Theory and Application of the Composed Fuzzy Measure of L-Measure and Delta-Measures

Hsiang-Chuan Liu, Chin-Chun Chen, Der-Bang Wu, and Tian-Wei Sheu

Abstract—The well known fuzzy measures, λ -measure and P-measure, have only one formulaic solution. Two multivalent fuzzy measures with infinitely many solutions were proposed by our previous works, called L-measure and δ -measure, but the former do not include the additive measure as the latter and the latter has not so many measure solutions as the former. Due to the above drawbacks, in this paper, an improved fuzzy measure composed of above both, denoted L_{δ} -measure, is proposed. For evaluating the Choquet integral regression models with our proposed fuzzy measure and other different ones, a real data experiment by using a 5-fold cross-validation mean square error (MSE) is conducted. The performances of Choquet integral regression models with fuzzy measure based L_{δ} -measure, L-measure, δ -measure, λ -measure, and P-measure, respectively, a ridge regression model, and a multiple linear regression model are compared. Experimental result shows that the Choquet integral regression models with respect to extensional L-measure based on γ -support outperforms others forecasting models.

Keywords—Lambda-measure, P-measure, Delta-measure, Gamma-support, composed fuzzy measure, Choquet integral regression model.

I. INTRODUCTION

W hen there are interactions among independent variables, traditional multiple linear regression models do not perform well enough. The traditional improved methods exploited ridge regression models [1]. In this paper, we suggest using the Choquet integral regression models [7-15] based on some single or compounded fuzzy measures [2-5, 7-15] to improve this situation. The well-known fuzzy measures, λ -measure [2-4] and P-measure [5] have only one formulaic

Manuscript received May 20, 2009: Revised version received June 28, 2009. This work was supported in part by the National Science Council grant of Taiwan Government (NSC 97-2410-H-468-014).

H. C. Liu, is with the Department of Bioinformatics, Asia University, Taichung, 41345, Taiwan (e-mail: lhc@asia.edu.tw).

C. C. Chen, is with National Taichung University, Taichung, 40306, Taiwan. He is now with Department of General Education, Min-Hwei College, Tainan 736, Taiwan. (e-mail: ccchen@mail.mhchcm.edu.tw).

D. B. Wu, is with National Taichung University, Taichung, 40306, Taiwan. He is now with the Graduate Institute of Educational Measurement and Department of Mathematics Education, National Taichung University, Taichung, 40306 Taiwan. (phone: 886-93673-1088; fax: 886-42218-3500; e-mail:wudb@hotmail.com).

T. W. Sheu, is with National Taichung University, Taichung, Taiwan 40306. He is now with the Graduate Institute of Educational Measurement, National Taichung University, Taichung, 40306 Taiwan. (e-mail: sheu@mail.ntcu.ed u.tw).

solution of fuzzy measure, the former is not a closed form, and the latter is not sensitive enough. Two multivalent fuzzy measures with infinitely many solutions were proposed by our previous works, called L-measure [7-9] and δ -measure [10,11], but L-measure do not include the additive measure and δ -measure has not so many measure solutions as L-measure. Due to the above drawbacks, in this paper, an improved fuzzy measure composed of above two multivalent fuzzy measures, denoted L_{δ} -measure, is proposed. This improved multivalent fuzzy measure is not only including the additive measure, but also having the same infinitely many measure solutions as L-measure. For evaluating the Choquet integral regression models with our proposed fuzzy measure and other different ones, a real data experiment by using a 5-fold cross-validation mean square error (MSE) is conducted. The performances of Choquet integral regression models with fuzzy measure based L_{δ} -measure, L-measure, δ -measure, λ -measure, and P-measure, respectively, a ridge regression model, and a multiple linear regression model are compared.

This paper is organized as follows: The multiple linear regression and ridge regression [1] are introduced in section II; two well known fuzzy measure, λ -measure [2] and P-measure [5], are introduced in section III; our new measure, δ -measure, is introduced in section IV; the fuzzy support, γ -support [7] is described in section V; the Choquet integral regression model [6-8] based on fuzzy measures are described in section VI; experiment and result are described in section VII; and final section is for conclusions and future works.

II. THE MULTIPLE LINEAR REGRESSION, RIDGE REGRESSION

Let $\underline{Y} = X \underline{\beta} + \underline{\varepsilon}$, $\underline{\varepsilon} \sim N(\underline{0}, \sigma^2 I_n)$ be a multiple linear

model, $\hat{\beta} = (XX)^{-1} XY$ be the estimated regression

coefficient vector, and $\underline{\hat{\beta}}_{k} = (X'X + kI_n)^{-1} X'Y$ be the estimated ridge regression coefficient vector, Hoerl, Kenard and Baldwin [1] suggested

$$\hat{k} = \frac{n\hat{\sigma}^2}{\underline{\hat{\beta}'}\underline{\hat{\beta}}} \tag{1}$$

III. FUZZY MEASURES

The two well known fuzzy measures, the λ -measure proposed by Sugeno in 1974, and P-measure proposed by Zadah in 1978,

are concisely introduced as follows.

