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The Multistage Fuzzy Logic-Based Decision Support Model to Determine the Salary of New Employees

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Abstract: Salary determination for prospective new employees is critical in determining the level of employee satisfaction that can motivate people. The goal of this research is to develop a decision support model to determine salaries for prospective new employees by combining three methods: Multistage fuzzy logic, and conventional and simple mathematical models. Fuzzy logic is used to calculate fuzzy parameters, while conventional methods are used to calculate non-fuzzy parameters by multiplying parameter values by their weights. In this study, data amounted to approximately 30 data obtained via a questionnaire, which describes the personal data of prospective new employees at a company. There are 18 parameters in this study divided into four main categories that determine the amount of salary for prospective new employees. This decision support model generates a salary for prospective new employees that the company can use as a reference when providing salaries.

Keywords: Decision Support Model, Fuzzy Logic, Conventional Method, Simple Mathematical Models, New Employee, Salary Determination

Introduction

A company is a legal entity founded by a group of people to sell products or services. Human Resources (HR) are one of the most valuable assets of a company (Sadikin and Purwanto, 2021). According to a previous study, the company's business operations can function smoothly if the personnel work effectively together (Setiawan *et al*., 2018). Human resources in a company must be appropriately managed in order to support the development of company growth (Sahir *et al*., 2017) (Sadikin and Purwanto, 2021).

One of the challenges in the HR division of a company is the turnover rate of its employees (Belete, 2018). A high turnover rate in the company can be detrimental to the company because it will cost a lot. The turnover intention at the company refers to employees who have considered losing their job position and leaving the company (Hung *et al*., 2018). Previous studies have said that employee turnover can be caused by stress levels at work, high workload, low work motivation, lack of compensation, and lack of compatibility with leaders (Silaban and Syah, 2018). Companies need to overcome the turnover rate to retain the best employees and achieve the goals of the company.

Employee performance is one of the keys to the company's success. According to a study, companies must provide excellent employee support in order to encourage people at work (Kabir and Parvin, 2011). Employee salary or wages are a significant aspect of employee performance (Nagaraju and Pooja, 2017). Employee retention is influenced by benefits and compensation.

Paying new employees will have a significant impact on their level of happiness and will drive them to work hard. High pay and benefits help attract and keep high-quality employees (Iqbal *et al*., 2017). When an employee is satisfied with his or her salary, the desire to change jobs is low, however when the satisfaction level with the salary is poor, the desire to change jobs is high (Hung *et al*., 2018). As a result, an automated system that can calculate salaries or employee payments faster and more correctly is required (Shaout and Yousif, 2014). Salary for new employees can be calculated depending on the employee's skill or performance, as well as other considerations.

As a result, a DSM is required to assist the HR division in calculating the salary amount for prospective new employees. The HR division frequently makes subjective decisions to establish employee salaries because it lacks a reasonable Decision Support Model (DSM) (Sadikin and Purwanto, 2021), one of which is a decision-support model to decide salary payments to prospective new employees. One of the factors that may be evaluated is an employee's performance, which contains ambiguity and ambiguity (Shaout and Yousif, 2014). There is no right or incorrect way to evaluate an employee's performance or ability. Employee salary determination has a significant impact on employee satisfaction with their salary.

Several studies have utilized various ways to automatically determine salary incentives for employees. Fuzzy Inference System (FIS) (Sadikin and Purwanto 2021), Adaptive Neural Fuzzy Inference System (ANFIS), Fuzzy Multiple Attribute Decision Making (FMADM) (Marpaung, 2018), Fuzzy TOPSIS (FTOPSIS) (Eka and Silmi, 2019; Kafabih and Budiyanto, 2020) and Simple Additive Weighting (SAW) are some methods used (Irawan, 2020; Syahreza, 2020). The findings of these investigations are presented in the form of DSM, which is used to determine employee salary bonuses. The DSM can identify which employees are eligible for a salary bonus as well as the amount of the bonus.

Previous research did not address the issue of determining salary payments to prospective new employees. Many of these studies address the annual payment of additional salaries or incentives to employees. Providing a suitable salary at the beginning stage of recruiting can boost employee satisfaction with their income and can perform well. Since the recruiting process contains ambiguous criteria, the application of the fuzzy technique is also useful in developing DSM.

In this study, researchers want to create DSM using multistage Fuzzy Logic (FL) to determine salaries for potential new employees at the company. Multistage FL may be used to search for and categorize parameters in order to obtain more exact calculations and compute the weights on each parameter more precisely, as well as numbers to generate a value in the form of the wage that prospective new workers would earn. The MPK that is constructed is supposed to generate the greatest salary for prospective new employees and can boost employee salary satisfaction.

Constructing DSM will be based on reasonable calculations on defined parameters and it will be acceptable to all employees. The parameters specified are also criteria that may be examined and owned by each employee. The FL computation will then be utilized to compute the weights for each parameter as well as alternative weights on each specified parameter, resulting in precise and accurate calculations.

Literature Review

There are various studies that perform research on the subject of DSM or DSS to determine the amount of compensation or salary rise that may be offered to corporate employees. The most common method is to use SAW, which searches for the weight value on each criterion to find the most optimum alternative value. The alternative value will serve as a reference for managers to calculate the amount of salary or increase in employee salaries.

There are also other approaches that use fuzzy logic to achieve a precise assessment of preset criteria, such as the Fuzzy Inference System (FIS), Fuzzy Multi-Attribute Decision Making (FMADM), and Fuzzy-TOPSIS (FTOPSIS). The criteria or characteristics employed also differ, such as job knowledge, abilities, responsibility, absenteeism, loyalty, working speed, and so on. Managers can utilize salary increase parameters to decide the amount of pay that new workers will earn.

