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Fuzzy Multiple Moderation and Moderated-Mediation Analysis based on and Metrics with Evolutionary Algorithms and Neural-Networks

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**Abstract** Many researchers have conducted empirical studies with multiple moderators to better understand the complex mechanisms underlying causal relations. In real-world settings, linguistic expressions and ambiguous human experiences cannot be accurately modeled using crisp numbers; thus, fuzzy theory offers a more suitable framework. While existing studies have applied fuzzy methods to simple models, more complex structures remain largely unexplored. This paper proposes Fuzzy Multiple Moderators Analyis (FMMA), integrating fuzzy least squares estimation (FLSE) and fuzzy least absolute deviation (FLAD) based on and metrics. To estimate model coefficients, we provide a closed-form solution in FLSE, and apply optimization algorithms such as Genetic Algorithm (GA), Harmony Search (HS), and neural networks. Empirical analysis was conducted using real-world datasets in psychology, solar power generation, and bike rental counts. These datasets encompass both subjective survey-based and sensor-driven variables, offering diverse degrees of ambiguity and nonlinearity. The proposed FLSE method achieved lower fuzzy mean squared errors (FMSE) and higher fuzzy values compared to classical models, demonstrating superior fit and explanatory power in contexts involving ambiguous data. Particularly, the fuzzy moderated-mediation model captured nuanced indirect effects and multi-way moderator interactions that were overlooked by crisp models. FLAD further demonstrated robustness in handling asymmetric errors and outlier-prone conditions. This study highlights the potential of fuzzy analytical frameworks in complex social and environmental domains, providing robust estimation and interpretability even in the presence of vague or imprecise information.

**Keywords** Fuzzy multiple moderation ·Fuzzy multiple moderated-mediation · Fuzzy least squares estimation · Fuzzy least absolute deviation · Evolutionary Algorithms · Neural-Networks

# 1 Introduction

Social science is a branch of science that investigates human social behavior and social phenomena that occur in human-to-human relationships. Since social science is based on logical empiricism, it has proved the cause and effect of social phenomena, that is, causality, through empirical evidence. Mediation and moderation analyses are prevalent statistical methods to explain causality, especially in psychology [1-6]. There are two variables, a mediator and a moderator, first introduced by Baron and Kenny in 1986 [2] that play an important role in each analysis. A mediator explains the causal relationship between the independent variable () and the dependent variable () by being located between them. Mediation analysis is a method of analyzing the indirect effect of on through a mediator. On the other hand, a moderator plays a role of strengthening or weakening the effect of on . Moderation analysis is a method to analyze the effect of a moderator whether it is statistically significant. Mediation and moderation analyses have also been conducted by being integrated into a single statistical model. Several researchers mentioned the necessity of analysis of integrated model, moderated-mediation and mediated-moderation [1, 2, 7], and the following research has provided definite analytic procedures of them [8]. In addition, the moderated-mediation was conducted with various models using the concept of path analysis [9] in which a moderator controls each path of the mediation model, and also analysis of conditional indirect effects was conducted [10, 11]. The moderated-mediation model was redefined as a conditional process analysis [6], and the index of moderated-mediation, a quantification of the relationship between a moderator and an indirect effect, was continuously studied by many other authors [12, 13].

It is undeniable that it is often proper to use models with several moderators [14] due to the complexity of the real world. For instance, in psychology, as a company's job demand for an employee increases, the employee's dissatisfaction with the company will also increase. This situation can be moderated by a person's work environment such as the atmosphere of the team to which the employee belongs and the company's welfare, etc. It suggests that it is more helpful to the company itself to consider several factors at the same time, not just one factor, to reduce its employees' dissatisfaction. As in the example, if two moderators affect the causal relationship between and , the model is called a multiple moderation model [6]. The multiple moderation model is divided into two types of models, the multiple additive moderation model, and moderated-moderation model, depending on the relationship between two moderators. The former's moderators moderate the effect of on independently. On the other hand, in the latter case, the effect of on by a primary moderator is dependent on the secondary moderator. Furthermore, the mediation model also can be moderated by multiple moderators. If two moderators independently control the indirect effect by influencing a common path, such as or , in mediation model, these models are called partial moderated-mediation [15]. In contrast, if the moderation of the indirect effect by the primary moderator depends on the secondary moderator, these models are named moderated moderated-mediation [15]. A few research of these models with various domains of data have been conducted so far [16-19]. These types of models were statistically analyzed using the intensified concepts such as the index of partial moderated-mediation and the index of moderated moderated-mediation [15, 20]. More active research into the analysis of these models should be conducted since it is necessary to analyze the models with interest so that we can explain complex scientific and social circumstances occurred in the real world more precisely.

Until now, most of the studies of the above models especially in humanities fields have been done on crisp numbers. However, there are many ambiguous data that cannot be precisely expressed as real numbers. For example, there are numerically ambiguous expressions such as 'about 7', 'a few', 'somewhat', and also linguistic expressions like 'small', 'moderate', 'big' that present the degree of something. In addition, there are lots of cases that we need to express human feelings with numbers in psychology, such as the degree of how much a person feels depressed. We cannot express it accurately if we use a crisp number rather than a soft number such as a fuzzy number. As mentioned above, most of analyses in humanities fields have been studied by crisp numbers which caused the loss of information. Therefore, those data which are ambiguous and vague should be expressed with a fuzzy number, which was first introduced by Zadeh [21], to increase the precision of analysis. Researches that used fuzzy numbers in mediation, moderation, and moderated-mediation model were conducted by Yoon in 2020 [22, 23]. In addition, fuzzy mediation analysis with multiple mediators was introduced by Lee et al. [24]. These researches showed that it is more reasonable to use fuzzy data in those models shown in Fig. 1 because it gives more reliable outcomes than using crisp numbers. However, fuzzy analyses that include models with multiple moderators, such as the multiple moderation model and multiple moderated-mediation model, have not been studied yet despite their necessity for explaining data.

By using triangular fuzzy numbers, we suggest two key estimation method; fuzzy least squares estimation (FLSE) [22, 23, 25-35] and fuzzy least absolute deviation (FLAD) based on distance approach, each of which are and -metric based method.

However, prior fuzzy modeling studies have predominantly focused on simple models with a simple mediator or moderator, limiting their ability to capture the multifaceted causal interactions present in real-world data. There is a lack of comprehensive methodologies for applying fuzzy theory to complex frameworks involving multiple moderators or multi-stage moderated-mediation structures. This gap is critical because many practical datasets—particularly in psychology, behavioral science, and environmental systems—contain multiple interacting fuzzy variables that cannot be adequately handled using crisp or basic fuzzy approaches.