A. Axioms of Fuzzy Measures

Definition 1 fuzzy measure [2-4] A fuzzy measure μ on a finite set X is a set function $\mu: 2^{X} \rightarrow [0,1]$ satisfying the following axioms:

1)
$$\mu(\phi) = 0, \mu(X) = 1$$
 (boundary conditions) (2)

2)
$$A \subseteq B \Longrightarrow \mu(A) \le \mu(B)$$
 (monotonicity) (3)

B. Singleton Measures

Definition 2 singleton measure [2-7]

A singleton measure of a fuzzy measure μ on a finite set X is a function $s: X \rightarrow [0,1]$ satisfying:

$$s(x) = \mu(\lbrace x \rbrace), x \in X$$
(4)

s(x) is called the fuzzy density of singleton x.

C. λ -measure

Definition 3 λ -measure [3]

For a given singleton measures s, λ -measure, g_{λ} , is a fuzzy measure on a finite set X, satisfying:

$$A, B \in 2^{X}, A \cap B = \phi, A \cup B \neq X$$

$$\Rightarrow g_{\lambda} (A \cup B)$$

$$= g_{\lambda} (A) + g_{\lambda} (B) + \lambda g_{\lambda} (A) g_{\lambda} (B)$$
(5)

$$\prod_{i=1}^{n} \left[1 + \lambda s(x_i) \right] = \lambda + 1 > 0, \ s(x_i) = g_{\lambda}(\{x_i\})$$
(6)

Where the real number, λ , is also called the determine coefficient of λ -measure.

Note that once the singleton measure is known, we can obtain the values of λ uniquely by using the previous polynomial equation. In other words, λ -measure has a unique solution without closed form. Moreover, for given singleton measures s,

If
$$\sum_{x \in X} s(x) = 1$$
 then $g_{\lambda}(A) = \sum_{x \in A} s(x)$, in other word,
if $\sum_{x \in X} s(x) = 1$ then λ -measure is just the additive measure

D. P-measure

Definition 4 P-measure [5]

For given a singleton measures s, P-measure, g_P , is a fuzzy measure on a finite set X, satisfying:

Note that for any subset of X, A, P-measure considers only the maximum value and will lead to insensitivity.

E. L-measure

Definition 5 L-measure [7-9]

For given a singleton measure s(x), L-measure, g_L , is a fuzzy

measure on a finite set X, |X| = n, satisfying: 1) $L \in [0, \infty)$

2)
$$\forall A \subset X, n - |A| + (|A| - 1)L > 0 \Rightarrow$$

$$g_L(A) = \max_{x \in A} \left[s(x) \right] + \frac{(|A| - 1)L \sum_{x \in A} s(x) \left[1 - \max_{x \in A} \left[s(x) \right] \right]}{\left[n - |A| + (|A| - 1)L \right] \sum_{x \in X} s(x)}$$
(9)

(8)

Where the real number, L, is also called the determine coefficient of L-measure.

Theorem 1 [7-9]

(i) for each $L \in [0, \infty)$, L-measure is a fuzzy measure, in other words, L-measure has infinitely many solutions of fuzzy measures, for each $L \in [0, \infty)$.

(ii) $L \in [0, \infty)$, L-measure is an increasing function on real number L.

(iii) if L = 0 then L-measure is just the P-measure

F. δ -measure

Definition 6 δ-measure [10,11]

For given singleton measure s(x), a δ -measure, g_{δ} , is a fuzzy measure on a finite set X, |X| = n, satisfying:

1)
$$\delta \in [-1,1], \sum_{x \in X} s(x) = 1$$
 (10)

2)
$$g_{\delta}(\phi) = 0, g_{\delta}(X) = 1$$
 (11)
3) $\forall A \subset X, A \neq X \Rightarrow$

$$g_{\delta}(A) = \left[1 + \delta \max_{x \in A} s(x)\right] \frac{(1+\delta) \sum_{x \in A} s(x)}{1 + \delta \sum_{x \in A} s(x)} - \delta \max_{x \in A} s(x)$$
(12)

Where the real number, δ , is also called the determine coefficient of δ -measure.

Theorem 2 [11]

(i) $\delta \in [-1,1]$, δ -measure is an increasing function on δ

(ii) if $\delta = -1$, then δ -measure is just the P-measure

- (iii) if $\delta = 0$, then δ -measure is just the additive measure
- (iv) if $-1 < \delta < 0$, then δ -measure is a sub-additive measure
- (v) if $0 < \delta < 1$, then δ -measure is a supper-additive measure.