Fuzzy Inference System (FIS) research is being conducted to determine extra salary estimates for employees (Sadikin and Purwanto, 2021). As a result, salary increases become more diverse, rather than just 5, 15 and 20%. Another study used the fuzzy-TOPSIS approach to calculate the yearly employee salary increase and the best employee award (Kafabih and Budiyanto, 2020). According to the computations, the 21st employee received the highest score with a fuzzy value of 0.656 and a wage raise of Rp 100,000. Another example of study is the use of Fuzzy Multi-Attribute Decision Making (FMADM) (Eka and Silmi, 2019) to decide which civil servants are entitled to periodic salary increases. This model provides 90% of the data eligible for a monthly salary increase based on the parameters out of the 40 data input.

According to the study done on the topic of DSM and salary increases, the usage of Fuzzy Logic is extensively employed since it has a high computational level. Fuzzy logic may convert the bias value of the parameters into objective crisp values. Making DSM using Fuzzy Logic has the potential to become an effective model for calculating the salary amount of new employees in a company.

Employee Recruitment

According to a previous study, employees are one of the company's most essential assets and must be managed and developed in order for the organization to achieve its goals (Irawan, 2020). An employee can be recruited through a recruiting procedure based on the job position required by the organization. According to several research, the recruiting process is a major issue in Human Resource (HR) management (Hsiao *et al*., 2011).

The recruiting process's purpose is to find high-quality individuals at the lowest feasible cost who are suitable for the company's organization (Hsiao *et al*., 2011). Poor recruiting decisions can lead to underperformers and high turnover rates (Pessach *et al*., 2020). Employee turnover has a direct influence on the expenses associated with the process, such as interviewing and re-hiring costs, training and productivity costs, and overtime costs for other employees (Pessach *et al*., 2020).

One of the actions that occur later in the recruitment process is salary negotiation (Porter *et al*., 2004). The goal of the compensation negotiating process is to secure and keep the company's human resources (Porter *et al*., 2004).

Employee salary or wages are an essential aspect in determining employee performance (Nagaraju and Pooja, 2017). Paying new employees will have a significant impact on their level of happiness and will drive them to work hard. High pay and perks help attract and keep high-quality employees (Iqbal *et al*., 2017).

Turnover Intention

Turnover intention is a movement made by an employee to enter and leave a company (Silaban and Syah, 2018). Turnover intention is one of the challenges that must be faced by the Human Resources (HR) division of a company (Belete, 2018). The emergence of turnover intention in an employee can be triggered by reasons of salary, promotion, job satisfaction, or relationship with superiors (Hung *et al*., 2018). A high turnover rate can be detrimental to the company because the company will lose experienced employees and must retrain new employees (Indrasari *et al*., 2018).

Decision Support Model

DSM is a model that is intended to provide a Decision Support System (DSS) that facilitates accurate and efficient objective decision-making (Mahsus and Utama, 2021). Gorry and Scott Morton developed DSM in the early 1970s to suit the demands of a Management Information System (MIS) in semi-structured or unstructured decision-making operations (Eom *et al*., 1998). In a company, MIS is a crucial aspect in creating good planning and allocating resources for information systems jobs (Gorry and Scott Morton, 1971).

DSM is defined as a computer-based interactive system that helps in decision-making by utilizing data and methods to solve unstructured problems (Kurniawan and Utama, 2021) fuzzy-based Decision Support Model for Deciding the Students' Academic Performance, 2021. In order to achieve a goal, a decision must be founded on a problem (Setyono and Aeni, 2018) the objective is to address an issue effectively and efficiently. The stages in the decision-making process are shown in the Fig. 1. The phases in the decision-making process that must be completed (Muslihudin *et al*., 2019):

1) Intelligence is the process of identifying the problem to be investigated. The data will also be acquired at this step, after which it will be processed and tested based on the difficulties that arise (Setyono and Aeni, 2018)
2) Design In this phase, a decision maker must create a model to identify, develop and assess all possible solutions to the problem (Susilowati *et al*., 2019). Model validation and verification are also required to determine the model's correctness in solving the problem
3) Selection This phase includes choosing the best solution to the problems that arise
4) Implementation of this phase includes carrying out the implementation procedure for the developed system design. System success is defined by resolved issues, whereas system failure is defined by unresolved problems (Susilowati *et al*., 2019)

Fuzzy Logic

FL is an approach or methodology that uses "degrees of truth" rather than "true or false" (1 or 0) Boolean logic (LA, 1988). Because the values in Boolean logic are not particular and just have true or false values, they might be called biased (LA, 1988). FL provides a membership method that may determine an object's size or value (LA, 1988). The membership function returns a number between 0 and 1. FL uses linguistic variables to express the value of an item. For example, consider the height of a tree, which might be represented as short, medium, fairly tall, or towering. The membership function values can be used to represent the quantitative value of an object (Osiro *et al*., 2014).

FL is frequently used when there is ambiguity, inaccuracy, or other difficulty (Chen *et al*., 2021). The FL method correctly combines computer and human language to bring out the meaning of a value (Chen *et al*., 2021). The degree value in the membership function contributes to bringing out this meaning. FL can be classified as low, medium, high, or extremely high (Özger and Şen, 2007).

Fuzzification, inference (rule basis), and defuzzification are the three primary processes of FL (Utama *et al*., 2020). Fuzzification is an input transformation procedure that involves measuring crisp input and delivering it to the machine for processing with F before converting it to fuzzy output (Kurniawan and Utama, 2021) Fuzzy based Decision Support Model for Deciding the Students' Academic Performance, 2021. The process of calculating the degree of membership of each input fuzzy set is known as fuzzification (Thendean and Sugiarto, 2008). The inference process is the process of producing fuzzy output based on predefined fuzzy rules. Defuzzification is a procedure that generates quantifiable outcomes based on a predefined membership function (Utama *et al*., 2020).