Furthermore, the inability to model nonlinear and hierarchical interactions among fuzzy moderators may lead to biased or incomplete interpretations of causal mechanisms.

In this paper, we present the methodology of estimation and statistical inference of fuzzy multiple moderators analysis (FMMA). In the case of FLSE, the coefficient estimation that used closed-form formula is suggested which is the true solution and applied to data analysis in section 6. As additional methods for coefficient estimation, evolutionary algorithms are introduced to estimate coefficient with optimization, especially genetic algorithm (GA) and Harmony Search (HS). Moreover, neural-network algorithm is suggested where we use -metric based objective function and utilize four optimization methods based on gradient descent to estimate the coefficients. For the methodology of statistical inference, a fuzzy T-test is defined to judge the significance of the estimated coefficients. In addition, fuzzy F-test and fuzzy are presented as model fit measurements [36]. Using closed-form formula in FLSE and statistical inference methods, we compare the statistical outcomes of FMMA against those of CMMA to discern changes caused by missed information. In addition to the primary purpose of the mediation and moderation analysis, aimed at explaining causal relationships between the variables and estimating their effect on the dependent variables, we conduct the comparisons of the accuracy of FLSE and FLAD methods respectively with regards to fuzzy mean squared error (FMSE) and fuzzy mean absolute error (FMAE). In FLSE, we measure the performances of a range of estimation methods, including closed-form formula, evolutionary algorithms, and neural-network algorithm. On the other hand, FLAD focuses on the performance comparison solely between GA and HS by the measurements of accuracy above, as the objective function is non-differentiable.

The main contributions of this study are summarized as follows:

▪ *A new fuzzy framework for multiple moderation and moderated-mediation:* This study proposes a unified fuzzy analytical model—Fuzzy Multiple Moderators Analysis (FMMA)—that extends traditional causal models to handle multiple fuzzy moderators and indirect paths simultaneously.

▪  *Robust fuzzy estimation techniques:* Two fuzzy estimation methods are introduced—Fuzzy Least Squares Estimation (FLSE) based on the metric and Fuzzy Least Absolute Deviation (FLAD) based on the ​ metric—to flexibly model fuzzy causal structures.

▪ *Hybrid optimization-based solutions:* In addition to closed-form formulas, the study incorporates evolutionary and neural optimization algorithms (Genetic Algorithm, Harmony Search, and Neural Networks) to efficiently estimate models, especially under non-differentiable conditions.

*▪ Fuzzy statistical inference tools*: The paper develops fuzzy inference measures such as fuzzy , fuzzy F-tests, and fuzzy t-tests to support model comparison and hypothesis testing under ambiguity.

▪ *Empirical validation with real-world fuzzy data:* The proposed models are applied to actual datasets in psychology, solar energy prediction, and public bike usage, demonstrating superior performance in modeling ambiguous and nonlinear causal relationships compared to crisp models.

In summary, section 2 provides some basic concepts of the multiple moderation model and multiple moderated-mediation model. Section 3 provides basic concepts of fuzzy theory and our proposed fuzzy model. Section 4 elaborates on the methodology of estimation, FLSE and FLAD, including closed-form formula, evolutionary algorithms, and neural-network algorithm. In section 5, we detail the methodology of statistical inference using -metric. Section 6 provides data analysis based on LSE and FLSE using closed-form formula in the psychology field and also data related to our daily life, especially solar power data, applying to models proposed in section 2, 3. Section 7 offers a comparison of the performance among our methods in fuzzy model respectively, and finally, the conclusion is suggested in section 8.

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| 스케치, 도표, 라인, 디자인이(가) 표시된 사진  AI가 생성한 콘텐츠는 부정확할 수 있습니다.  (a) simple mediation model | **도표, 라인, 직사각형, 스케치이(가) 표시된 사진  AI가 생성한 콘텐츠는 부정확할 수 있습니다.**  (b) simple moderation model |
| **도표, 라인, 스케치, 기술 도면이(가) 표시된 사진  AI가 생성한 콘텐츠는 부정확할 수 있습니다.**  (c) moderated-mediation model | **도표, 라인이(가) 표시된 사진  AI가 생성한 콘텐츠는 부정확할 수 있습니다.**  (d) parallel multiple mediation model |

**Fig. 1.** Simple models, moderated-mediation model and parallel multiple mediation model

# 2 Multiple Moderation Analysis and Moderated-Mediation Analysis with Multiple Moderators

In this section, the basic concepts of multiple moderation analysis and mediation analysis with multiple moderators are proposed, involving the regression equation and the meaning of some coefficients [6, 15].

**2.1. Multiple Moderation Model**

**2.1.1 Multiple Additive Moderation Model**

The model is illustrated in Fig. 2. Two moderators of this model, and , control the effect of on independently. Before mentioning the regression equation of the model, consider a multiple linear regression model with three antecedent variables ,, and which is basic for the multiple moderation model.

. (1)

We could replace with an additive linear function of both and , as follows:

, (2)

. (3)

Then, we can get the regression equation (4) by substituting (3) for in (2), and expansion of (4) is (5).

, (4)

. (5)

It can be expressed with the conditional effect of on () as follows:

,

. (6)

The regression coefficients of the product of and () and and () estimate the rate of change in the conditional effect of on as or changes by one unit when or is constant, respectively.

|  |  |
| --- | --- |
| (a) Conceptual diagram | (b) Statistical diagram |

**Fig. 2.** A multiple additive moderation model

|  |  |
| --- | --- |
| (a) Conceptual diagram | (b) Statistical diagram |

**Fig. 3.** A moderated-moderation model

**2.1.2 Moderated-Moderation Model**

Illustrated in Fig. 3, this model is also called *three-way interaction*, since ,, and interact. In this model, a moderator 's moderation of effect of on depends on another moderator (). The product and are added to (5) as following equation.

. (7)

This can be rewritten as follows:

. (8)

It can be expressed with the conditional effect of on () as follows:

,

. (9)

To find out how the effect of on by is moderated by , we can rewrite (8) again.

. (10)

Seeing , the moderation of the effect of on by is moderated by , and the conditional effect of by , which can be represented as , is , so-called the conditional moderation of by . In this model, estimates three-way interaction of , , and .

**2.2 Moderated-Mediation Model with Multiple**

**Moderators**

**2.2.1 Partial Moderated-Mediation Model**

This model is integration of multiple additive moderation and mediation, shown in Fig. 4. In this model, two moderators and independently moderate either the first path () or the second path (, where is a mediator.