- (vi) If $\sum_{x} s(x) = 1$ and $\delta = 0$ then δ -measure is just the λ -measure
- (vii) P -measure, additive measure and λ -measure are the special cases of δ -measure

IV. COMPARISON BETWEEN TWO FUZZY MEASURES

Definition 7 μ_1 – measure $\leq \mu_2$ – measure,

 μ_2 -measure $\geq \mu_1$ -measure [8,9]

For any given fuzzy density function, s(x), on a finite set, X, If μ_1 and μ_2 are two fuzzy measures, satisfying

 $g_{\mu}(A) \leq g_{\mu}(A), \forall A \subset X$, then we say that μ_1 -measure is not larger than μ_2 -measure, or μ_2 -measure is not smaller

than μ_1 -measure, denoted as μ_1 -measure $\leq \mu_2$ -masure, or

 μ_2 -measure $\geq \mu_1$ -measure

Theorem 3 [8,9]

For any given fuzzy density function, s(x), on a finite set, X, P-measure is not larger than any other fuzzy measure, μ , that is $P-measure \leq \mu-measure$

V. COMPOSED MEASURE OF L- METHOD AND-**DELTA-MEASURES**

A. Definition of Generalized L-measure

Definition 8 Generalized L-measure

For given singleton measure s(x), a generalized L-measure based on a fuzzy measure, μ , L_{μ} , is a fuzzy measure on a finite set X, |X| = n, satisfying:

1)
$$L \in [0, \infty)$$
 (13)
2) $\forall A \subset X, n - |A| + (|A| - 1)L > 0 \Rightarrow$
 $g_{L_{\mu}}(A) = \max_{x \in A} [s(x)] + \frac{[(|A| - 1)L]\mu(A)[1 - \max_{x \in A} [s(x)]]}{[n - |A| + (|A| - 1)L]\mu(X)}$

Where the real number, L, is also called the determine coefficient of L_{μ} -measure.

Theorem 4

(i) For each $L \in [0, \infty)$, L_{μ} -measure is a fuzzy measure, In other words, L_{μ} -measure has infinite many fuzzy measures with determine coefficient L, $L \in [0, \infty)$.

(ii) $L \in [0, \infty)$ L_u -measure is an increasing function on L,

(iii) if L = 0 then L_{μ} -measure is just the μ -measure (iv) if μ -measure is the P-measure then L_{μ} -measure is just the L-measure

(v) for each $L \in [0, \infty)$,

P-measure \leq L-measure \leq L_{μ} -measure

Proof. (i) the boundary conditions are trivial, Now to prove the monotonicity.

Let
$$\forall A, B \in 2^{X}, A \subset B$$
 to prove $g_{L_{\mu}}(A) \le g_{L_{\mu}}(B)$ (15)

$$\lim_{x \in A} \max_{x \in A} [s(x)] = \max_{x \in B} [s(x)],$$

since $\frac{(|B|-1)L\mu(B)}{[n-|B|+(|B|-1)L]} \ge \frac{(|A|-1)L\mu(A)}{[n-|A|+(|A|-1)L]}$ (16)

We can obtain $g_{L_u}(B) \ge g_{L_u}(A)$

If
$$\max_{x \in B} \left[s(x) \right] = \max_{x \in A} \left[s(x) \right] + a, a > 0$$
(17)

$$g_{L_{\mu}}(B) - g_{L_{\mu}}(A) = a \left[1 - \frac{(|B| - 1)L\mu(B) \left[1 - \max_{x \in A} \left[s(x) \right] \right]}{\left[n - |B| + (|B| - 1)L \right] \mu(X)} \right] + \left[\frac{(|B| - 1)L\mu(B)}{\left[n - |B| + (|B| - 1)L \right]} - \frac{(|A| - 1)L\mu(A)}{\left[n - |A| + (|A| - 1)L \right]} \right] \frac{\left[1 - \max_{x \in A} \left[s(x) \right] \right]}{\mu(X)}$$
(18)

Since
$$1 - \frac{\left(|B|-1\right)L\mu(B)\left[1-\max_{x\in A}\left[s\left(x\right)\right]\right]}{\left[n-|B|+\left(|B|-1\right)L\right]\mu(X)} \ge 0$$
(19)

$$\frac{\left\lfloor 1 - \max_{x \in A} \left\lfloor s(x) \right\rfloor \right\rfloor}{\mu(X)} \ge 0$$
(20)

and

We can also obtain that $g_{L_{\mu}}(B) \ge g_{L_{\mu}}(A)$, therefore

 L_{μ} -measure is a fuzzy measure.

