

# Mediation and Fuzzy Mediation Analysis for Multiple Covariates and Its Applications to Solar Power Data

Department of Mathematics and Statistics, Sejong University

Department of Digital Content, Sejong University

Yeon Kyung Lee<sup>1</sup>, Jung Eun Lee<sup>1</sup>, Sung Wook Balk<sup>2</sup> and Jin Hee Yoon <sup>1\*</sup>









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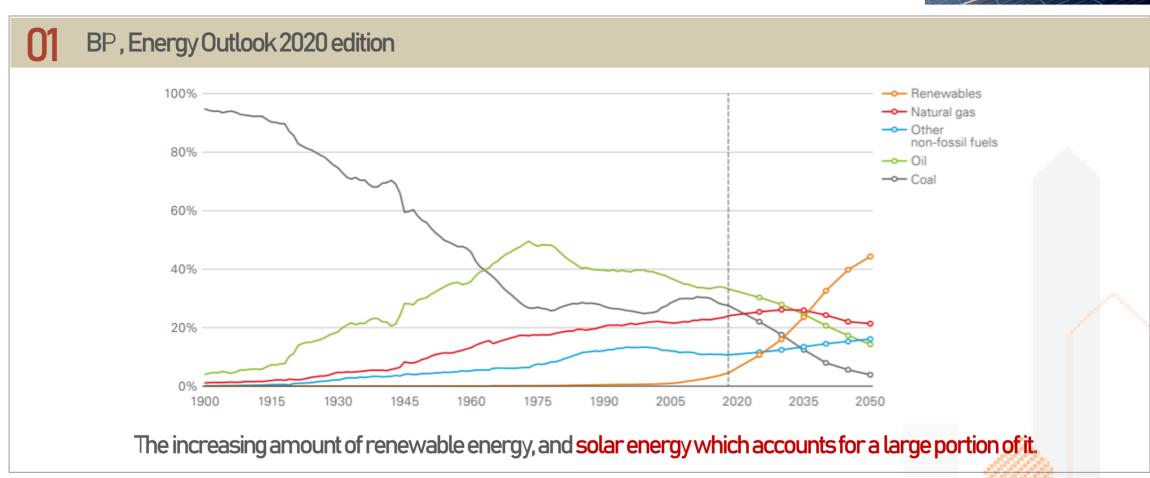
# 1 Introduction



## 01 Introduction

## [Background] The importance of accurately predicting solar energy





## Solar power generation

- Advantages: free development location conditions, safe and long equipment life, infinite energy source
- Disadvantages: fluctuating output depending on the position of the sun, the season, and the weather



Many studies have been conducted on solar power prediction models



## 01 Introduction

#### Prior research and the need for our research

In Solar Prediction models, lack of research to understand the relationships with variables

- Statistic model: ARMA, ARIMA
- Machine learning methods: SVM, ANN, LSTM

Our study will prevent excessive interpretation of the results.



In mediation models,

## lack of model for multiple independent variables or covariates with mediators

various mediation models for multiple mediators, moderators or confounding variables have been proposed. But, unfortunately, a mediation model for multiple independent variable or covariates has not been dealt with.

Observations require fuzzification

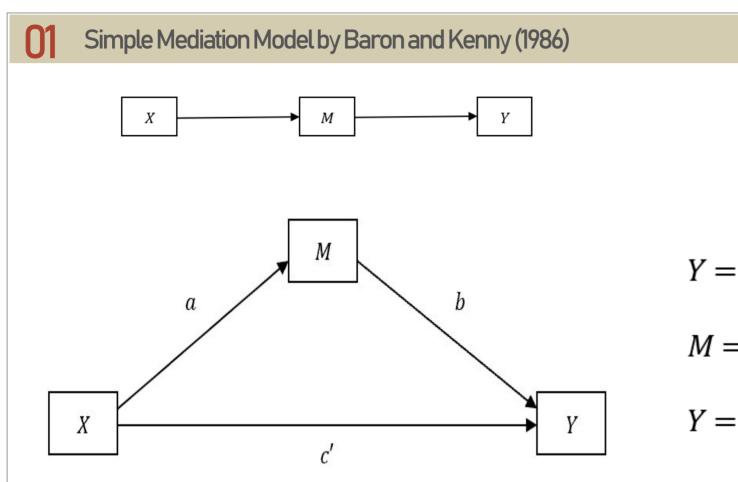
Observations such as actual weather information, solar radiation, and solar energy generation require fuzzification because they are observed with ambiguous values rather than crisp values

