_2, \ldots, x_{27}), k \in \{1, 2, \ldots, 11\}$ of the appropriate RBs of the 11 subsystems, where f is the functional dependence of the output coordinate y_k to the inputs $x_1, x_2, \ldots, x_{27}$ in the form of a fuzzy RBs [9, 14, 33].

The structure of the corresponding fuzzy DSS provides the choice of one of the four basic (system) solutions ($y \in \{A1, A2, B, C\}$), since 4 LTs were used to describe the output variable y. This structure provides the possibility of choosing additional (program) $\{A1(OR)A2, A1(OR)B, A1(OR)C, A2(OR)B, A2(OR)C, B(OR)C\}$ solutions, in the case where exponents of the degrees of membership $\mu^{d^*}(X^*)$, for example, of two system solutions are of the same value. Program solutions can also be formed for possible (in similar cases) combinations with 3 and 4 system solutions.

To estimate the input $X = \{x_j\}, j = 1, \ldots, 27$, 3 LTs with a triangular form of membership function (MF), in particular “low - L”, “medium - M” and “high - H”, are chosen. We should represent some of the above-mentioned coordinates: x_4 - level of IT experience of students of the university department; x_5 - participation of students in international exchange programs; x_6 - the level of student co-work with IT-companies; x_7 - students’ success in studying. Subsequently, the pre-developed RBs of all subsystems are transformed into a matrixes of knowledge by a combination of rules for the source LT of the corresponding consequent, for example, for the 2nd $y_2 = f_2(x_4, x_5, x_6, x_7)$ fuzzy subsystem $y_2 \in \{L, LM, M, HM, H\}$ (Table 1) [14].

When user inserts the data $X^{(2)*} = (x_4^*, x_5^*, x_6^*, x_7^*)$ to the inputs of the second subsystem, its output result y_2^* is generated based on the corresponding LTs: $y_2^* \in \left\{ LT_j^{(2)} \middle| LT_j^{(2)} \in \{L, LM, M, HM, H\}, j = 1, \ldots, 5 \right\}$. The output of the second subsystem y_2^* is transferred in the form of the accumulated LT to the RB of the next (in terms of the hierarchy) subsystem $y_8 = f_8(y_1, y_2)$.

Implementation of the procedure of fuzzy logical output in more details is represented in researches [9, 14, 31, 33].

Table 1. Partial set of rules of knowledge matrix for subsystem $y_2 = f_2(x_4, x_5, x_6, x_7)$

Number of rule and combination		Coordinates of Subsystem $y_2 = f_2(x_4, x_5, x_6, x_7)$				
		x_4	x_5	x_6	x_7	y_2
1	1,1	L	L	L	L	L
…	…	…				
55	1,8	H	L	L	L	
5	2,1	L	L	M	M	LM
…	…	…				
64	2,19	H	M	L	L	
9	3,1	L	L	H	H	M
…	…	…				
73	3,31	H	H	L	L	
18	4,1	L	M	H	H	HM
…	…	…				
79	4,18	H	H	H	L	
54	5,1	M	H	H	H	H
…	…	…				
81	5,5	H	H	H	H	

4 Antecedent-Consequent Method of Rules Bases Correction of Fuzzy DSS for Choosing the Rational UIC Model

In the process of decision making using fuzzy hierarchical DSSs with a variable structure of the input vector, it is necessary to apply effective approaches for reconfiguring (correction) of fuzzy RBs. This is due to the fact that the values of input coordinates that cannot be estimated at the time of decision making are uncertain and due to the corresponding fuzzy rules negatively affect the result y. The limited properties of existing approaches of reduction of the RBs do not allow them to be used directly to optimize fuzzy hierarchical DSSs with a variable structure of the input vector [29].

To solve this problem, the authors propose: (a) to use the two-stage method of fuzzy RBs correction, which allows for correction of RBs (antecedents and consequents of rules) in hierarchically-organized DSSs with variable structure of the input data vector (N) [9, 11, 13, 14, 20, 33]; (b) to modify this two-stage method by introducing embedded preliminary procedure for additional verification of the consequents before the start of their correction.