FL has essentially been used to reduce the degree of bias in a parameter (Pah and Utama, 2020). In practice, FL is frequently used to handle challenges involving expert systems and real-time systems that must adapt to an imperfect environment with varied, volatile, and fuzzy characteristics (Kurniawan and Utama, 2021) Fuzzy based Decision Support Model for Deciding the Students' Academic Performance, 2021.

There has been a study on the use of FL to examine the profile of prospective employees who would work in manufacturing companies (Karatop *et al*., 2015). According to the findings of this study, FL generates a more accurate and effective assessment and evaluation of prospective employee profiles to be placed in a job, as well as lowers employee turnover rates. The FL approach can assist HR managers in making more objective selections when hiring new staff (Karatop *et al*., 2015).

Materials and Methods

The research framework specifies how the research concept will be implemented in the course of conducting research. Salary determination for new employees is a topic discussed in this study and DSM is a solution developed to address this issue. Salary determination for new employees is frequently done subjectively by looking at the new employee's assessment. The use of DSM is intended to make salary determination more objective and to increase employee satisfaction with their salary.

The DSM model is constructed through the process of selecting and weighing parameters. These parameters are the model inputs. The DSM model will use a hybrid of three methods: Fuzzy logic, conventional, and simple mathematical models. Fuzzy logic will be employed for fuzzy parameters in each category, while conventional approaches, such as multiplying the values by weights, will be used for non-fuzzy parameters. The fuzzy logic method is used only for fuzzy parameters, in which each parameter has a membership function and a fuzzy rule for each category. The conventional method is used only for non-fuzzy parameters, in which the value of the parameter will be multiplied by each weight. The results of fuzzy logic and conventional logic will then be combined with a basic mathematical model.

There are 2 stages of fuzzy logic in this model. The first stage is to calculate 18 parameters and the result is 4 categories of values, such as personal information, skills, attitude, and achievement. If the categories consist of fuzzy parameters and non-fuzzy parameters, the model will use the combined methodology. If the categories only consist of fuzzy parameters, the model only uses fuzzy logic methodology.

The second stage of the model is to calculate 4 category values with fuzzy logic and the result is the salary amount of the prospective employee. At this stage, the membership function of 4 categories has the same graphic form and linguistic variable. Based on expert judgment, the 'experience' category has plus point in the salary determination. Therefore, the fuzzy rule for salary determination has more emphasis on that category.

The stages of the research to be carried out are shown in Fig. 2. The stages of research carried out in making DSM will follow procedures in accordance with the Decision Support Model (DSM) Wheel which can assist in the process of making and evaluating DSM. The first step is to analyze the case which is then followed by the decision-determining stage. The next stage is to determine the parameters of the research, which can be done with an in-depth analysis process and literature study.

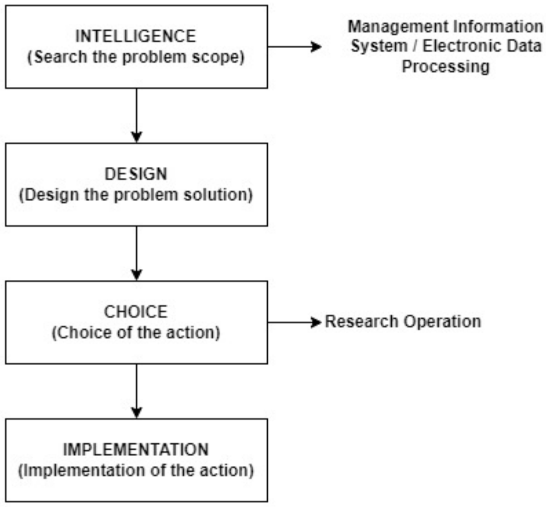

Fig. 1: Decision-making process (Setyono and Aeni, 2018)

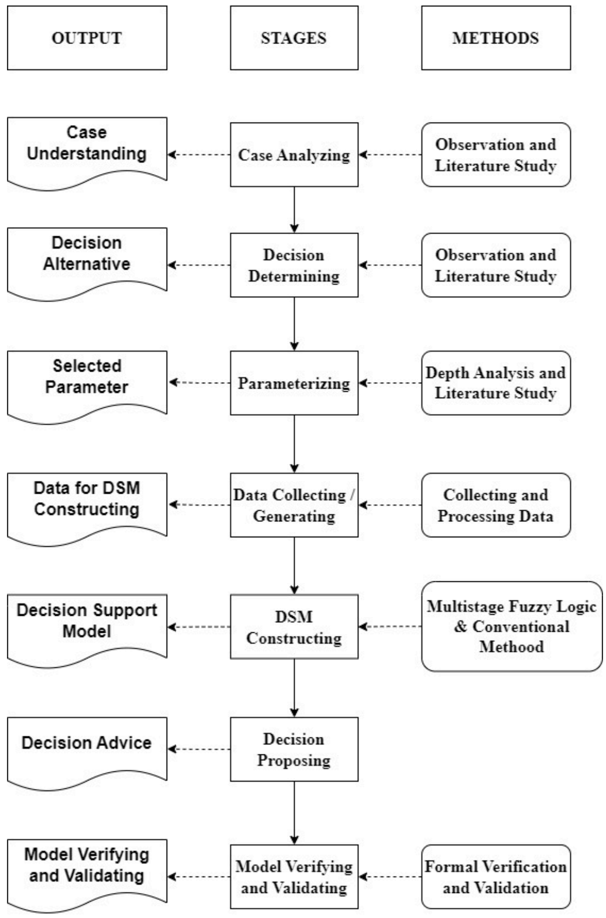

Fig. 2: Research stages

The next step is to gather data relevant to the determined parameters. These data will represent the prospective new employee's personal information, ability level, attitude and behavior, and work experience. Data that was successfully collected amounted to 30 data. The collected data is processed manually first to match the data format so that it is easier for the model to read. Data were collected using questionnaires provided to a specific group of respondents, namely those working in the field of informatics technology. Afterward, the data will be processed and used as a data source in the DSM.