# 2 Preliminaries



# **02** Simple Mediation Analysis and Fuzzy Mediation Analysis

## 1. Simple Mediation Analysis



$$Y = \beta_{10} + \beta_{11}X + \varepsilon_1$$

$$M = \beta_{20} + \beta_{21}X + \varepsilon_2$$

$$Y = \beta_{30} + \beta_{31}X + \beta_{32}M + \varepsilon_3$$

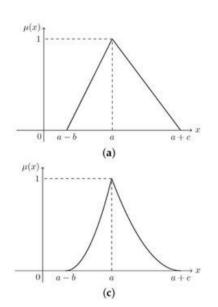
- Total effect:  $\beta_{11}$
- Indirect effect:  $\beta_{21}\beta_{32}$
- Direct effect:  $\beta_{31}$

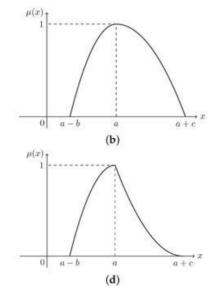
# **02** Simple Mediation Analysis and Fuzzy Mediation Analysis

## 2. Simple Fuzzy Mediation Analysis

## Fuzzy numbers by Zadeh (1965)

## <LR-fuzzy number>





$$\mu_{A}(x) = \begin{cases} L\left(\frac{m-x}{l}\right) & \text{if } x \leq m \\ R\left(\frac{x-m}{l}\right) & \text{if } x > m \end{cases}$$

Generalization of a real number by representing a continuous set of possible values between 0 and 1, not one value

L: left shape function
R: right shape function

m: mode of the fuzzy number

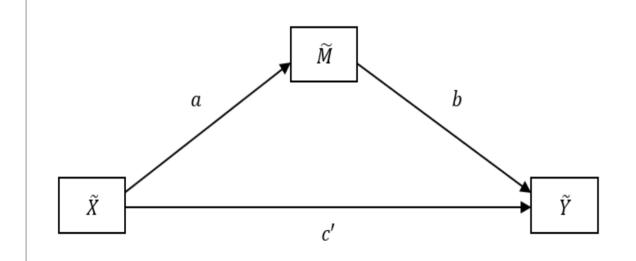
: width of the left

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# **02** Simple Mediation Analysis and Fuzzy Mediation Analysis

## 2. Simple Fuzzy Mediation Analysis





$$\widetilde{Y} = \beta_{10} \oplus \beta_{11} \widetilde{X} \oplus \widetilde{E}_1$$
,

$$\widetilde{M} = \beta_{20} \oplus \beta_{21} \widetilde{X} \oplus \widetilde{E}_2,$$

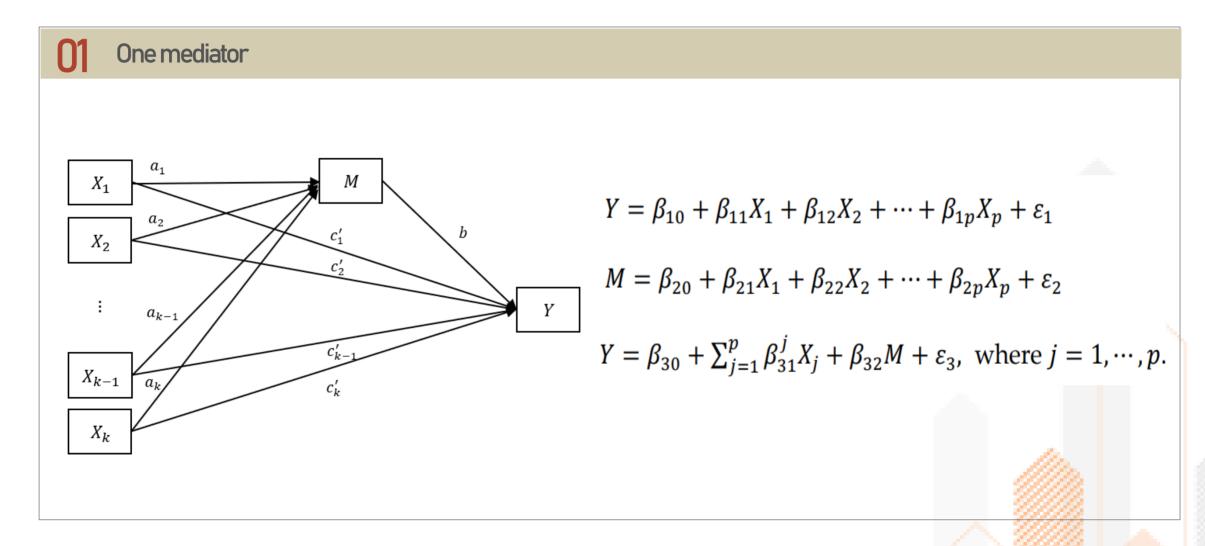
$$\widetilde{Y} = \beta_{30} \oplus \beta_{31} \widetilde{X} \oplus \beta_{32} \widetilde{M} \oplus \widetilde{E}_3$$