Let's discuss the implementation of the first multi-step cascade of the considered two-stage method, which is responsible for correcting the rules' antecedents, for the case when the DM is not able to evaluate some specific input coordinates (N_{NE}).

Step 1. Assessment of the general characteristics of each particular subsystem (dimensionality of input coordinates and rules structure).

Step 2. Checking the state of the input coordinates. If DM is not able to evaluate the value of any of the input coordinates of a particular subsystem, then the output of this subsystem will automatically be excluded from further consideration.

Step 3. Assigning to all LT $\left(LT_i^j, i \in \{1, \ldots, N\}, j \in \{1, \ldots, K\}\right)$ the *i*-th input coordinate of the *j*-th rule (*K*- number of rules in a particular subsystem) of the corresponding numerical values. For example, for three LTs: $LT_i^j = 1$ if $LT_i^j = L$, $LT_i^j = 2$ if $LT_i^j = M$, $LT_i^j = 3$ if $LT_i^j = H$. In the case, for example, for five LTs: $LT_i^j = 1$ if $LT_i^j = L$, $LT_i^j = 1.5$ if $LT_i^j = LM$, $LT_i^j = 2$ if $LT_i^j = M$, $LT_i^j = 2.5$ if $LT_i^j = HM$, $LT_i^j = 3$ if $LT_i^j = H$.

Step 4. Correction of the antecedents of the rules based on the analysis of the inputs of the coordinates, which DM has no opportunity to evaluate (N_{NE}). In this case, all LTs $\left(LT_i^j, i \in \{1, \ldots, N\}, j \in \{1, \ldots, K\}\right)$, for which the input coordinates cannot be assessed $x_i = NE$, are assigned a zero numerical value $LT_i^j = 0$. This means that in the future, the corresponding LT will not influence the decision-making process.

Step 5. Of all the rules that have the same antecedents after correcting them (step 4), there is only one rule, the first in the list in the RB.

Step 6. Formation of a reduced RB with corrected antecedents.

Second cascade [9, 11, 13, 14, 20, 33], *which* is responsible for correction of the rules' consequents (in the reconfigured RB [28] by the first cascade), can be modified on the step 3 by introducing embedded preliminary procedure for additional verification of the consequents before the start of their correction. In this case, the modified second cascade consists of the next steps:

Step 1. Processing of the information on the reduced RB, checking the presence of the LTs with the assigned zero numerical value $LT_i^j = 0$.

Step 2. Processing of corrected antecedents of the rules. In this case, the numerical values of the antecedents for each *j*-th rule (first cascade, step 3, step 4) of the reduced RB are added. Next, the amount is divided by the number of input coordinates that the DM has the ability to evaluate $(N_e = N - N_{NE})$, for each *j*-th rule:

$$\text{Result}_j = \sum_{i=1}^{N} LT_i^j \Big/ N_e. \quad (1)$$

Step 3. Using the proposed preliminary procedure which is based on the proposition: if the existing numerical value ($LT_i^j = 1$ for *L*, $LT_i^j = 1.5$ for *LM*, $LT_i^j = 2$ for *M*, $LT_i^j = 2.5$ for *HM*, $LT_i^j = 3$ for *H*) of the *j*-th rule consequent corresponds (is equal to) the calculated value of the result (1), then there is no need to make a correction of the consequent (step 4) of the corresponding *j*-th rule and in this case we need to go over to the next $(j+1)$-th rule's consequent correction. This avoids the process of overwriting the value of the program variable (in our case, the value of the consequent of the *j*-th rule) at the physical level (in RAM). The appropriate procedure for additional verification of the consequents before the beginning of their correction allows increasing the speed of the proposed correction method of fuzzy RBs and reducing its energy intensity by eliminating the process of allocating additional RAM when modifying the consequent. If the existing numerical value of the j-th rule consequent does not correspond to the value of the generated result (1), then it is necessary to correct this consequent (step 4).