(ii)

(14)

$$f(L) = g_{L_{\mu}}(A) = \max_{x \in A} \left[s(x) \right] + \frac{\left[(|A| - 1)L \right] \mu(A) \left[1 - \max_{x \in A} \left[s(x) \right] \right]}{\left[n - |A| + (|A| - 1)L \right] \mu(X)}$$

$$\Rightarrow f'(L) = \frac{(|A| - 1)\mu(A) \left[1 - \max_{x \in A} \left[s(x) \right] \right] \left[n - |A| \right]}{\mu(X) \left[n - |Al| + (|A| - 1)L \right]^2} \ge 0$$
(21)

Hence L_{μ} -measure is an increasing function on L. (iii), (iv) and (v) are trivial.

B. Definition of L_{δ} -measure

Definition 9 L_{δ} -measure

For given singleton measure s(x), the composed measure of L-measure and $\delta\text{-measure}$, denoted L_{δ} -measure, $g_{L_{\delta}}$, is a fuzzy measure on a finite set X, |X| = n, satisfying:

1)
$$L \in [-1, \infty), \sum_{x \in X} s(x) = 1$$
 (22)

2)
$$g_{L_{\delta}}(\phi) = 0, g_{L_{\delta}}(X) = 1$$
 (23)

3)
$$\forall A \subset X \Rightarrow$$

$$g_{L_{s}}(A) = \begin{cases} \max_{x \in A} s(x) & \text{if } L = -1 \\ \frac{(1+L)\sum_{x \in A} s(x) \left[1+L\max_{x \in A} s(x)\right]}{1+L\sum_{x \in A} s(x)} - L\max_{x \in A} s(x) & \text{if } L \in (-1,0] \\ \frac{L(|A|-1)\sum_{x \in A} s(x) \left[1-\sum_{x \in A} s(x)\right]}{\left[n-|A|+L(|A|-1)\right]\sum_{x \in X} s(x)} + \sum_{x \in A} s(x) & \text{if } L \in (0,\infty) \end{cases}$$
(24)

C. Important Properties of L_{δ} -measure

Theorem 5 Important Properties of L_{δ} -measure

(i) L∈ [-1,∞), L_δ-measure is a fuzzy measure family
(ii) L∈ [-1,∞), L_δ-measure is an increasing function on L
(iii) if L = -1 then L_δ-measure is just the P-measure
(iv) if L = 0 then L_δ-measure is just the additive measure
(v) if -1 < L < 0 then L_δ-measure is a sub-additive measure
(vi) if 0 < L < ∞ then L_δ-measure is a supper-additive measure

(vii) If $\sum_{x \in X} s(x) = 1$ and L = 0 then L_{δ} -measure is just the

 λ -measure

(viii) P -measure, additive measure and λ -measure are the special cases of L_{δ} -measure

Proof.

(i) if $L \in [-1,0)$, then L_{δ} -measure is a special case of δ -measure, since δ -measure is a fuzzy measure, then L_{δ} -measure is also a fuzzy measure.

if $L \in [0, \infty)$, then L_{δ} -measure is a special case of generalized L-measure based on the additive measure, since any generalized L-measure is also a fuzzy measure, then L_{δ} -measure is also a fuzzy measure.

Therefore, for each $L \in [-1, \infty)$, L_{δ} -measure is a fuzzy measure.

(ii) if $L \in [-1,0)$, then L_{δ} -measure is a special case of δ -measure, since δ -measure is an increasing function with upper bound, additive measure, then L_{δ} -measure is also an increasing function with upper bound, additive measure.

if $L \in [0, \infty)$, then L_{δ} -measure is a special case of generalized L-measure based on the additive measure, since generalized L-measure based on the additive measure is also an increasing function with lower bound, additive measure, then L_{δ} -measure is also an increasing function with lower bound, additive measure bound, additive measure.

Therefore, for each $L \in [-1,\infty)$, L_{δ} -measure is also an increasing function on L' (iii), (iv), (v), (vi), (vii) and (viii) are trivial.

VI. Γ- SUPPORT

Definition 10: γ -support [7]

For given singleton measure s of a fuzzy measure μ on a finite set X, if $\sum_{x \in X} s(x) = 1$, then s is called a fuzzy support measure of μ , or a fuzzy support of μ , or a support of μ . One of fuzzy supports is introduced as below. Let μ be a fuzzy measure on a finite set $X = \{x_1, x_2, ..., x_n\}, y_i$ be global response of subject *i* and $f_i(x_j)$ be the evaluation

of subject *i* for singleton x_i , satisfying:

$$0 < f_i(x_j) < 1, i = 1, 2, ..., N, j = 1, 2, ..., n$$
(25)

$$\gamma(x_{j}) = \frac{1 + r(f(x_{j}))}{\sum_{k=1}^{n} [1 + r(f(x_{k}))]}, \quad j = 1, 2, ..., n$$
(26)

where
$$r(f(x_j)) = \frac{S_{y,x_j}}{S_y S_{x_j}}$$
 (27)

$$S_{y}^{2} = \frac{1}{N} \sum_{i=1}^{n} \left(y_{i} - \frac{1}{N} \sum_{i=1}^{N} y_{i} \right)^{2}$$
(28)