1) A first stage dual moderated-mediation

Two moderators moderate the path. The two regression equations can be expressed like below.

,

. (11)

The conditional effect of on is

. (12)

The conditional indirect effect of is equal as the multiplication of and as follows:

(13)

2) A second stage dual moderated-mediation

Two moderators moderate the path, and it is illustrated in Fig. 4. The two regression equations can be expressed like below.

,

. (14)

The conditional effect of on is

. (15)

The conditional indirect effect of is equal as the multiplication of , the effect of on , and .

. (16)

|  |  |
| --- | --- |
| (a) Conceptual diagram | (b) Statistical diagram |
| (c) Conceptual diagram | (d) Statistical diagram |

**Fig. 4.** A first stage dual moderated-mediation model(a, b) and a second stage dual moderated-mediation(c, d)

**2.2.2 Moderated Moderated-Mediation Model**

This model is integration of moderated-moderation and mediation, represented in Fig. 5. In this model, two moderators that a primary moderator is moderated by the other moderator are involved in the first stage () or the second stage (.

1) A first stage moderated moderated-mediation model

A three-way interaction by ,, is involved in path in this model. Two regression equations are below.

,

(17)

The conditional effect of on , and the conditional indirect effect of are below.

, (18)

(19)

2) A second stage moderated moderated-mediation model

A three-way interaction by ,, is involved in path in this model. Two regression equations are below.

,

(20)

The conditional effect of on , and the conditional indirect effect of are below.

, (21)

(22)

More complex models that multiple moderators influence mediation are illustrated in Fig. 6.

|  |  |
| --- | --- |
| (a) Conceptual diagram | (b) Statistical diagram |
| (c) Conceptual diagram | (d) Statistical diagram |

**Fig. 5.** A first stage moderated moderated-mediation model(a, b) and A second stage moderated moderated-mediation model(c, d)

|  |  |
| --- | --- |
|  |  |
|  |  |
|  | |

**Fig. 6.** More complex moderated-mediation models

# 3 Proposed Fuzzy Multiple Moderation Analysis and Fuzzy Mediation Analysis with Multiple Moderators

# In this section, some features of fuzzy numbers and some kinds of them are mentioned [21, 37]. Moreover, applying basic concepts from section 2, fuzzy multiple moderation and fuzzy multiple moderated-mediation analysis are proposed.

**3.1 Fuzzy Numbers**

Whether an element is included in a set can be expressed by the membership function. If the element is included in which is a crisp subset of , the value of membership function is also expressed as , and if not, . In other words, the membership function matches the element to a set , called mapping. However, if is a fuzzy subset of , the membership function matches to . Thus, the possibility of the element's belonging, or the membership function, becomes a value between 0 and 1. It means that the boundary of a fuzzy set is ambiguous. For any the crisp is called the -cut or -level set of . If a fuzzy set defined in is convex, normalized, and its membership function is continuous, this fuzzy set is called a fuzzy number. There are various types of fuzzy numbers, and they are usually expressed with the membership function. Among them, we often use a special form of fuzzy numbers, the so-called -fuzzy numbers, defined as follows:

, (23)

where means the mode of the fuzzy number , and mean left and right spread respectively. and are reference functions of X where are fixed left-continuous and non-increasing functions with and . We express the -fuzzy number as . The degree of fuzziness of the number depends on the value of and that a fuzzy number could be either symmetric or asymmetric. If , the number has no fuzziness, so it can be regarded as a crisp number. We can get -cuts of fuzzy numbers expressed as the intervals . Particularly, if and its reference functions are , then we regard as a triangular fuzzy number and expressed as . Let , triangular fuzzy numbers. Basic operations based on extension principle [21] can be applied to , as follows:

,

,

where . (24)

**3.2 Fuzzy Multiple Moderation Model**

**3.2.1 Fuzzy Multiple Additive Moderation**

**Model**

Fuzzy simple moderation model was studied by Yoon previously [23]. Applied to this, if  is a fuzzy explanatory variable and  is a fuzzy response variable, then  and  are fuzzy moderators which controls the effect of on . Thus, the proposed fuzzy multiple additive moderation model can be expressed with additive function as follows:

,

(25)

It can be rewritten as

(26)

The constant term is actually , where . The effect of on depends on and , so the conditional effect of on () is equal to .

**3.2.2 Fuzzy Moderated-Moderation Model**

In this model, the effect of on by a primary fuzzy moderator depends on a secondary fuzzy moderator , and it can be expressed as follows:

(27)

The fuzzy conditional effect (FCE) of on is where . The fuzzy conditional moderation effect (FCME) is where , which quantifies the changes of moderation of the effect of on through by . If is statistically significant, we can say that influences 's moderation of the effect of on .

**3.3 Fuzzy Moderated-Mediation Model with Multiple Moderators**

**3.3.1 Fuzzy Partial Moderated-Mediation**

**Model**

Fuzzy moderated-mediation model was first introduced by Yoon [23].

1) A first stage dual fuzzy moderated-mediation

This model can be expressed as following equations:

,

*,* (28)

where and are fuzzy moderators, and is the conditional effect of on a fuzzy mediator , represented as . The fuzzy conditional indirect effect (FCIDE) [23] of on through is , which represented as .

2) A second stage dual fuzzy moderated-mediation

This model can be expressed as following equations:

,

(29)

where is conditional effect of on , represented as . The fuzzy conditional indirect effect (FCIDE) of on through is , which is represented as .

**3.3.2 Fuzzy Moderated Moderated-Mediation Model**

(1) A first stage moderated moderated-mediation model

The model can be expressed by following equations with a primary fuzzy moderator , a secondary fuzzy moderator , and a fuzzy mediator :

,

, (30)

where is conditional effect of on , expressed as . The fuzzy conditional indirect effect (FCIDE) of on through can be expressed as follows:

(31)

(2) A second stage moderated moderated-mediation model

The model can be expressed by following equations:

,

(32)

where is conditional effect of on , expressed as . The fuzzy conditional indirect effect (FCIDE) of on through can be expressed as follows:

(33)

**4 Methodology: Estimation**

**4.1 Estimation of the Proposed Model with Distance Approach**

In order to analyze the fuzzy multiple moderation models based on regression, it is first necessary to clearly define the fuzzy subtraction operation to express the difference between two fuzzy numbers. The reason is that since the subtraction operation of the fuzzy number is not identically defined, different values are derived depending on the calculation method even if it is the same equation. Therefore, by defining this operation as a distance approach using the -metric, the coefficient estimation in fuzzy model was previously studied in [25-28]. We denote the estimation method using -metric as FLSE. In addition, we also suggest the method of estimating coefficients, FLAD, by using -metric as described in section 4.1.2.