Step 4. Determining the new linguistic term $\text{LT}_{\text{Result}} \subset \{L, LM, M, HM, H\}$ for the j-th rule consequent, using of the value of the calculation result (1) and the scale:

$$\text{Result}_j \in \{L \in [1, 1.5), LM \in [1.5, 2), M \in [2, 2.5), HM \in [2.5, 3), H \in [3, 3]\},\\ j \in \{1, \ldots, K\}.$$

Step 5. Correcting of the consequent according to the formation of the corresponding modified LTs at the step 4.

Step 6. Formation of reconfigurable RB based on corrected fuzzy rules.

Introduction of additional verification of the consequents before their correction is a necessary procedure for increasing the speed and decreasing the energy intensity of the antecedent-consequent method of reconfiguring fuzzy RBs developed by the authors. This procedure is especially relevant and useful in using the proposed method of correction of the RBs in the subsystems of DSSs with a large dimension of the vector of the input coordinates ($N \geq 5$). This is due to the fact that in the RBs of such subsystems the number of rules is considerably larger compared to other subsystems, which in turn leads to increased energy intensity and slow performance when correcting consequents of rules (second cascade) without the need for additional verification.

Consider the application of an antecedent-consequent method of fuzzy RBs correction using an example of a second subsystem $y_2 = f_2(x_4, x_5, x_6, x_7)$ of the developed DSS for choosing a cooperation model. If, for example, DM is not able to evaluate at the moment two input coordinates $x_5 = NE$, $x_7 = NE$, then when implementing the first cascade, the initial RB (Table 1) is transformed into a reduced RB [28, 37, 38].

From the results of the implementation of the first cascade, it is seen that the number of rules decreased from 81 to 9. But since the initial values of the consequents of the relevant rules do not correspond to the actual expert estimates, the implementation of the second cascade for the correction of consequents is necessary. After realization of the second cascade, the RB has the final corrected form [9, 33].

Table 2 shows some actual set of input coordinates for the second subsystem, which characterize different types of actual situations [13, 19].

Table 2. Some actual sets of the second subsystem $y_2 = f_2(x_4, x_5, x_6, x_7)$

Input coord.	Actual sets of input coordinates							
	I	II	III	IV	V	…	XIV	XV
x_4	(L,M,H)	NE	NE	NE	NE		(L,M,H)	(L,M,H)
x_5	(L,M,H)	NE	NE	NE	(L,M,H)	…	(L,M,H)	(L,M,H)
x_6	(L,M,H)	NE	(L,M,H)	(L,M,H)	NE		NE	(L,M,H)
x_7	(L,M,H)	(L,M,H)	NE	(L,M,H)	NE		(L,M,H)	NE

After applying the first cascade of the method of fuzzy RBs correction, the RB of the second subsystem is transformed into a reduced RB by number of rules (Table 3).

Table 3. Reduced RB of the second subsystem in accordance with the actual sets

Actual sets	Function of output coordinate	Amount of rules	Number of rules
I	$y_2 = f_2^I(x_4, x_5, x_6, x_7)$	81	1,2,…,81
II	$y_2 = f_2^{II}(x_7)$	3	1,2,3
…		…	…
XV	$y_2 = f_2^{XIV}(x_4, x_5, x_6)$	27	1,4,7,10,13,16,19,22,25,28,31,34,37,40, 43,46,49,52,55,58,61,64,67,70,73,76,79

The scheme of the application of the antecedent-consequent method of fuzzy RBs correction for the second subsystem $y_2 = f_2(x_4, x_5, x_6, x_7)$ on the actual sets of II-XV input data (Tables 2, 3) is presented in Fig. 1.