$$S_{x_j}^2 = \frac{1}{N} \sum_{i=1}^{n} \left[f_i(x_j) - \frac{1}{N} \sum_{i=1}^{N} f_i(x_j) \right]^2$$
(29)

$$S_{y,x_{j}} = \frac{1}{N} \sum_{i=1}^{N} \left(y_{i} - \frac{1}{N} \sum_{i=1}^{N} y_{i} \right) \left[f_{i}(x_{j}) - \frac{1}{N} \sum_{i=1}^{N} f_{i}(x_{j}) \right]$$
(30)

satisfying
$$0 \le \gamma(x_j) \le 1$$
 and $\sum_{j=1}^{n} \gamma(x_j) = 1$ (31)

then the function $\gamma: X \to [0,1]$ satisfying $\mu(\{x\}) = \gamma(x)$, $\forall x \in X$ is a fuzzy support of μ , called γ -support of μ .

VII. CHOQUET INTEGRAL REGRESSION MODELS

A. Choquet Integral

Definition 11 Choquet Integral [2-6]

Let μ be a fuzzy measure on a finite set X. The Choquet integral of $f_i: X \to R_+$ with respect to μ for individual *i* is denoted by

$$\int_{C} f_{i} d\mu = \sum_{j=1}^{n} \left[f_{i} \left(x_{(j)} \right) - f_{i} \left(x_{(j-1)} \right) \right] \mu \left(A_{(j)}^{i} \right) , i = 1, 2, ..., N$$
(32)

where $f_i(x_{(0)}) = 0$, $f_i(x_{(j)})$ indicates that the indices have been permuted so that

$$0 \le f_i\left(x_{(1)}\right) \le f_i\left(x_{(2)}\right) \le \dots \le f_i\left(x_{(n)}\right) \tag{33}$$

$$A_{(j)} = \left\{ x_{(j)}, x_{(j+1)}, \dots, x_{(n)} \right\}$$
(34)

B. Choquet Integral Regression Models

Definition 12 Choquet Integral Regression Models [7-15] Let $y_1, y_2, ..., y_N$ be global evaluations of N objects and $f_1(x_j), f_2(x_j), ..., f_N(x_j), j = 1, 2, ..., n$, be their evaluations of x_j , where $f_i: X \to R_+$, i = 1, 2, ..., N.

Let μ be a fuzzy measure, $\alpha, \beta \in R$,

$$y_i = \alpha + \beta \int_C f_i dg_\mu + e_i , e_i \sim N(0, \sigma^2) , i = 1, 2, ..., N$$
 (35)

$$\left(\hat{\alpha},\hat{\beta}\right) = \arg\min_{\alpha,\beta} \left[\sum_{i=1}^{N} \left(y_i - \alpha - \beta \int_C f_i dg_\mu \right)^2 \right] \quad (36)$$

then $\hat{y}_i = \hat{\alpha} + \hat{\beta} \int f_i dg_{\mu}$, i = 1, 2, ..., N is called the

Choquet integral regression equation of μ , where

$$\beta = S_{yf} / S_{ff} \tag{37}$$

$$\hat{\alpha} = \frac{1}{N} \sum_{i=1}^{N} y_i - \hat{\beta} \frac{1}{N} \sum_{i=1}^{N} \int f_i dg_\mu$$
(38)

$$S_{yf} = \frac{\sum_{i=1}^{N} \left[y_i - \frac{1}{N} \sum_{i=1}^{N} y_i \right] \left[\int f_i dg_{\mu^*} - \frac{1}{N} \sum_{k=1}^{N} \int f_k dg_{\mu^*} \right]}{N - 1}$$
(39)

$$S_{ff} = \frac{\sum_{i=1}^{N} \left[\int f_i dg_{\mu^*} - \frac{1}{N} \sum_{k=1}^{N} \int f_k dg_{\mu^*} \right]^2}{N - 1}$$
(40)

VIII. EXPERIMENT AND RESULT

A. Education Data

The total scores of 60 students from a junior high school in Taiwan are used for this research [9-13]. The examinations of four courses, physics and chemistry, biology, geoscience and mathematics, are used as independent variables, the score of the Basic Competence Test of junior high school is used as a dependent variable.

The data of all variables listed in Table III is applied to evaluate the performances of five Choquet integral regression models with P-measure, λ -measure and δ -measure, L-measure measure and L_{δ} -measure based on γ -support respectively, a ridge regression model, and a multiple linear regression model by using 5-fold cross validation method to compute the mean square error (MSE) of the dependent variable. The formula of MSE is

$$MSE = \frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2$$
(41)

The singleton measures, γ -support of the P-measure, λ -measure, δ -measure, L-measure and L_{δ} -measure are listed as follows which can be obtained by using the formula (26).