- Total effect:  $\beta_{11}$
- Indirect effect:  $\beta_{21}\beta_{32}$
- Direct effect:  $\beta_{31}$

# 3 Our study

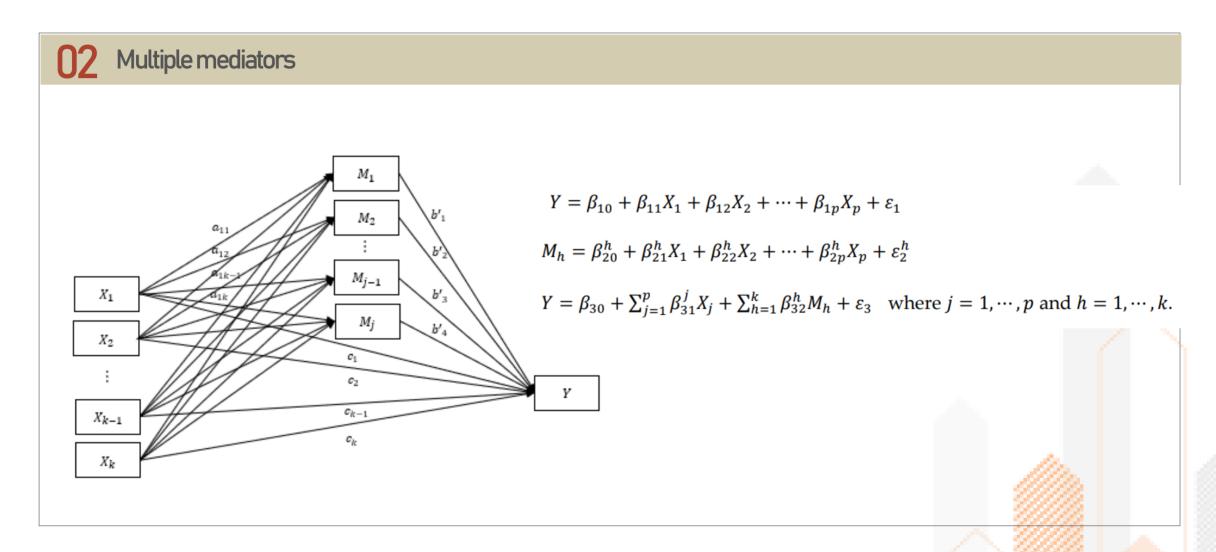


1. Mediation Analysis for Multiple Covariates with one mediator



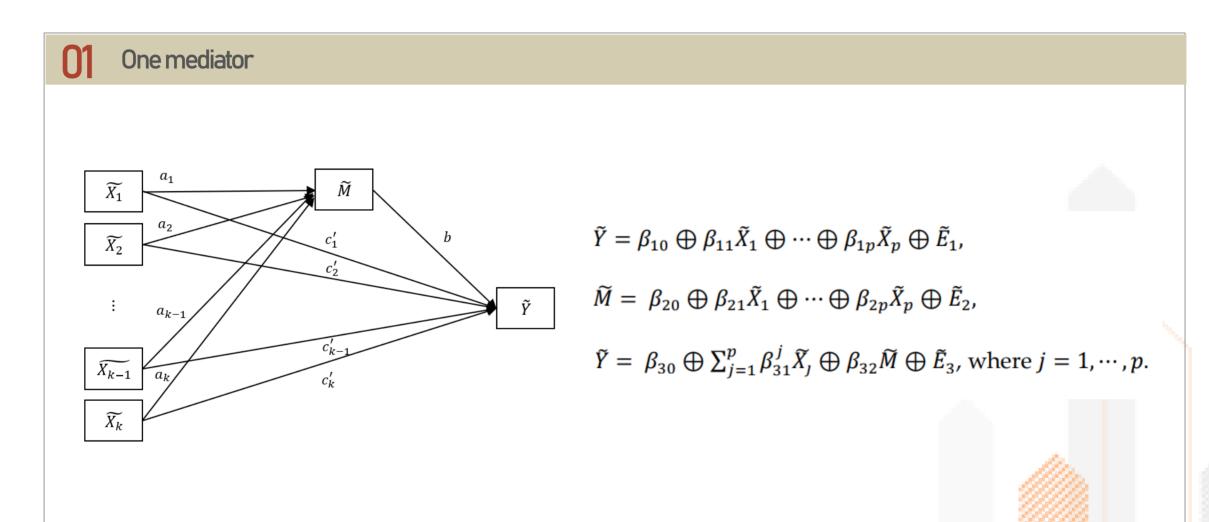
- Total effect :  $\beta_{1j}$
- Indirect effect:  $\beta_{2j}\beta_{32}$
- Direct effect:  $\beta_{31}^{j}$