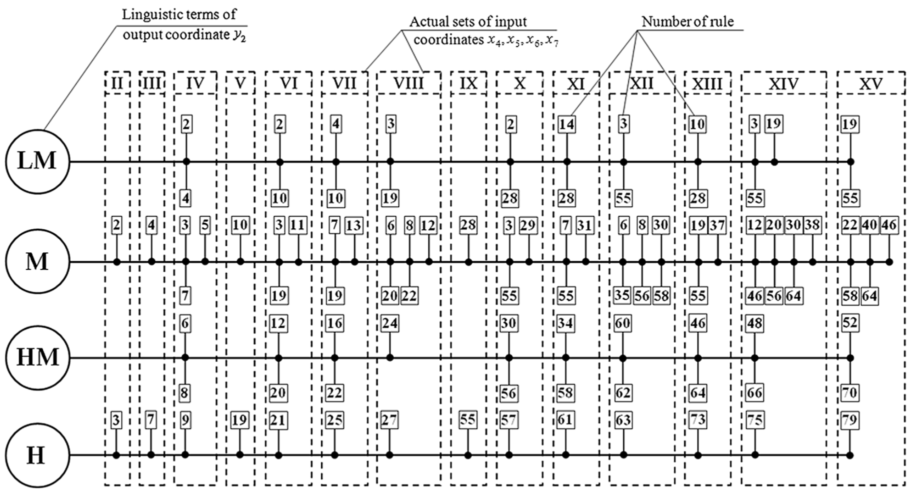


Fig. 1. The implementation scheme of consequents correction

The corresponding scheme (Fig. 1) shows exactly which rules are subject to correction for various types of input data sets. For example, rules with numbers 3, 12, 19, 20, 30, 38, 46, 48, 55, 56, 64, 66, 75 (Table 3) are subject to correction for the current set of input data XIV. In particular, for the rules with numbers 3, 19, 55 the modified consequent corresponds LT "LM", and for the rule No. 75 - "H". In this current set of XIV, this made it possible to increase the speed of the proposed method of correction of fuzzy RBs by 19% and reduce the energy intensity by 8% [13, 14, 20]. The application of the proposed preliminary procedure for additional verification of the consequents before the start of their correction (for the second subsystem in the actual set XIV) allowed avoiding the need for correction of 14 rules (1, 2, 10, 11, 21, 28, 29, 37, 39, 47, 57, 65, 73, 74) from 27 (Table 3). The main conception of the proposed preliminary procedure is described in step 3 of the second cascade.

On all the actual sets of input data of the second subsystem, the number of reduced rules, after the application of the first cascade, is 174 (Table 3, Fig. 1). At the same time, after applying the procedure for additional verification of the consequents before the start of their correction for the method of the correction of fuzzy RBs proposed by the authors, the number of rules, for which the consequent correction needs to be done, decreased from 174 to 99.

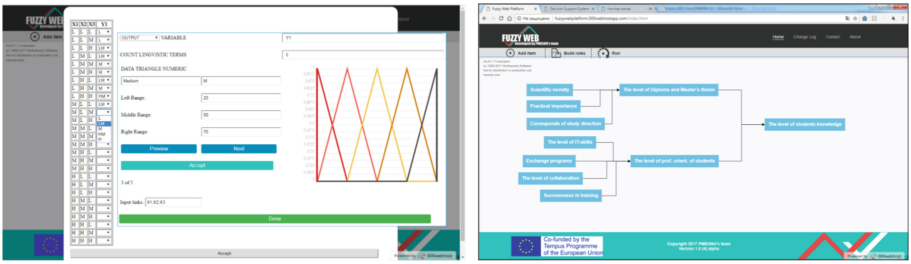
The comparative analysis shows that without the application of the proposed method of RBs correction, in particular for the second subsystem ($x_5 = NE$, $x_7 = NE$), there is a deformation of results, since the output of the unmodified subsystem corresponds LT M for which $\mu^{y_2^*}\left(X^{(2)*}\right) = \max_{j=\overline{1,5}}\left(\mu^{LT_j^{(2)}}(60, 0, 90, 0) \in \{0; 0.1; 0.8; 0; 0\}\right)$. At the same time, the result of the DSS (y) for choosing a cooperation model deforms to some extent, recommending the choice of a rational **model A2** [31, 33].