The following stage is decision proposing, in which the findings of the DSM will be suggested as one of the lists of decisions in determining salaries for prospective new employees. Following that, the DSM will conduct a verification and validation procedure to determine if the resulting decisions are in accordance with the data.

Results and Discussion

Parameterizing

Following the case analyzing and decision-determining stages, the parameterizing stage will be performed. The parameters obtained aim to determine the best salary that prospective employees in a company can obtain. At this point, the method of in-depth analysis and literature review was used. This method yielded 18 parameters, which were then classified into four categories.

There are four main categories personal information, skills, attitude, and experience. Personal information parameters include age, marital status, distance, dependents, and formal education. Work expertise, job knowledge, work speed, work quality, and number of jobs are all parameters in the skills category. The behavioral parameters in the attitude category include the level of discipline, honesty, and responsibility. Achievement, current position, current salary, and work experience are the parameters for the experience category. There are three non-fuzzy parameters: Marital status, formal education, and current position. The remaining 15 parameters are fuzzy.

The developed DSM model will employ a hybrid of multistage fuzzy logic, conventional and mathematical models. The multistage fuzzy logic method involves the execution of two fuzzy processes. The first fuzzy process converts 18 parameters into four category values. The four category values are then processed through the second fuzzy, yielding the best salary amount for prospective employees in a company. To determine the limits of each parameter, triangular and trapezoidal fuzzy membership functions with linguistic variable constraints are used. Those types of membership functions are common in fuzzy logic because easy to implement, flexible, and can be adjusted to fit different situations and applications.

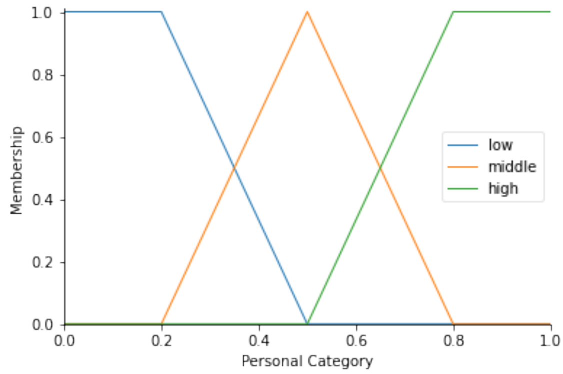

Fig. 3: Membership function for main category personal information

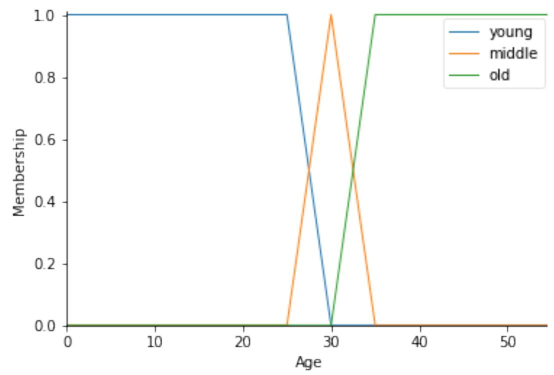

Fig. 4: Membership function for parameter age

The four main categories all have membership functions with linguistic variables and the same limit values: 'Low,''middle,' and 'high' (Fig. 3). The trapezoidal membership function (0, 0, 0.2, 0.5) is used by the linguistic variable 'low,' the triangular membership function (0.2, 0.5, 0.8) is used by the linguistic variable' middle,' and the trapezoidal membership function is used by the linguistic variable 'high' (0.5, 0.8, 1). Three linguistic variables are present in the membership function for 13 parameters from each category. The limit value of each parameter is determined through extensive analysis and literature research.

For example, in the 'personal information' category, there is the 'age' parameter, which has three linguistic variables (Fig. 4), namely 'young' (0, 0, 25, 30), 'middle' (25, 30, 35) and 'old' (25, 30, 35). (30, 35, 60, 60). There are 'quality of work' parameters with three linguistic variables for the 'skills' category, namely 'low' (0, 0, 2, 5), 'middle' (2, 5, 8), and 'high' (2, 5, 8). (5, 8, 10, 10). There are 'honesty' parameters with three linguistic variables for the 'attitude' category (Fig. 5), namely 'low' (0, 0, 2, 5), 'middle' (2, 5, 8), and 'high' (5, 8, 10, 10). There is a 'current salary' parameter with three linguistic variables for the 'experience' category: 'Low' (0, 0, 60, 130), 'middle' (60, 130, 200), and 'high' (130, 200, 500, 500).

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Table 1: Fuzzy Rules for salary determination

No	Personal Information	Skills	Attitude	Achievement	Salary
1	Low	Low	Low	Low	Low
2	Low	Low	Low	Middle	Low
…	…	…	…	…	…
38	Middle	Middle	Middle	Low	Middle
39	Middle	Middle	Low	High	Middle
…	…	…	…	…	…
80	High	High	High	Middle	High
81	High	High	High	High	High

Every fuzzy calculation process will include an inference step in which the created rule base will be used. The rule base is based on weighting done by experts in the field of human resources and an in-depth analysis of the weighting results. The rule base will be used to determine the fuzzy process's final value, which will become a crisp value. Table 1 shows an example of a fuzzy rule that is used to determine salaries for prospective new employees.