2. Mediation Analysis for Multiple Covariates with multiple mediators



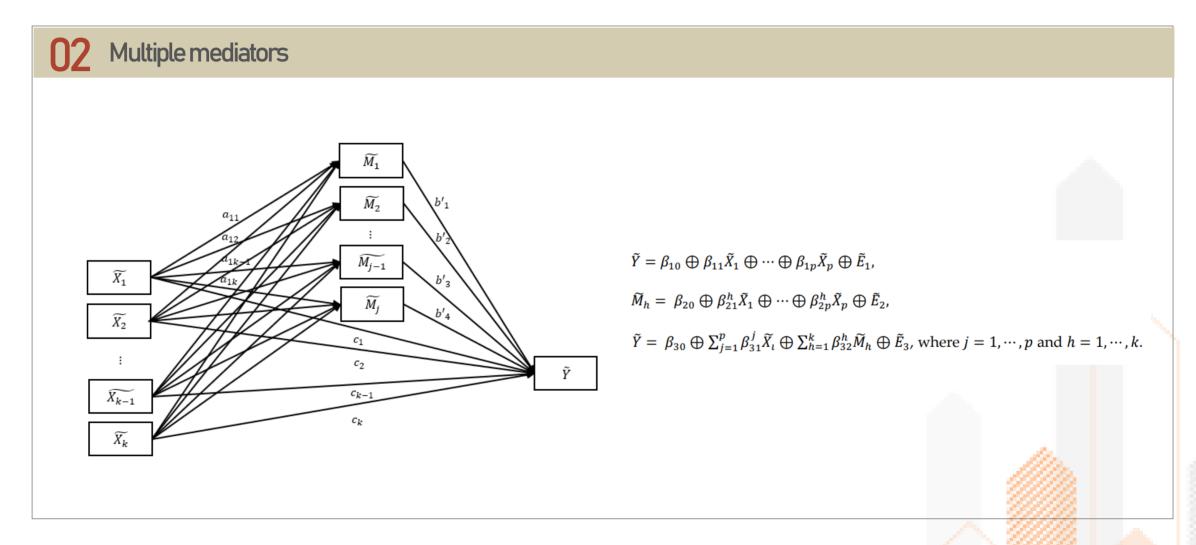
- Total effect :  $\beta_{1j}$
- Indirect effect :  $\beta_{2j}^h \beta_{32}^h$
- Direct effect:  $\beta_{31}^{j}$

## 1. Fuzzy Mediation Analysis for Multiple Covariates with one mediator



- Total effect :  $\beta_{1j}$
- Indirect effect:  $\beta_{2j}\beta_{32}$
- Direct effect:  $\beta_{31}^{j}$