When applying the proposed method with $x_5 = NE$, $x_7 = NE$, the output signal of the second subsystem remains unchanged and corresponds LT HM, for which $\mu^{y_2^*}\left(X^{(2)*}\right) = \max_{j=\overline{1,5}}\left(\mu^{LT_j^{(2)}}(60, 80, 90, 45) \in \{0; 0.1; 0.4; 0.6; 0.2\}\right)$. In this case, the result of the DSS (y) coincides with the result for a complete set of input data – the rational cooperation **model B** [9, 14, 31, 33].

The proposed method of two-stage correction of fuzzy RBs in case of change in the dimension of the input vector, allows in interactive mode to perform automatic correction of fuzzy rules without changing the structure of DSS, which provides an increase in the efficiency and speed of DSS for decision-making in various situations.

5 Design of Fuzzy DSS for Decision Making About Most Rational UIC-Model Based on Developed Web-Oriented Tool

To enhance the effectiveness of the design of DSSs of this class, the authors have developed specialized software and a tool WOTFS-1 (Fig. 2), which has web orientation. The use of WOTFS-1 prevents the formation of the structure of the DSS on choosing a model of cooperation and obtaining an effective result: (a) operatively (including in the absence of time for decision-making), (b) at any given time in the presence of the Internet and (c) without local linking to expert data/knowledge. This feature is important because the ability to evaluate and select a model for collaboration for DM (heads of structural subdivisions of universities and IT-companies) without any restrictions of the time and place of access to DSS is a priority [12, 24].



a) b)

Fig. 2. WOTFS-1 for design of fuzzy DSS: a – inputs and LTs, b – hierarchical structure

A fragmentary (demonstration) structure (3 subsystems: $y_1 = f_1(x_1, x_2, x_3)$, $y_2 = f_2(x_4, x_5, x_6, x_7)$, $y_8 = f_8(y_1, y_2)$) of a fuzzy hierarchical DSS with a discrete logical output for choosing a cooperation model also is presented in Fig. 2.

All data/knowledge from experts are stored on the server side of the web-oriented tool. This avoids making mistakes and increases the system's protection against possible external influences. In addition, the independent global servers provide access to the management of the process of DSSs development (linguistic variables, terms, knowledge bases, etc.) with the limited rights (for example, only for experts). In this way, the expert and client can be in different places and work on creating a DSS and its subsequent testing at different times, which will significantly save time on design and technical resources [10]. The author's web-oriented tool WOTFS-1 is intended for the development of fuzzy hierarchical DSSs with discrete logical output, which allows obtaining the resulting evaluation in the form of a linguistic term, which in turn corresponds to the cooperation model, since for DM it's a more understandable result.

The developed WOTFS-1 tool allows you to develop in real time, without localization of data, your own fuzzy hierarchical DSS with discrete logical output for various purposes, in particular, for solving logistic problems [13, 33], assessing innovation and investment projects [5–7], choosing a cooperation model within a consortium "University – IT-company" [9], optimization in control systems [10, 21] and others. The developed tool is user-friendly and adapted to modern visualization means.

6 Conclusions

The results of the testing of the developed DSS for choosing a model of cooperation within the consortium "University – IT-company" with different variants of the size of the input vector confirm the effectiveness of the proposed two-stage (antecedent-consequent) method of correction of fuzzy RBs and its invariance with respect to (a) the limits on the number of subsystems and (b) the number of input variables of DSS, (c) the number of fuzzy rules and (d) the number of LTs for evaluating input and output coordinates. The application of the procedure for additional verification of the consequents before the beginning of their correction has allowed to increase the speed of the developed by the authors method of the reconfiguration of fuzzy RBs by 8–22% and reduce the energy intensity by 3–12% (depending on the degree of uncertainty of the input information and the size of the current set of input data).

The author's approach and the tool WOTFS-1 can be widely used for implementation of the decision-making processes under uncertainty, in particular when selecting partners for investment objectives in the marine business [33], when choosing cooperation models within academic-industry consortia [9, 14], while optimizing and planning routes [13, 19] etc.

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