**4.1.1 Estimation by FLSE using Closed-Form Mathematical Formula**

On the spaces of crisp sets, we normally use the least square estimation to estimate the regression coefficients. There also exist several metrics that are suitable for fuzzy sets applied for the least square estimation [38-40]. Generally, the distance between two fuzzy numbers is based on the distance between their -cuts. A metric which is useful can be defined through support functions. The support function of any compact convex set is defined as a function given by for all . , where is the unit sphere of dimension in and represents the scalar product on . Note that the support function is uniquely determined for convex and compact . An -metric on a fuzzy number set is defined on the space of Lebesgue integrable as below:

. (34)

Based on this equation, an -metric for triangular fuzzy numbers can be defined as follows:

(35)

where .

A fuzzy regression model introduced previously [25, 26] is suggested as follows:

, (36)

where , , and are presumed as fuzzy error terms that indicate fuzziness.

All cases can be encompassed by

(37)

where and are the left and right spreads of , respectively. Now we can get estimators by minimizing following function:

(38)

for , where is the number of the regression model in this fuzzy analysis. This function can be acquired based on the -metric (35).

To minimize (38), we obtain the normal equation applying for each and for as follows:

(39)

and for each the normal equation which has as solutions can be obtained as follows:

. (40)

Since the introduction of fuzzy regression analysis in 1982, only numerical methods have been used to estimate the coefficients of fuzzy regression models due to the complexity of fuzzy numbers. This was because there had been no fuzzy-number operations that could yield a closed-form solution. For this reason, the following operations were proposed by Yoon in [25] to obtain a closed-form solution for fuzzy regression analysis.

To obtain the solution vector , we introduce the additional operations [25, 28]. Given triangular fuzzy numbers and ,

,

, (41)

which are both triangular fuzzy numbers.

Furthermore, we define the following fuzzy matrix operations with a *triangular fuzzy matrix* *(t.f.m.)*, whose elements are triangular fuzzy numbers. Let and be  *triangular fuzzy matrices (t.f.m.),* a crisp matri and a scalar. Then, the operations are defined as:

, ,

, *.* (42)

Finally, to compute the solution, we define the *t.f.m.* as:

This matrix is denoted as simply, where is a triangular fuzzy number for . Also, a tringular fuzzy vector is defined.

Using these operations and algebraic properties, we obtain solutions of normal equation fuzzy estimators for each by

, (43)

where

for . Note that (43) exists if . The closed-form formula (43) is true solution of FLSE method.

**4.1.2 Estimation by FLAD**

Least absolute deviation (LAD) is a statistical optimality measure and statistical optimization technique based on minimizing an absolute deviation. Unlike the more commonly used LSE, LAD offers a more robust solution in the presence of outliers, which can significantly influence the outcome. LAD does not have a closed-form formula for estimating coefficients due to the non-differentiability of absolute values. Therefore, we can only attain approximate solutions through optimization methods.

Based on the LAD, we propose fuzzy least absolute deviation (FLAD) as another coefficient estimation method, and -metric for fuzzy numbers is defined in this paper as follows:

(44)

where *.*

If we set a fuzzy regression model represented as (24) where *,* , we can get an objective function by applying the -metric above as follows:

(45)

for *,* where is the number of the regression model in this fuzzy analysis.

To minimize (45), we use GA and HS for the optimization, which are mentioned in section 4.2, and we repeatedly update coefficients to the direction of minimizing the objective function (45).

**4.2 Estimation of the Proposed Model with Evolutionary Algorithms**

In this study, two evolutionary algorithms, namely GA and HS, are employed. The flowcharts of each algorithm are visually presented in Fig. 7 [41, 42]. These two methods were used to estimate the coefficients of a fuzzy model, and this process is elaborated in detail in Algorithm 1. As described in Algorithm 1, the objective function corresponding to FLAD or FLSE is set, and evolutionary algorithms are utilized to minimize this function.

**4.2.1 Genetic Algorithm (GA)**

Genetic Algorithm (GA) is a well-known optimization algorithm among meta-heuristic method, which is inspired from natural selection. GA was first proposed by J.H. Holland in 1992 [43]. GA is highly effective because there is no fixed optimization algorithm, which enables the potential for a wide range of diverse outcomes and is applicable to various forms of problems. By exploring various solutions, the likelihood of getting stuck in local optima is low, making it useful for finding global optimum solutions that other optimization algorithms can miss. The implementation of the GA typically starts with a population of chromosomes, often generated randomly. New populations are generated through the repeated application of genetic operators to individual chromosome in the population. The genetic operators are selection, crossover, and mutation. In selection, chromosomes are chosen based on their fitness score for subsequent processing. The fitness score of each chromosome is obtained by fitness function which corresponds to the objective function for the problem. By the iterative application of these genetic operators, optimal solutions with higher fitness can be obtained.

4.2.2 Harmony Search (HS)

Harmony Search (HS) is a meta-heuristic optimization algorithm proposed by Geem in 2001 [44], inspired by the process of finding musical harmony in natural phenomena. HS is applicable to a wide range of optimization problems and is characterized by its exceptional flexibility and rapid convergence. Its simplicity in implementation and ease of parameter tuning makes it highly effective in practical applications.

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(a) Genetic algorithm flowchart

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(b) Harmony search flowchart

Fig. 7. Evolutionary algorithm flowcharts

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Algorithm 1. Application of Evolutionary Algorithms for fuzzy model analysis

Moreover, it offers a natural-inspired approach to exploring creative solutions and has demonstrated strong optimization performance across various application domains. The algorithm of HS begins by creating an initial set of candidate solutions, known as the harmony memory. Each of these candidates is evaluated based on the problem's objective function to determine their fitness. Next, it goes through a series of iterations, including memory consideration, pitch adjustment, and randomization. This iteration process continues until a predefined termination criterion is met. Common termination criteria include reaching a fixed number of iterations, exceeding a specified time limit, or observing convergence in fitness values.

**4.3 Estimation of the Proposed Model with Neural-Network Algorithm**

In recent times, there has been an increasing adoption of models based on neural-network algorithm, which have proven effective in addressing a diverse range of problems. Motivated by this, we aim to contribute to the development of an algorithm that incorporates neural-network in moderation and mediation analyses. We propose Algorithm 2 for conducting FMMA by applying neural-network, and we use gradient descent-based optimization methods to minimize the loss function. As described in Algorithm 2, we separate three elements of the triangular fuzzy number, and estimate regression coefficients for each element. Finally, we compute the average of the coefficients of the three elements, and that average is estimated coefficients for triangular fuzzy data.