Non-fuzzy parameters have varying values. The parameter 'marital status' has two values: 0 for 'unmarried' and 1 for 'already married.' The 'formal education' parameter has a value of 1, 'SMP' with a value of 2, 'SMA/SMK' with a value of 3, 'D3' with a value of 4, 'S1' with a value of 5, 'S2' with a value of 6 and 'S3' with a value of 7. The parameter ‘Last Position / Job’ has the options of 'Student' with a value of 1, 'Junior Level' with a value of 2, 'Middle Level' with a value of 3, 'Senior Level' with a value of 4 and 'Managerial' with a value of 5. Examples of values on non-fuzzy parameters can be seen in Table 2.

Table 2: Examples of values of parameter marital status

Marital status	Values
Unmarried	0
Already married	1

Fig. 5: Membership function for parameter employee attitude

The Constructed Model

The model in this study is described using a class diagram, which is a top-level diagram that shows the entities in the model as well as the relationships between these entities. The model's class diagram is shown in Fig. 6. Several classes or entities are required for this model, including NewEmployee, Salary, FuzzyLogic, FuzzyRule, MembershipFunction, TriangularMF, TrapezoidaMF and CurveMF. The NewEmployee class describes the characteristics or parameters of a company's assessment of prospective new employees.

There are three operations in the NewEmployee class: Fuzzy logic, conventional and mathematical models. Fuzzy logic functions are used to compute fuzzy parameters, while conventional functions are used to compute non-fuzzy parameters. The calculation results will then be added up using a simple mathematical model Fuzzify, infer, and defuzzify are the three stages of the fuzzy logic process. Weight considerations in each parameter category are used to create fuzzy rules. The weight is determined through interviews with human resource experts.

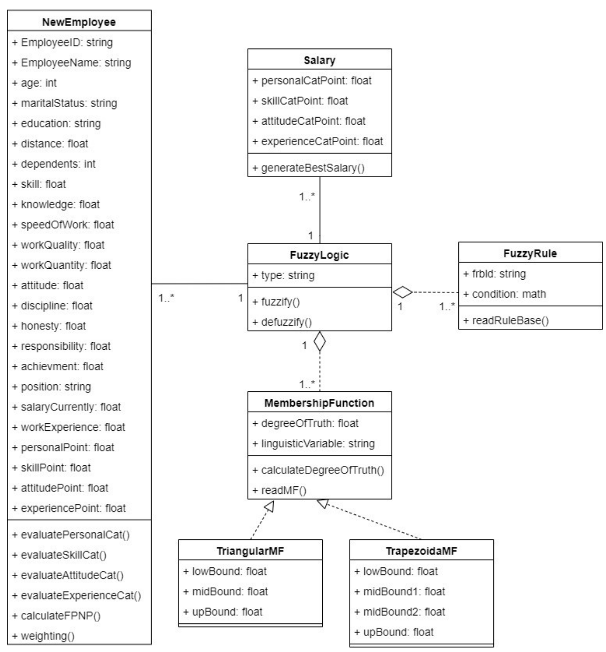

Fig. 6: Class diagram of the model

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Table 3: Parameters to determine employee salary

Code	Parameter	Weight	Weight normalization
P1	Age	5	0.036231884
P2	Marital status	1	0.007246377
P3	Distance	6	0.043478261
P4	Dependents	6	0.043478261
P5	Formal education	5	0.036231884
P6	Skill of work	8	0.057971014
P7	Knowledge of work	9	0.065217391
P8	Speed of work	9	0.065217391
P9	Quality of work	10	0.072463768
P10	Quantity of work	10	0.072463768
P11	Employee attitude	10	0.072463768
P12	Discipline	10	0.072463768
P13	Honesty	10	0.072463768
P14	Responsibility	10	0.072463768
P15	Achievement	5	0.036231884
P16	Last position/job	7	0.050724638
P17	Current salary	8	0.057971014
P18	Work experience	9	0.065217391

There are 18 assessment parameters for prospective new employees to determine the amount of salary they are entitled to receive. There are 15 fuzzy parameters and 3 are non-fuzzy parameters. Each parameter will have a weight, which will also be used to determine the fuzzy rule. Table 3 shows these parameters. The non-fuzzy parameters are marital status, formal education, and last position/job.

The model will read the data first, then the values of the fuzzy and non-fuzzy parameters. The fuzzy parameters will then enter fuzzy logic operations, while non-fuzzy parameters will enter conventional operations. These values will then be added to form the four main category values. The main category values will then be entered into the second stage of fuzzy logic operations, which will produce the final result in the form of salary amounts for new employees. Figure 7 shows the model algorithm.

In this study's decision support model, the combined use of three methods: Fuzzy logic, conventional, and simple mathematical models can assist in calculating parameter values that are both fuzzy and non-fuzzy. The decision support model for determining the amount of salary for new employees is also novel, as previous studies focused on discussing annual salary bonuses. The parameters used in this study are also a combination of those used in previous studies, so many parameters are used in determining salaries for new employees in this study.

The data for this study came from a distributed questionnaire that included self-data questions as well as ability test questions, particularly in the field of web programmers. The questionnaire includes questions for each of the 18 parameters in the decision support model. The data will then be used to put the developed decision support model to the test. Table 4 shows an example of the data obtained.