 $\{0.2488, 0.2525, 0.2439, 0.2547\}$ (42)

For any fuzzy measure, μ -measures, once the fuzzy support of the μ -measure is given, all event measures of μ can be found, and then, the Choquet integral based on μ and the Choquet integral regression equation based on μ can also be found by using above corresponding formulae.

The experimental results of seven forecasting models are listed in Table I. We find that the Choquet integral regression model with L_{δ} -measure based on γ -support outperforms other forecasting regression models.

TABLE I MSE OF REGRESSION MODELS

Regressior	5-fold CV			
	measure	MSE		
Choquet	L_{δ}	47.5722		
Integral	L	48.4610		
Regression	δ	48.7672		
model	λ	49.1832		
	р	53.9582		
Ridge reg	59.1329			
Multiple regress	65.0664			

B. Fat Data

In this study, anthropometric dimensions were measured following a standard protocol [11, 16]. High was measured to the nearest 0.1 cm using anthropometers. Body weight was measured to the nearest 0.1 kg at the same time the bioelectric impedance was measured using a body fat analyzer (TBF310; Tanita, Tokyo, Japan) to estimate the percentage of body fat (% fat). Skinfold thicknesses at biceps, triceps, subscapular, and suprailiac of the right side of body were measured with GMP skinfold calipers (Siber Hegener and Co. Ltd, Switzerland). The measurements were performed by one experienced operator that took two repeated measurements at the test site of the same subject. The mean of the two readings from each site was used to calculate body composition. A real data set with 128 samples from a elementary school in Taiwan including the independent variables, 4 Skinfold determination values, and the dependent variable, the measurements of the BIA of each student listed in Table IV is applied to evaluate the performances of three Choquet integral regression models with P-measure, λ -measure, δ -measure, L-measure and L_{δ} -measure based on γ -support respectively, a ridge regression model, and a multiple linear regression model by using 5-fold cross validation method to compute the mean square error (MSE) of the dependent variable.

The singleton measures, γ -support of the P-measure, λ -measure, δ -measure, L-measure and L_{δ} -measure are listed as follows which can be obtained by using the formula (26).

$$\{0.2396, 0.2466, 0.254, 0.2596\}$$
(43)

The formulas of MSE is by using 5-fold cross validation method to compute the mean square error (MSE) of the dependent variable.

Regression	5-fold CV			
Choquet	measure	MSE		
	L_{δ}	13.7136		
Integral	L	14.2344 14.4228		
Regression	δ			
model	λ	14.9218		
	р	18.3846		
Ridge reg	15.7434			
Multiple regres	16.1122			

TABLE II MSE OF REGRESSION MODELS

The experimental results of seven forecasting models are listed in Table II. We also find that the Choquet integral regression model with L_{δ} -measure based on γ -support outperforms other forecasting regression models.

IX. CONCLUSION

In this paper, a multivalent composed fuzzy measure of L-measure and δ -measure, called L_{δ} -measure, is proposed. This new measure is proved that it is of closed form with infinitely many solutions, and it can be considered as an extension of the two well known fuzzy measures, λ -measure and P-measure. Furthermore, this improved multivalent fuzzy measure is not only including the additive measure, but also having the same infinitely many measure solutions as L-measure. By using 5-fold cross-validation MSE, two experiments are conducted for comparing the performances of a multiple linear regression model, a ridge regression model, and the Choquet integral regression model with respect to P-measure, λ -measure, δ -measure and our proposed L_{δ} -measure -measure

based on γ -support respectively. The result shows that the Choquet integral regression models with respect to the proposed L_{δ} -measure based on γ -support outperforms other forecasting models.

In the future, we will apply the proposed Choquet integral regression model with the new fuzzy measure based on γ -support to develop multiple classifier system.

ACKNOWLEDGMENT

This paper is partially supported by the grant of National Science Council of Taiwan Government (NSC 97-2410--H-468-014).