We employ the closed-form formula (43), evolutionary algorithms, and neural-network algorithm to the estimation in FLSE. However, when dealing with -metric, closed-form formula and neural-network algorithm are not applicable due to the impossibility of the differentiation. Thus, evolutionary algorithms are only used for the estimation in FLAD.

텍스트, 스크린샷, 폰트, 라인이(가) 표시된 사진

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Algorithm 2. Application of neural-network for fuzzy model analysis

**5 Methodology: Statistical Inference**

In statistical modeling, it is essential not only to achieve low prediction errors but also to ensure that the estimated coefficients and the model as a whole are statistically valid. The fuzzy T-test serves this purpose at the parameter level by verifying whether each fuzzy regression coefficient significantly contributes to explaining the dependent variable, even under conditions of uncertainty. Similarly, the fuzzy F-test evaluates the model at the global level, determining whether the set of predictors collectively improves model fit compared to a null model. Incorporating these tests in fuzzy regression analysis ensures that the proposed model is both predictive and statistically reliable, thereby enhancing its interpretability and robustness in real-world applications. Accordingly, in our study, to verify the statistical validity of the proposed fuzzy regression framework, the fuzzy T-test and fuzzy F-test were formally defined and subsequently performed.

**5.1 Sum of Squares for the Proposed Fuzzy Model Analysis**

In the fuzzy regression model, a fuzzy total sum of squares (FTSS), a fuzzy residual sum of squares (FSSE), and a fuzzy regression sum of squares (FSSR) using -metric are defined [29] as follows:

,

,

. (46)

Unlike the crisp regression model, the formula (47) is not always guaranteed because the fuzzy sum of squares also requires additional consideration of the square of the difference between the left and right spread of the fuzzy number.

. (47)

Fuzzy , which measures how well the object is represented by a regression model, is expressed using FTSS and FSSE.

*Fuzzy* . (48)

**5.2 Proposed Fuzzy F-test**

After regression analysis, the regression model can be evaluated with various indicators, one of which is  introduced above. The other is an F-test that checks the significance of the estimated regression model [36]. First, a fuzzy F-statistic is obtained, and then the null hypothesis is established and verified to determine significance. The hypothesis used to confirm the significance of the model as follows:

The null hypothesis means that since all regression coefficients are zero, the necessity of doing regression analysis is gone. In other words, it means that the estimated model is not significant.

For this test, we obtain a fuzzy F-statistic approximately following the F distribution as follows:

(49)

Then, the p-value is obtained using the calculated fuzzy F-statistic. Finally, comparing this with the significance level, we can determine whether the null hypothesis can be rejected.

**5.3 Proposed Fuzzy T-test**

and the F-test evaluate the estimated overall regression model. We can also conduct a T-test to determine the degree to which a linear relationship exists between each independent variable and dependent variable. Unlike the F-test which evaluates several coefficients at the same time, the T-test has the advantage of being able to evaluate only one regression coefficient. The hypothesis is used to determine the significance of each regression coefficient as follows:

The null hypothesis means that the corresponding regression coefficient is zero. In other words, it means that there is no relationship between the independent variable and the dependent variable.

To do the T-test, the standard error of is obtained, and the T-statistic is obtained. So, we have

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*.* (50)

After calculating the p-value through this statistic, it is compared with the significance level to determine whether to reject the null hypothesis.

Now, we define the standard error of in fuzzy model using FSSE, the fuzzy residual sum of squares, and , the fuzzy operation defined above, and we newly define the fuzzy T-statistic in fuzzy model. The fuzzy T-statistic below roughly follows the t-distribution for the same reason as the fuzzy F-statistic.

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*.* (51)

After that, similarly, the p-value is obtained, and it is possible to check whether the null hypothesis is rejected by comparing it with the significance level.

**6 Data Analysis based on Least Squares Estimation**

In this section, we compare CMMA and FMMA using the estimation method of LSE and FLSE with close-form mathematical formula respectively. Furthermore, we conduct statistical inference following the estimation, a methodology introduced in section 5.

**6.1 Fuzzy Moderated Moderated-Mediation Analysis for SOLAR POWER Data**

This data was originally created by Rami Mashkouk, who combined Daily Power Production of Solar Panels dataset from [45] and dataset of weather status in Antwerp, Belgium from ‘Timeanddate’ website [46]. It contains several weather conditions and solar power data. We used data from January 1, 2016 to November 19, 2019 and about 20 missing values were replaced by cubic spline interpolation. Consequently, we proceeded with the analysis using 1332 data. The variables ‘Temp’ (), ‘Wind’ (), and ‘Humidity’ () represent the daily average of temperature, wind speed, and humidity. ‘Day Power’ () indicates the daily power production obtained by solar panels. ‘Sky Cover’ () literally indicates the sky cover at 3 p.m. in a day when solar energy comes with a peak, and it is classified into eight categories based on sky cover percent by ‘WeatherSTEM’ as follows: ‘Sunny’, ‘Partly sunny’, ‘Passing clouds’, ‘Scattered clouds’, ‘Broken clouds’, ‘fog’, ‘Ice fog or Haze’, ‘Overcast’. These were coded from ‘Sunny’ as 1 to ‘Overcast’ as 8, and the higher the value, the greater the amount of clouds or fog covering the sky. Temperature, wind, and humidity are not fixed but continuous values so loss of information can be occurred if we use crisp data intact. Therefore, we transformed the crisp values of the above three variables into triangular fuzzy numbers with spreads defined as half of the difference between values of two consecutive days. For instance, if the temperature in a certain period is 10(℃) and the next period is 20(℃), the triangular fuzzy number of 10 becomes (5,10,15). In the case of ‘Sky Cover’, the categories are in linguistic expressions and their boundaries are ambiguous. For example, the criteria for classifying ‘Passing clouds’ and ‘Scattered clouds’ varies from an observer. Thus, it is better to express them as fuzzy numbers so we fuzzified them with spread 1. All variables except ‘Sky cover’ are normalized from 0 to 1. The model of this data is shown in Fig. 8.

The terminology CMMA that we defined earlier means an analyses of models with multiple moderators on crisp numbers. Based on CMMA, the regression equations of this model applied above data are estimated as follows:

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We suggest fuzzy multiple moderators analysis (FMMA). In FMMA, the regression coefficients are estimated using fuzzy least squares estimation with each spread mentioned above.