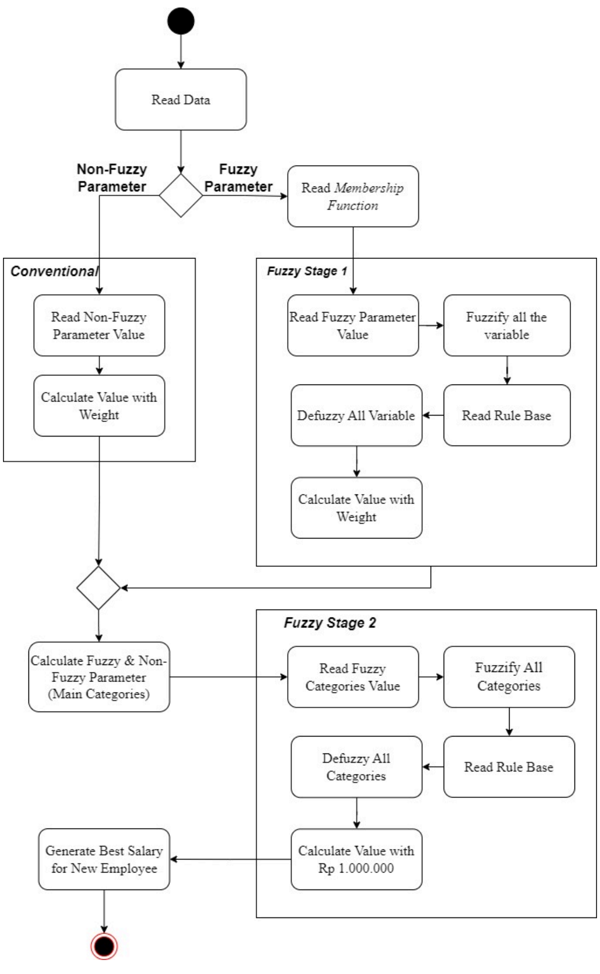

Fig. 7. Modeling algorithm

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Table 4: Sample data

Code	Parameter	Weight	Weight normalization
P1	Age	21	28
P2	Marital status	Not married	Not married
P3	Distance	0	3
P4	Dependents	0	0
P5	Formal education	Senior high school	Bachelor
P6	Skills of work	5	3
P7	Knowledge of work	5	5.5
P8	Speed of work	6	16
P9	Quality of work	5	4.25
P10	Quantity of work	7	10
P11	Employee attitude	10	10
P12	Discipline	10	9.5
P13	Honesty	10	9
P14	Responsibility	10	10
P15	Achievement	0	1
P16	Last position/job	Student	Account representative
P17	Current salary	0	50
P18	Work experience	1	6

Table 5: Calculation of fuzzy parameter in the personal information category

Name	P1	P3	P4	Ax	W	WA
Employee 0	21	0	0	0.81429	0.12319	0.10031
Employee 4	22	48	0	0.50000	0.12319	0.06159
Employee 7	41	16	2	0.35023	0.12319	0.04314
Employee 9	28	20	2	0.63621	0.12319	0.07834
Employee 11	34	20	1	0.33055	0.12319	0.04720
Employee 15	30	20	0	0.81429	0.12319	0.10031
Employee 16	37	15	0	0.36379	0.12319	0.04482
Employee 21	20	0	0	0.81429	0.12319	0.10031
Employee 27	28	3	0	0.79171	0.12319	0.09753
Employee 29	21	20	0	0.81429	0.12319	0.10031

Table 6: Calculation of non-fuzzy parameter in the personal information category

Name	P2	P5	WB_P2	WB_P5
Employee 0	0	0.42857	0.00000	0.01553
Employee 4	0	0.71429	0.00000	0.02588
Employee 7	1	0.71429	0.00725	0.02588
Employee 9	1	0.71429	0.00725	0.02588
Employee 11	1	0.85714	0.00725	0.03106
Employee 15	0	0.71429	0.00000	0.02588
Employee 16	0	0.71429	0.00000	0.02588
Employee 21	0	0.71429	0.00000	0.02588
Employee 27	0	0.71429	0.00000	0.02588
Employee 29	0	0.71429	0.00000	0.02588

The model will perform the first stage, which is to read the 18 parameters. The text data will then be converted into numeric data. For the parameter 'marital status,' for example, a value of 'unmarried' will be converted to a value of 0, and a value of 'already married' will be converted to a value of 1. The model will then calculate the first stage of fuzzy logic (ax) for fuzzy parameters. The fuzzy logic results will be multiplied by the total Weight (W) of the fuzzy parameters (WA). While non-fuzzy parameters will be calculated using conventional methods (WB), which involve multiplying the value by the parameter Weight (W). The results of the two values calculations will then be added together and will be normalized by dividing the value by the total weight category. This first stage will calculate 18 parameters and produce values for the four main categories (C1, C2, C3, C4).

Data from 8 prospective employees for the 'personal information' category can be seen in Tables 5-7. Calculations for fuzzy parameters will be performed using fuzzy logic, which produces ax, which is then divided by the Weight (W) of all fuzzy parameters to produce WA.

Table 7: Total points for the personal information category

Name	WA	WB_P2	WB_P5	W	C1
Employee 0	0.10031	0.00000	0.01553	0.16667	0.69503
Employee 4	0.06159	0.00000	0.02588	0.16667	0.52484
Employee 7	0.04314	0.00725	0.02588	0.16667	0.45762
Employee 9	0.07834	0.00725	0.02588	0.16667	0.66899
Employee 11	0.04720	0.00725	0.03106	0.16667	0.47414
Employee 15	0.10031	0.00000	0.02588	0.16667	0.75714
Employee 16	0.04482	0.00000	0.02588	0.16667	0.42417
Employee 21	0.10031	0.00000	0.02588	0.16667	0.74931
Employee 27	0.09753	0.00000	0.02588	0.16667	0.74045
Employee 29	0.10031	0.00000	0.02588	0.16667	0.75714