REFERENCES

- A. E. Hoerl, R. W. Kenard, and K. F. Baldwin, Ridge Regression: Some Simulation, *Communications in Statistics*, vol. 4, No. 2, pp. 105-123, 1975.
- [2] Z. Wang, and G. J. Klir, *Fuzzy Measure Theory*, Plenum Press, New York, 1992.
- [3] Z. Wang, and G. J. Klir, *Generalized Measure Theory*, Springer Press, New York, 2009.
- [4] M. Sugeno, *Theory of Fuzzy Integrals and its Applications*, unpublished doctoral dissertation, Tokyo Institute of Technology, Tokyo, Japan, 1974.
- [5] L. A. Zadeh, Fuzzy Sets and Systems, vol. 1, pp. 3, 1978.
- [6] G. Choquet, Theory of Capacities, *Annales de l'Institut Fourier*, vol. 5, pp. 131-295, 1953.
- [7] H.-C. Liu, Y.-C Tu, C.-C. Chen, and W.-S. Weng, "The Choquet Integral with Respect to λ-Measure Based on γ-support", 2008 International Conferences on Machine Learning and Cybernetics, Kunming, China, July 2008.
- [8] H.-C. Liu, "Type 2 L-fuzzy measure and its Choquet integral regression model" 2009 Cross-Strait Conferences on Information Science and Information Technology, Ilan, Taiwan 22-24 June, 2009.(in Chinese)
- [9] H.-C. Liu, "A theoretical approach to the completed L-fuzzy measure", 2009 International Institute of Applied Statistics Studies (2009IIASS) 2nd conference, Qindao, China, July 24-29, 2009.
- [10] H.-C. Liu, D.-B. Wu, Y-D Jheng, and T.-W. Sheu, "Delta-Fuzzy Measures and its Application", *Proceedings* of the 8th WSEAS International Conference on Applied Computer and Applied Computational Science, pp. 289-293, May 2009.
- [11] H.-C. Liu, D.-B. Wu, Y-D Jheng, and T.-W. Sheu, "Theory of Multivalent Delta-Fuzzy Measures and its Application", WSEAS Transactions on Information Science and Application, vol. 6, no. 6, pp. 1061-1070, July 2009.
- [12] J.-I Shieh, H.-H. Wu, H.-C. Liu, Applying Complexity-based Choquet Integral to Evaluate Students' Performance, *Expert Systems with Applications*, 36, pp. 5100-5106, 2009.
- [13] S. Srivastava, A. Bansal, D. Chopra, G. Goe, Modeling and Control of a Choquet Fuzzy Integral Based Controller on a Real Time System. WSEAS Transactions on Systems, vol. 7, no. 5, pp. 1571-1578, July 2006.

- [14] H.-C. Liu, Chen, C.-C., Chen, G.-S., & Jheng, Y.-D. (2007). Power-transformed-measure and its Choquet Integral Regression Model, *Proc. of 7th WSEAS International Conference on Applied Computer Science* (ACS'07), pp.101-104, 2007.
- [15] G.S. Chen, Y.-D. Jheng, H.-C. Yao, and H.-C. Liu, Stroke Order Computer-based Assessment with Fuzzy Measure Scoring. WSEAS Transactions Information Science & Applications, vol. 2, no. 5, 62-68, 2008.
- [16] J. S. Weiner, and J. A. Lourie, *Practical Human Biology*, Academic Press, London, 1981.



Hsiang-Chuan Liu received the Ph.D. degree in Statistics from National Taiwan University, Taiwan. He is a professor at the Department of Bioinformatics, Asia University, Taiwan since August 2001 and also a honored professor at the Graduate Institute of Educational Measurement and Statistics, National Taichung University, Taiwan. He was the President of National Taichung University, Taiwan from 1993 to 2000. Dr. Liu is a

member of IEEE since 2007. He has funded research and published articles in the areas of Biostatistics, Bioinformatics, Fuzzy Theory, Educational Measurement, and E-Learning.



Chin-Chun Chen is an Associate Professor and the President of Min-Hwei College, Taiwan. He is now also a doctoral student of Graduate Institute of Educational Measurement and Statistics, Taichung University since 2006. His studies focus in Fuzzy Measure, Grey System, etc.



Der-bang Wu, Ph.D. (M'07) became a Member (M) of **NAUN** in 2007. He was born in Yun-Lin County, Taiwan on July, 1958. He earned his first doctoral degree (Ph.D.) from Department of Mathematics, Graduate School of University of Northern Colorado, Greeley, Colorado, USA in 1994. Also, in order to earn his second doctoral degree, he is a doctoral student of Graduate Institute of Educational Measurement

and Statistics, Taichung University since 2007. His studies focus in Fuzzy c-mean, Fuzzy Measure, Grey System, Rough set, Educational Measurement, and e-Learning, etc.

Wu is an Associate Professor of Graduate Institute of Mathematics, Education, Taichung University, Taichung, Taiwan. He was a teacher of Elementary School for 4 years (1979-1983) and work in Taichung University for 24 years (1985-2009), mainly engaged in the design and the development of Mathematics Textbooks, Research Instruments, van Hiele Geometrical Thinking, etc.

Dr. Wu is a member of IEEE, Taiwan Association of Mathematics Education, Taiwan Association of Science Education, and International Group of Psychology of Mathematics Education, etc.



Tian-Wei Sheu received the Ph.D. degree in Mathematics from National Osaka University, Japan in 1990. He is the Dean of College of Education and a professor of Graduate Institute of Educational Measurement, National Taichung University, Taichung, 40306 Taiwan. His studies focus in IRT, Educational Measurement, and e-Learning, etc.