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The estimated coefficients and each p-value both on crisp and fuzzy numbers are shown in Table 1. The noticeable change has shown that the sign of , which estimates the effect of on , was changed to positive. This represents that humidity actually increases if the sky becomes cloudy, but it was misinterpreted in CMMA. In the meantime, the p-value of becomes much smaller from to while other is similar or slightly increases in CMMA and FMMA. These results occurred because using crisp numbers on ambiguous data caused the loss of information.

The conditional indirect effect (CIDE) of on in CMMA and the fuzzy conditional indirect effect (FCIDE) of on in FMMA can be expressed as below:

,

.

They are estimated as ,

, respectively. Shown in Fig. 9, the graph is divided according to the value of ‘Sky Cover’ (mean-1sd, mean, mean+1sd). As Sky Cover get bigger, the amount of change in slope of FMMA is smaller than CMMA. In other words, FCIDE is less sensitive than CIDE in this data.

The validity of the model can be determined by and F-statistic in a F-test. Using these statistical methods, the necessity of transforming ambiguous values to fuzzy numbers can be proven by comparing original methods with fuzzy and fuzzy F-statistic which are proposed in previous section. In this model, firstly, fuzzy is slightly less than . However, this result never means that FMMA is less convincing than CMMA. We should not approach in a quantitative way, but consider that it can be estimated exaggeratingly without considering fuzziness of data. Fuzzy F-statistic was estimated less than F-statistic in CMMA , suggesting that the significance of the model is slightly magnified, but they were both considered significant as a result.

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(a) Conceptual diagram

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(b) Statistical diagram

**Fig. 8.** Fuzzy moderated moderated-mediation model for SOLAR POWER data

**6.2 Fuzzy Multiple Additive Moderation Analysis for CLIMATE CHANGE Data**

Climate change data are introduced in [6]. These data were collected in online surveys from 815 residents of the United States including 417 females and 398 males. Participants of surveys responded to a question asking how often they feel each of three negative emotions (“worried”, “alarmed”, “concerned”) when they think about global warming ( : Negative Emt). The response options of frequency were numerically coded 1 (“not at all”) to 6 (“a great deal”), which means that the higher score, the more often they feel the emotions respectively. The sum of scores of all three emotions were averaged which is a measure of . Participants were also asked five questions about how much he or she supports several policies or actions by the government to alleviate the threat of climate change ( : Government Act). The questions’ responses were measured 1 (“Strongly opposed”) to 7 (“Strongly support), and the average of the questions was used. Prior to the research, each respondent answered his or her sex () and age (). As you can see, the response options in the online surveys are in linguistic forms such as “not at all”, “a great deal”, “Strongly support”, etc. When the linguistic responses are changed into numbers, the loss of information is inevitable. Thus, it is reasonable to analyze ambiguous data like linguistic expressions with fuzzy numbers. The variables and in the data are fuzzified with spread 1. The model of this data is illustrated in Fig. 10.

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**Fig. 9.** Conditional indirect effects of on in CMMA and FMMA

Based on CMMA, the regression equation of this model applied above data is estimated as follows:

.

In FMMA, the regression coefficients are estimated using fuzzy least squares estimation with spread mentioned above.

The estimated coefficients and each p-value both on crisp and fuzzy numbers are shown in Table 2. Shown in table, the absolute value of coefficients slightly decreased except for . In other words, the influence of on has increased. In CMMA, p-value of coefficient of ( is which isnot significant, but in a linear regression model without moderators, the coefficient of is estimated as and is actually significant with very small p-value, which means is an important variable. However, in FMMA, was significant that it involves the fact that is an meaningful variable in the analysis. In other words, FMMA reflects more information of ambiguous data.

Here, the conditional effects of on in this model in CMMA and FMMA are expressed as , . Those in CMMA and FMMA are , , respectively. Fig. 11 shows both conditional effects of on depending on age and sex in CMMA and FMMA. indicates the moderation effect of sex , and indicates the moderation effect of age . Each coefficient is estimated when the other is constant. In Fig. 11, the slopes of lines represent . The slopes of lines of FMMA () are gradual than those of CMMA in both graphs, which means that the conditional effect of FMMA is less sensitive than of CMMA. In case of sex (), when age is constant, the difference in the conditional effect when sex is 0 and 1 () of FMMA, is less than of CMMA, 0.2208, which also means the moderation effect by sex is slightly exaggerated when we use crisp numbers for expressing ambiguous information.

Now we mention and F-test of both crisp and fuzzy models, and compare them to judge the validity of the models. In this model, fuzzy (0.460) in FMMA is significantly higher than (0.368) in CMMA, which implies the regression model explains given data reflecting fuzziness better. Moreover, F-statistic of the model in FMMA (138.78) is much higher than CMMA’s (94.40). But each p-value is very small, so the model is considered significant in both CMMA and FMMA.

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(a) Conceptual diagram

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(b) Statistical diagram

**Fig. 10.** Fuzzy multiple additive moderation model for CLIMATE CHANGE data

**6.3 Fuzzy Moderated-Moderation Analysis for CLIMATE CHANGE Data**

The climate change data is also used to analyze moderated-moderation model. The model for this data is shown in Fig. 12. In this model, the moderation of effect of on by sex depends on age . Both in CMMA and FMMA, estimated regression equations are expressed respectively as follows:

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.

The estimated coefficients and each p-value both in CMMA and FMMA are presented in Table 3. The absolute value of coefficients except for were all gotten a bit smaller. In addition, p-values except for slightly declined, which suggests that the significances of coefficients were a little bit exaggerated with using crisp numbers. Especially, quantifies the moderated-moderation of ’s effect on by and , which is estimated as in CMMA and in FMMA. Although the moderated-moderation effect of FMMA is less significant than CMMA in Table 3, this absolutely does not mean that considering fuzziness is not reasonable. We can say that the effect is estimated in an exaggerated way due to the ignorance of fuzziness.

The conditional effect of on in this model is expressed as , and in CMMA and FMMA respectively. Using estimated coefficients, those effects can be written as follows:

,

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**Fig. 11.** Conditional effect of on in CMMA and FMMA

The conditional effects of on both in CMMA and FMMA are shown in Fig. 13. When sex is , the slopes of lines of CMMA and FMMA are parallel, but it increases more in CMMA than FMMA when sex is . In other words, since the difference in the conditional effects of on by sex is bigger in CMMA than FMMA when age is , for example, and , we can notice that the moderation effect of the conditional effect depending

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(a) Conceptual diagram

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(b) Statistical diagram

**Fig. 12.** Fuzzy moderated-moderation model for CLIMATE CHANGE data

on sex when age increases becomes greater in CMMA than FMMA. This represents that the conditional effects are less sensitive when data is fuzzified.