Table 8: Calculation of fuzzy parameters in the skills category

Name	P6	P7	P8	P9	P10	AX	W	C2
Employee 0	5.0	5.0	6	5.00	7.00	0.49999	0.33333	0.49999
Employee 4	8.5	7.0	22	7.75	10.00	0.75639	0.33333	0.75639
Employee 7	5.5	5.5	16	5.50	10.00	0.55297	0.33333	0.55297
Employee 9	6.0	7.5	13	6.75	10.00	0.67587	0.33333	0.67587
Employee 11	5.5	8.0	42	6.75	10.00	0.66212	0.33333	0.66212
Employee 15	8.5	7.0	36	7.75	9.75	0.75639	0.33333	0.75639
Employee 16	5.0	2.0	23	3.50	10.00	0.36379	0.33333	0.36379
Employee 21	0.0	0.0	2	0.00	0.00	0.18571	0.33333	0.18571
Employee 27	3.0	5.5	16	4.25	10.00	0.55297	0.33333	0.55297
Employee 29	2.0	3.0	190	2.50	3.25	0.33879	0.33333	0.33879

Table 9: Calculation of fuzzy parameters in the attitude category

Name	P11	P12	P13	P14	AX	W	C3
Employee 0	10.0	10.0	10.0	10.0	0.81429	0.28986	0.81429
Employee 4	9.0	9.0	9.0	9.0	0.81429	0.28986	0.81429
Employee 7	10.0	9.0	9.0	10.0	0.81429	0.28986	0.81429
Employee 9	8.5	9.0	7.5	9.5	0.80556	0.28986	0.80556
Employee 11	10.0	8.5	9.0	9.5	0.81429	0.28986	0.81429
Employee 15	10.0	10.0	10.0	10.0	0.81429	0.28986	0.81429
Employee 16	10.0	9.0	9.0	9.5	0.81429	0.28986	0.81429
Employee 21	10.0	10.0	8.0	10.0	0.81429	0.28986	0.81429
Employee 27	10.0	9.5	9.0	10.0	0.81429	0.28986	0.81429
Employee 29	7.5	7.5	6.0	7.5	0.72706	0.28986	0.72706

Non-fuzzy parameters will be calculated in a conventional way by multiplying the value by the parameter Weight (W) and obtaining WB. The WA and WB values are then added together and divided by the Weight (W) of the category to yield C1. Table 6 shows the calculation between non-fuzzy parameters because this category has 2 non-fuzzy parameters. The value of each parameter will be multiplied by each weight.

Table 7 shows the value of the 'personal information' category for each prospective employee. For example, Employee 0 gets 0.69503 for the 'personal information' category. According to Table 7, Employee 15 has the highest 'personal information' category value. With a fuzzy parameter value of 0.10031, a 'marital status' parameter value of 0, and a 'formal education' parameter value of 0.02588. Employee 16 has the lowest 'personal information' category value, with a value of 0.42417.

The "Skills" and "Attitude" category scores were determined based on Tables 8-9. Since the parameters for the two categories are all ambiguous, the values for these categories can be obtained using a single calculation process. The calculation process only involves fuzzy calculations for each existing parameter. Based on Table 8, the value of Employee 4 and Employee 15 has the highest score with a value of 0.75639 from 8 data on new prospective employees in the 'Skills' category. Employee 21 has the lowest 'skills' category value, with a value of 0.18571. According to Table 9, only Employee 29 has a low category value for 'Attitude,' with a value of 0.72706. Other Employee data has a value of 0.81429.

Data on 8 new prospective employees for the 'achievement' category can be found in Tables 10-12. This category includes three fuzzy parameters and one non-fuzzy parameter. As a result, the calculation of fuzzy logic and conventional methods will be performed. The non-fuzzy parameters in the 'achievement' category are shown at P16. The value of P16 is text data, which will be converted into numeric data. After being converted, the value of the parameter will be multiplied by the weight of the parameters. For the result, the calculation from fuzzy logic will be added to the calculation from the conventional method.

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Table 10: Calculation of fuzzy parameters in the achievement category

Name	P15	P17	P18	AX	W	C3
Employee 0	0	0	1.0	0.18571	0.15942	0.02961
Employee 4	0	122	1.0	0.19116	0.15942	0.03054
Employee 7	0	0	15.0	0.81429	0.15942	0.12981
Employee 9	0	158	4.0	0.33362	0.15942	0.05319
Employee 11	1	190	8.0	0.50000	0.15942	0.07971
Employee 15	0	90	9.0	0.57590	0.15942	0.09181
Employee 16	3	28	12.0	0.79583	0.15942	0.12687
Employee 21	0	0	0.0	0.18571	0.15942	0.02961
Employee 27	1	50	6.0	0.36379	0.15942	0.05799
Employee 29	0	100	1.5	0.21010	0.15942	0.03349

Table 11: Calculation of non-fuzzy parameters in the achievement category

Name	P16	WB_P16
Employee 0	0.2	0.01014
Employee 4	0.6	0.03043
Employee 7	0.1	0.05072
Employee 9	0.8	0.04058
Employee 11	0.8	0.04058
Employee 15	0.4	0.02029
Employee 16	0.2	0.01014
Employee 21	0.2	0.01014
Employee 27	0.4	0.02029
Employee 29	0.6	0.03043

Table 12: Total points for achievement category

Name	WA	WB_P16	w	C4
Employee 0	0.02961	0.01014	0.21014	0.18916
Employee 4	0.03054	0.03043	0.21014	0.29017
Employee 7	0.12981	0.05072	0.21014	0.85911
Employee 9	0.05319	0.04058	0.21014	0.44619
Employee 11	0.07971	0.04058	0.21014	0.57241
Employee 15	0.09181	0.02029	0.21014	0.53345
Employee 16	0.12687	0.01014	0.21014	0.65201
Employee 21	0.02961	0.01014	0.21014	0.18916
Employee 27	0.05799	0.02029	0.21014	0.37253
Employee 29	0.03349	0.03043	0.21014	0.30421

Table 10 shows the calculation for fuzzy parameters in the 'achievement' category, which has 3 parameters. Each parameter has the same weight. Table 11 shows the calculation for the non-fuzzy parameters. Table 12 shows the results of the calculation for the 'achievement' category. These results are obtained by adding up the value of fuzzy parameters with the non-fuzzy parameter. Employee 7 has the highest score in the 'achievement' category, with a value of 0.85911. This shows that the employee has a lot of experience and accomplishments in his career. Employee 0 has the lowest value in this category, with a value of 0.18916.