2. Fuzzy Mediation Analysis for Multiple Covariates with multiple mediators



- Total effect :  $\beta_{1j}$
- Indirect effect:  $\beta_{2j}^h \beta_{32}^h$
- Direct effect:  $\beta_{31}^{j}$

3. Estimation for Fuzzy Mediation Analysis for Multiple Covariates with mediators

## 03

$$\widetilde{Y}_i = \beta_0 \oplus \beta_1 \widetilde{X}_{1i} \oplus \beta_2 \widetilde{X}_{2i} \oplus \cdots \oplus \beta_p \widetilde{X}_{pi} \oplus \widetilde{E}_i.$$

The variables are represented by

$$X_{ij} = (l_{x_{ij}}, x_{ij}, r_{x_{ij}})$$
 and  $Y_i = (l_{y_i}, y_i, r_{y_i})$  for  $i = 1, ..., n, j = 1, ..., p$ .

It is assumed that  $\widetilde{E}_i$  are the fuzzy random errors for expressing fuzziness.

The objective function can be obtained based on the LSE, and here the LSE can be expressed as follows

$$d^2(\tilde{Y}_i, \sum_{j=0}^p \beta_{kj} \tilde{X}_{ij}) = \left(l_{y_i} - \sum_{j=0}^p \beta_{kj} l_{x_{ij}}\right)^2 + \left(y_i - \sum_{j=0}^p \beta_{kj} x_{ij}\right)^2 + \left(r_{y_i} - \sum_{j=0}^p \beta_{kj} r_{x_{ij}}\right)^2$$

3. Estimation for Fuzzy Mediation Analysis for Multiple Covariates with mediators

## 03

To find the solution vector, we define a *triangular fuzzy matrix (t.f.m.)* which is expressed by

$$\tilde{X} = \begin{bmatrix} (1,1,1) & (l_{x_{11}}, x_{11}, r_{11}) & \cdots & (l_{x_{1p}}, x_{1p}, r_{1p}) \\ \vdots & \ddots & \vdots \\ (1,1,1) & (l_{x_{n1}}, x_{n1}, r_{n1}) & \cdots & (l_{x_{np}}, x_{np}, r_{np}) \end{bmatrix}$$

$$\widetilde{\mathbf{y}} = \left[ \left( l_{y_1}, y_1, r_{y_1} \right), \cdots, \left( l_{y_n}, y_n, r_{y_n} \right) \right]^t$$

$$\tilde{X} \diamond \tilde{Y} = l_x l_y + xy + r_x r_y$$

$$\widehat{\boldsymbol{\beta}_k} = \left(\widetilde{X}^t \circ \widetilde{X}\right)^{-1} \widetilde{X}^t \circ \widetilde{Y}$$

where

$$\tilde{X}^t \diamond \tilde{X} = \left[\sum_{i=1}^n (l_{x_{il}} l_{x_{ij}} + x_{il} x_{ij} + r_{x_{il}} r_{x_{ij}})\right]_{(p+1) \times (p+1)}$$

$$\tilde{X}^t \diamond \tilde{y} = [\sum_{i=1}^n (l_{x_{il}} l_{y_i} + x_{il} y_i + r_{x_{il}} r_{y_i})]_{(p+1) \times 1}$$
, for  $l = 0, 1, ..., p$ .

# 4) Application to data

### Data

- This data was collected every hour from 1 a.m. on January 1, 2015 to 11 p.m. on December 31, 2017 at a solar energy facility in Dangjin, Korea.
  - 1. Processing missing values => Linear interpolation

$$f(x_k) = f(x_{k-1}) + \frac{f(x_{k+1}) - f(x_{k-1})}{x_{k+1} - x_{k-1}} (x_k - x_{k-1})$$

2 Normalization

$$x_{new} = \frac{x - x_{min}}{x_{max} - x_{min}}$$

#### Data

- This data was collected every hour from 1 a.m. on January 1, 2015 to 11 p.m. on December 31, 2017 at a solar energy facility in Dangjin, Korea.
  - 3. Significant variables (after regression analysis)

	temp	rain	wind speed	humidity	sun hour	solar radiation	snow	cloud
p-value	0.000	0.019	0.000	0.000	0.000	0.000	0.000	0.000