As in the previous models using the same data, fuzzy (0.462) is also higher than that (0.372) of in CMMA, which highlights the fact that changing ambiguous data to fuzzified values can be more helpful in explaining data with the model. Furthermore, the fuzzy F-statistic of the model in FMMA (98.96) is fairly higher than F-statistic (68.11) in CMMA, but they are both considered significant with p-values near zero.

**6.4 Fuzzy Partial Moderated-Moderation Analysis for Bike Data**

This data is combination of bicycle rental data of Capital bike-share system from 2011 to 2012 [47] and the weather and season data [48], provided by Roberto Frias, totaling 10,948 data. We conducted the analysis of this data to show the usage of mediation and moderation in daily life and to emphasize the importance of using fuzzy numbers in this type of data. All variables of the raw data except ‘Rental cnt’, meaning the number of bicycle rented, were scaled from 0 to 1, so we scaled ‘Rental cnt’ from 0 to 1, too. Moreover, we sorted data in

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**Fig. 13.** Conditional effect of on in CMMA and FMMA

chronological order to transform it into time series data using variables ‘Dteday’ and ‘Hour’. ‘Hour’ () means the time data was collected. ‘Temp’ () means the temperature of the time. ‘Weathersit’ () indicates the conditions of the weather which was measured by Freemeteo [48]. The weather conditions are divided into 4 categories and coded 1 to 4 (1 : ‘Clear’, ‘Few clouds’, etc, 2 : ‘Mist+Cloudy’, etc, 3 : ‘Mist+Broken clouds’, etc, 4 : ’Snow+Fog’, etc). In the case of ‘Temp’ and ‘Humidity’, they are collected as fixed values but actually always changes. Thus, it is more reasonable to express them with numbers fuzzified rather than crisp numbers. We transformed crisp data of above two variables into triangular fuzzy numbers with spread defined as a half of difference between values of two consecutive periods. ‘Weathersit’ variable was expressed as linguistic forms and coded with crisp numbers, so we fuzzified with spread 1. The model of this data is shown in Fig. 14.

In this model, two moderators influence independently, so we can get estimated regression equation both in CMMA and FMMA as follows:

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(a) Conceptual diagram

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(b) Statistical diagram

**Fig. 14.** Fuzzy partial moderated-mediation model for BIKE data

In Table 4, estimated coefficients and their p-values are shown. All of the absolute value of estimated coefficients in FMMA are almost equal or slightly decreased than those of in CMMA. It represents that the influence of the products are actually exaggerated since it ignored the fuzziness data has. Also, some p-values increases slightly but are all significant with very small value.

The conditional indirect effect (CIDE) of X on Y in CMMA and the fuzzy conditional indirect effect (FCIDE) of on in FMMA can be expressed as below:

,

.

The estimation of the conditional effects above are , , respectively. Fig. 15 represents the graph of the conditional indirect effects of changes in ‘Weathersit’ () and ‘Humidity’ (). The gradient of the lines are all same as , the partial moderated-mediation effect of ‘Humidity’ () in each analysis, which are in CMMA and in FMMA. We can notice that partial moderated-mediation effect is estimated in an exaggeratedly way.

Fuzzy is estimated to be slightly lower than that of in CMMA, but it does not mean that FMMA is less effective analysis, as we mentioned in analysis of solar data. Regarding F-test, F-statistic and fuzzy F-statistic () are estimated, and these are considered significant with very small p-values.

|  |  |
| --- | --- |
|  |  |
| (c) | (d) |

Fig. 15. Conditional indirect effects of on in CMMA and FMMA

**Table 1** Estimated coefficients and p-values from moderated moderated-mediation model using SOLAR POWER data

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Method | Estimated coefficients | | | | | | | | |
|  |  |  |  |  |  |  |  |  |  |
| CMMA |  |  |  |  |  |  |  |  |  |
| FMMA |  |  |  |  |  |  |  |  |  |
|  | p-values |  |  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |  |  |  |
| CMMA |  |  |  |  |  |  |  |  |  |
| FMMA |  |  |  |  |  |  |  |  |  |

**Table 2** Estimated coefficients and p-values from multiple additive moderation model using CLIMATE CHANGE data

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Method | Estimated coefficients | | | | |
|  |  |  |  |  |  |
| CMMA |  |  |  |  |  |
| FMMA |  |  |  |  |  |
|  | p-values |  |  |  |  |
|  |  |  |  |  |  |
| CMMA |  |  |  |  |  |
| FMMA |  |  |  |  |  |

**Table 3** Estimated coefficients and p-values from moderated-moderation model using CLIMATE CHANGE data

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Method | Estimated coefficients | | | | | | |
|  |  |  |  |  |  |  |  |
| CMMA |  |  |  |  |  |  |  |
| FMMA |  |  |  |  |  |  |  |
|  | p-values |  |  |  |  |  |  |
|  |  |  |  |  |  |  |  |
| CMMA |  |  |  |  |  |  |  |
| FMMA |  |  |  |  |  |  |  |

**Table 4** Estimated coefficients and p-values from partial moderated-mediation model using BIKE data

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Method | Estimated coefficients | | | | | | |
|  |  |  |  |  |  |  |  |
| CMMA |  |  |  |  |  |  |  |
| FMMA |  |  |  |  |  |  |  |
|  | p-values |  |  |  |  |  |  |
|  |  |  |  |  |  |  |  |
| CMMA |  |  |  |  |  |  |  |
| FMMA |  |  |  |  |  |  |  |

**7 Comparison on Performance among FLSE and FLAD Methods**

In section 6, we estimated regression coefficients and analyzed causal relationships among variables using

closed-form formula (43) in FLSE. As mentioned earlier, we additionally compare the accuracy of the models under FLSE and FLAD methods, depending on or -metric based objective functions using solar power data in section 6.1.

The proposed accuracy measurements, FMSE and FMAE, are defined as follows:

,

. (52)

**7.1 -metric based method (FLSE)**

Using the -metric based function (38) as the objective function, we apply four gradient descent-based optimization methods in neural-network, SGD, Momentum, Adagrad, Adam, and two evolutionary algorithms, GA and HS, to estimate coefficients and calculate the accuracy. Prior to comparing accuracy, we examine the variation of FMSE and FMAE of gradient descent-based optimizations to confirm the convergence of solutions when the number of epochs increases, as illustrated in Fig. 16. In Table 5, the FMSE and FMAE values for the FLSE methods are presented, with the optimization methods based on gradient descent observed at 1000 epochs, when the measurements are top-notch.