Table 13 shows the calculation results of phase 2 fuzzy logic. Following the collection of the four main category values, these values will be recalculated using fuzzy logic to produce the final result in the form of salary amounts. Based on expert judgment, the 'experience' category has plus point in the salary determination. Therefore, the fuzzy rule for salary determination has more emphasis on that category. The calculation result will be multiplied by Rp 1.000.000 to produce the salary that the new employee is entitled to earn. Employee 21 receives a salary of Rp 4.514.285 based on Table 11, which is the lowest salary from the data used. Meanwhile, Employee 15 receives the highest salary from the data used, Rp. 23. 353.870. The salary calculation results are in accordance with the criteria held by each prospective new employee.

The calculations from the model are then compared with the expected salary of each new prospective employee. The goal is to get the model calculation accuracy value in determining the amount of salary of prospective employees. Table 14 shows the percentage of model calculation accuracy for each existing data. From 30 data that were used in making this model, an average accuracy rate of 82.79% was obtained. This shows that models built using multistage fuzzy logic, conventional methods, and simple mathematical models have fairly high accuracy. These results can be considered by the HR division in determining the salary of prospective new employees in their company.

Table 13: Calculation of final salary for new employee

Name	C1	C2	C3	C4	Salary (x Rp 1.000.000)
Employee 0	0.69503	0.49999	0.81429	0.18916	Rp 11.636.435
Employee 4	0.52484	0.75639	0.81429	0.29017	Rp 22.896.752
Employee 7	0.45762	0.55297	0.81429	0.85911	Rp 15.254.339
Employee 9	0.66899	0.67587	0.80556	0.44619	Rp 20.423.827
Employee 11	0.47414	0.66121	0.81429	0.57241	Rp 20.013.080
Employee 15	0.75714	0.75639	0.81429	0.53345	Rp 23.353.870
Employee 16	0.42417	0.36379	0.81429	0.65201	Rp 9.261.340
Employee 21	0.75714	0.18571	0.81429	0.18916	Rp 4.514.285
Employee 27	0.74045	0.55297	0.81429	0.37253	Rp 15.706.788
Employee 29	0.75714	0.33879	0.72706	0.30421	Rp 8.766.322

Table 14: Calculation of final salary for new employee

Name	Salary from model	Expected salary	Accuracy (%)
Employee 0	Rp 11.636.435	Rp 10.000.000	83.64
Employee 4	Rp 22.896.752	Rp 19.000.000	79.49
Employee 7	Rp 15.254.339	Rp 17.500.000	87.14
Employee 9	Rp 20.423.827	Rp 16.500.000	76.21
Employee 11	Rp 20.013.080	Rp 21.000.000	95.30
Employee 15	Rp 23.353.870	Rp 20.000.000	83.23
Employee 16	Rp 9.261.3400	Rp 11.000.000	84.28
Employee 21	Rp 4.514.2850	Rp 6.000.0000	75.24
Employee 27	Rp 15.706.788	Rp 13.500.000	83.69
Employee 29	Rp 8.766.3220	Rp 11.000.000	79.70

Conclusion

In this study, the DSM to determine the amount of salary of prospective new employees was created using 18 parameters and using three combined methods to determine the salary. The model produces a salary scale with an average accuracy rate of 82.79% of their expected salary. The model uses 30 data points derived from questionnaires distributed online. This model is expected to assist the HR division of a company in determining the salary of their prospective new employees and can reduce the turnover rate in their company. These parameters are divided into four major categories: 'Personal information', 'skills,' 'attitude,' and 'achievement.' These 18 parameters are age, marital status, distance, dependents, formal education, skills of work, knowledge of work, speed of work, quality of work, the quantity of work, employee attitude, discipline, honesty, responsibility, achievement, last position/job, current salary, and work experience. These parameters will be the input data describing the new employee candidates, which this Decision Support Model (DSM) will read and process.

The DSM was created using three combined methods to determine the salary of prospective new employees: Multistage fuzzy logic, conventional and mathematical models. There are two fuzzy logic processes used to calculate the value of the four main categories and the final salary amount. Non-fuzzy parameters are calculated using the conventional method, which includes multiplying the parameter values by their weights. The results of the fuzzy parameter calculation are then added to the results of the non-fuzzy parameter calculation using a simple mathematical model.

This research provides the use of 30 data points derived from questionnaires that describe the personal information of potential new employees. Employee 21 receives the lowest salary calculation, amounting to Rp. 4,514,285, with a value of 0.75714 in the 'personal information' category, 0.18571 in the 'skills' category, 0.81429 in the 'attitude' category, and 0.18916 in the 'achievement' category. Employee 15 received the highest salary calculation, amounting to Rp. 23,353,870, with a value of 0.75714 in the 'personal information' category, 0.75639 in the 'skills' category, 0.81429 in the 'attitude' category, and 0.53345 in the 'achievement' category. This is because the skills category has the most weight in determining salary, accounting for 33% of the total value.

Future research could improve the DSM's performance. One method is to include several parameters that determine the amount of salary for prospective new employees. Financial capability parameters for the company can also be added, allowing for more precise salary calculations for each company.

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Author's Contributions

Gregoryus Imannuel Perdana: Written developed and tested algorithm.

Ditdit Nugeraha Utama: Reviewed and supervised the research.

Ethics

The authors declare no conflict of interest.

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