4 fuzzification

For the last data, we use diff before that

Date	Before fuzzification	m,l,r	After fuzzification
2015-01-01-1:00AM	-4.4	M:-4.4, l, r:  -4.6-(-4.4) /2 = 0.1	(-4,5,-4,4,-4,3)
2015-01-01-2:00AM	-4.6	M:-4.6, l, r:  -4.7-(-4.6) /2 = 0.05	(-4.65, -4.6, -4.55)
2015-01-01-3:00AM	-4.7	M:-4.7, l, r:  -5-(-4.7) /2 = 0.15	(-4.85, -4.7, -4.55)

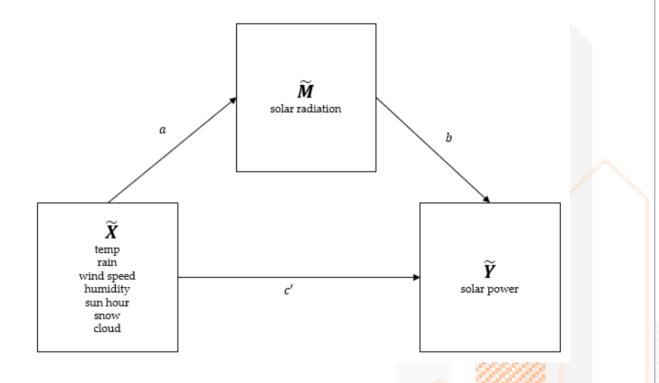
## Research hypothesis

Solar radiation mediates weather conditions with solar power

independent variables: weather data

mediator: radiation

dependent variable: solar power



**02** Fuzzy Mediation Analysis for Multiple Covariates will have more significant result than Mediation.

<sup>-</sup> H. Lee. Use of the Moving Average of the Current Weather Data for the Solar Power Generation Amount Prediction. KMMS. vol. 19, no. 8, pp. 1530-1537 (2016)

- J. Jeong, Y. Tae. Comparison Analysis for Characteristic of Short-Term Power generation Forecasting models for Building Integrated photovoltaics. AIK. vol. 36, no. 2, pp. 665-666 (2016)

<sup>-</sup> K. Lee, W. Kim. Forecasting of 24 hours Ahead Photovoltaic Power Output Using Support Vector Regression. JKIIT. vol. 14, no. 3, pp. 175-183 (2016)

- J. Jeong, Y. Chae. Improvement for Forecasting of Photovoltaic Power Output using Real Time Weather Data based on Machine Learning, KSLES. vol. 25, no. 1, pp. 119-125 (2018)

#### Model

## <Fuzzy Mediation Analysis for Multiple Covariates with one mediator>

$$\widetilde{Y} = \beta_{10} \oplus \beta_{11}\widetilde{X_1} \oplus \beta_{12}\widetilde{X_2} \oplus \beta_{13}\widetilde{X_3} \oplus \beta_{14}\widetilde{X_4} \oplus \beta_{15}\widetilde{X_5} \oplus \beta_{16}\widetilde{X_6} \oplus \beta_{17}\widetilde{X_7} + \varepsilon_1$$

$$\widetilde{M} = \beta_{20} \oplus \beta_{21}\widetilde{X_1} \oplus \beta_{22}\widetilde{X_2} \oplus \beta_{23}\widetilde{X_3} \oplus \beta_{24}\widetilde{X_4} \oplus \beta_{25}\widetilde{X_5} \oplus \beta_{26}\widetilde{X_6} \oplus \beta_{27}\widetilde{X_7} + \varepsilon_2$$

$$\widetilde{Y} = \beta_{30} \oplus \beta_{31}\widetilde{X_1} \oplus \beta_{32}\widetilde{X_2} \oplus \beta_{33}\widetilde{X_3} \oplus \beta_{34}\widetilde{X_4} \oplus \beta_{35}\widetilde{X_5} \oplus \beta_{36}\widetilde{M_6} \oplus \beta_{37}\widetilde{X_7} \oplus \beta_{38}\widetilde{X_8} + \varepsilon_3$$