Since the objective function is convex, there exists only one global minimum. Thus, the coefficients estimated by the closed-form formula is the true solution, resulting in the lowest FMSE (0.098). Similarly, CS shows superior performance in terms of FMAE (0.437), which is the convergence value. Therefore, using the formula (45), we can achieve better performance without the need for additional computational work. The other optimization methods aim to approximate the regression coefficients of this global minimum. In this data, it is confirmed that HS, Momentum, and Adam converge most closely to the global minimum.

It is worth noting that when performing coefficient estimation using optimization, the solutions can vary due to various factors. Despite the presence of such variability, it is essential to apply multiple optimization algorithms to address diverse problems, including non-linear functions, large-scale optimization problems, and situations where differentiation of the objective function is not possible, as discussed in the following section.

**7.2 -metric based method (FLAD)**

In this section, we utilize -metric based function (45) as the objective function for coefficient estimation and calculate accuracy. FLAD approximates the objective function since it is not differentiable in its original form. Therefore, we employ the evolutionary algorithms, namely GA and HS, as optimization methods for coefficient estimation. As shown in Table 5, we confirm that HS excels over GA in both FMSE and FMAE when minimizing the objective function with -metric applied.

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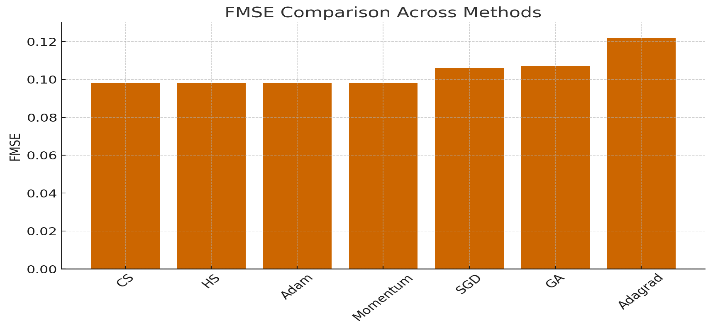
1. FMSE

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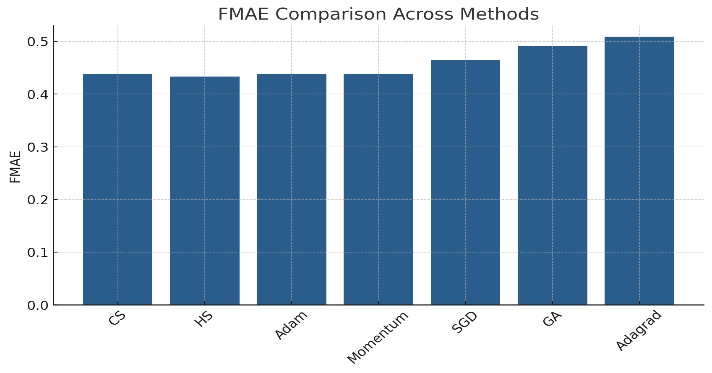
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1. FMAE

**Fig. 16.** Variation of FMSE and FMAE for neural-network algorithm according to epoch



1. FMSE



1. FMAE

**Fig. 17.** Comparisons of FMSE and FMAE for FLSE

Figure 17 visualizes the results of FLSE from Table 5, sorted from the smallest to the largest values. In this paper, the CS (Closed-Form Solution) presented in Equation (43) is mathematically rigorous and represents the exact optimal solution. Therefore, it is clear and self-evident that the CS method produces the best results. Among other optimization algorithms, the HS (Harmony Search) method produced the best results for both FMSE and FMAE for FLSE. GA(Genetic Algorithm) and Adagrad yielded the poorest result with a value of 0.107 and 0.112, respectively. For FMAE, HS again achieved the second-best performance (0.433), following CS, whereas Adagrad recorded the highest error (0.509). For FLAD as well, HS outperformed GA, achieving an FMSE of 0.098 and an FMAE of 0.433.

**Table 5** Measurements of the methods based on -metric (FLSE) and -metric (FLAD)

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Measurements | | FLSE |  |  |  |  |  |  | FLAD | |
| Closed-Form Solution (CS) | Evolutionary Algorithms | | Neural-Network | | | | Evolutionary Algorithms | |
| GA | HS | SGD | Momentum | Adagrad | Adam | GA | HS |
| FMSE |  |  |  |  |  |  |  |  |  |  |
| FMAE |  |  |  |  |  |  |  |  |  |  |

**8 Conclusion**

In this paper, we introduce fuzzy multiple moderators analysis based on FLSE and FLAD. In data analysis, we conducted estimation based on LSE and FLSE using closed-form formula. By employing fuzzy data in various domains, FMMA aims to address the limitations associated with using crisp data in previous research. According to the results of the data analysis, most of the independent variables’ influences were slightly decreased, and the p-value increased. However, some of them showed remarkable changes such as increases in coefficients, shifts in sign or significance. This is because crisp data does not reflect fuzziness and ambiguity of certain phenomena, so it cannot fully represent the relationship between the independent variables and the dependent variable.

In addition, the conditional effects of on by moderators were less sensitive in FMMA than in CMMA, and the moderation effects by moderators were estimated slightly excessively in CMMA.

In terms of fitness of the model, we compared the result of F-test and with fuzzy F-test and fuzzy . A slight

difference in F-statistic between CMMA and FMMA has occurred, but there was no change in significance. In the case of , both results that increased or decreased have appeared. Even though fuzzy is lower than , it does not mean that prediction of the fuzzy model is poor than the crisp model, and this is also a distorted result caused by loss of information.

Furthermore, we employed our evolutionary algorithms and neural-network algorithms to apply fuzzy model analysis. Using these algorithms, we compared the performance of those FLSE and FLAD methods respectively, with FMSE and FMAE. For the result of the comparison, model that used closed-form formula demonstrated superior performance among FLSE methods, and HS exhibited superior performance within FLAD.

For the future work, our neural-network algorithm can be extended to the application of the logic of fuzzy mediation and moderation analyses into the intricate structures of deep neural network (DNN). By doing so, we can develop models that exhibit both strong predictive capabilities and high interpretability, which are fundamental aspects of XAI. Consequently, this contribution can enhance the field of XAI by offering improved model explainability methods using our extended models that incorporate fuzzy analysis.

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사람, 의류, 인간의 얼굴, 넥타이이(가) 표시된 사진

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