Total effect = 
$$\sum_{i=1}^{7} \beta_{1i}$$

Direct effect = 
$$\sum_{i=1,i\neq 6}^{8} \beta_{3i}$$

Indirect effect = 
$$\sum_{i=1}^{7} \beta_{2i} \cdot \beta_{36} = \beta_{36} \cdot (\sum_{i=1}^{7} \beta_{2i})$$

#### Parameters estimates

CMA: classic mediation analysis

FMA: fuzzy mediation analysis

#### (a) Parameters estimates between weather conditions and solar power

Method	Parameter estimates								
	$oldsymbol{eta_{10}}{}_{ m const}$	$oldsymbol{eta_{11}}$ temp	$oldsymbol{eta_{12}}$ rain	$oldsymbol{eta_{13}}$ windspeed	$oldsymbol{eta_{14}}$ humidity	$oldsymbol{eta_{15}}$ sun hour	$oldsymbol{eta_{16}}$ snow	$oldsymbol{eta_{17}}$ cloud	
CMA	0.114	0.240	- 0.718	0.153	- 0.291	0.327	0.038	0.064	
FMA	0.112	0.248	- 0.585	0.170	- 0.291	0.316	0.043	0.056	

#### (b) Parameters estimates between weather conditions and solar radiation

Method	Parameter e	estimates						
	$oldsymbol{eta_{20}}{}_{ m const}$	$oldsymbol{eta}_{21}$ temp	$oldsymbol{eta_{22}}$ rain	$oldsymbol{eta_{23}}$ windspeed	$oldsymbol{eta_{24}}$ humidity	$oldsymbol{eta_{25}}$ sun hour	$oldsymbol{eta_{26}}$ snow	$oldsymbol{eta_{27}}$ cloud
CMA	0.107	0.201	-0.601	0.113	-0.255	0.360	0.063	0.054
FMA	0.104	0.208	- 0.487	0.130	- 0.254	0.350	0.067	0.047

#### (c) Parameters estimates between weather conditions + solar radiation and solar power

Method	Parameter e	stimates								33
	β <sub>30</sub> const	$oldsymbol{eta_{31}}$ temp	β <sub>32</sub> rain	$oldsymbol{eta}_{33}$ windspeed	$oldsymbol{eta_{34}}$ humidity	$oldsymbol{eta_{35}}$ sun hour	$oldsymbol{eta}_{36}$ solar radiation	$oldsymbol{eta_{37}}{ ext{snow}}$	β <sub>38</sub> cloud	
CMA	0.005	0.033	- 0.101	0.037	- 0.029	- 0.042	1.027	- 0.027	0.009	7/
FMA	0.006	0.035	- 0.088	0.038	- 0.031	- 0.041	1.027	- 0.026	0.008	7/
										_

### Effects of the solar radiation

Method	Effect		
	Total effect	Direct effect	Indirect effect
CMA	-0.187	-0.120	$-0.067^a$
FMA	-0.043	-0.105	$0.062^{b}$

$$a(-0.065)(1.027) = -0.067$$
  
 $b(0.061)(1.027) = 0.062$ 

FMA considers the spread of data rather than CMA using summarized data

FMA effect will be more reliable than CMA.

## 06 Conclusions

## 01 Need for our research

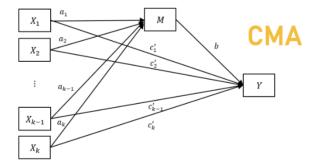
In Solar Prediction models, lack of research to understand the relationships with variables

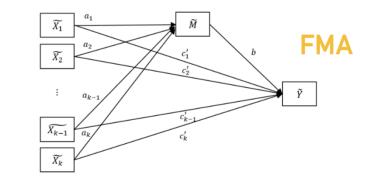
## 02 Research hypothesis

1. Solar radiation will mediate weather conditions and solar power.

2. Fuzzing the data will have more meaningful results than using crisp data

## 03 Model





04	4	Re	sul
			-

Method	Effect			
	Total effect	Direct effect	Indirect effect	
CMA	-0.187	-0.120	$-0.067^a$	7
FMA	-0.043	-0.105	$0.062^{b}$	

FMA effect will be more reliable than CMA.

05 Follow-up study

- Statistical Inferences about direct effect and indirect effect
- This theory is to be extended to other various mediation, moderation, mediation-moderation analysis