No.	C1	C2	C3	C4	ВСТ	No.	C1	C2	C3	C4	ВСТ
1	72	66	78	72	19	31	66	68	75	74	25
2	86	80	82	81	35	32	68	70	74	76	40
3	56	63	69	75	21	33	57	65	75	70	24
4	78	86	86	86	33	34	74	70	80	75	35
5	66	72	80	76	23	35	49	60	69	64	13
6	68	74	77	80	28	36	51	60	63	64	18
7	74	86	87	88	44	37	58	64	68	66	32
8	54	56	62	68	7	38	73	78	84	81	39
9	71	74	80	77	26	39	56	56	65	61	6
10	68	70	80	75	33	40	61	62	70	70	25
11	53	56	70	63	22	41	57	60	68	64	23
12	67	70	80	75	35	42	57	64	67	70	26
13	70	66	70	74	13	43	50	52	68	60	7
14	60	65	75	70	23	44	84	80	76	72	49
15	68	68	78	76	35	45	62	66	76	71	22
16	58	66	76	71	37	46	70	74	78	82	32
17	61	66	72	78	33	47	69	70	80	75	26
18	68	68	80	74	26	48	63	74	74	74	42
19	56	66	76	71	21	49	66	78	80	82	39
20	59	62	70	78	29	50	67	70	80	75	31
21	62	64	76	70	36	51	56	65	75	70	23
22	71	72	78	75	26	52	50	54	66	60	18
23	74	63	69	75	12	53	71	75	85	80	41
24	59	70	80	76	37	54	74	77	80	85	26
25	75	75	85	80	39	55	71	72	76	80	31
26	73	78	84	81	24	56	60	65	75	70	21
27	62	68	72	74	29	57	59	57	70	68	17
28	77	74	80	76	42	58	50	56	65	68	13
29	63	60	68	69	17	59	72	76	80	78	38
30	56	61	75	68	22	60	81	76	78	80	33

TABLE III THE DATA SET WITH FOUR COURSES AND SCIENCE SCORES OF THE BCT

C1 : physics and chemistry

C2 : biology

C3 : geoscience

C4 : mathematics

BCT : Basic Competence Test of nature science

Table IV Measurements of BIA and four skinfold determinations of percent body fat

					ts of BIA and	Ioui	Skilloid		÷		
No	BIA	biceps	triceps	Sub- scapular	Sup- railiac	No	BIA	biceps	triceps	Sub- scapular	Sup- railiac
1	11.8	15.8	16.2	27.6	16.3	65	22.8	27.4	32.2	33.6	24.5
2	17.8	20.4	10.2	35.6	23.0	66	5.4	14.4	8.0	17.2	17.5
3	6.2	10.4	9.4		8.2	67	8.6	9.6	11.4	17.2	17.3
4			9.4 5.6	12.6			7.4				
-	7.0	10.2		10.6	13.6	68		9.6	8.0	10.2	13.4
5	5.2	10.8	12.0	13.8	11.8	69	20.2	29.2	28.2	40.0	23.9
6	20.2	24.6	39.8	40.0	34.7	70	28.4	30.6	38.6	39.8	39.5
7	14.8	18.8	22.4	24.8	18.6	71	6.8	10.4	8.8	14.6	15.2
8	12.4	18.2	20.2	27.6	18.4	72	11.0	12.4	10.4	14.4	11.7
9	17.0	20.6	21.2	27.8	21.6	73	20.8	30.8	38.8	40.0	37.7
10	16.6	22.6	18.8	32.6	16.6	74	25.0	27.6	40.0	40.0	29.6
11	10.2	13.4	8.4	12.8	15.1	75	4.8	6.2	5.6	7.0	9.7
12	21.0	26.7	36.2	40.0	23.9	76	8.4	7.0	8.0	11.8	15.6
13	10.0	13.4	17.4	17.8	18.1	77	11.0	14.0	10.0	12.4	17.7
14	9.8	13.8	11.6	19.2	15.5	78	10.6	11.6	7.0	14.4	12.9
15	8.6	10.8	11.4	14.4	8.5	79	12.4	16.8	17.0	25.8	14.9
16	21.8	25.6	36.6	36.8	31.7	80	11.4	14.0	20.8	26.4	25.1
17	25.2	29.4	30.2	30.6	31.2	81	12.8	15.8	20.2	19.8	16.4
18	10.2	11.0	10.2	14.8	12.2	82	12.0	15.6	16.0	22.8	17.3
19	10.4	15.8	13.0	25.6	16.6	83	13.0	20.4	24.0	27.0	26.2
20	17.6	22.6	23.2	34.6	23.2	84	14.2	15.4	22.4	22.8	18.9
20	12.6	12.4	14.2	16.0	14.2	85	11.0	16.4	14.2	15.8	17.9
22	9.0	11.2	9.4	11.8	9.3	86	22.4	29.8	35.0	36.2	28.5
23	12.2	19.2	17.4	27.8	19.7	87	6.4	7.6	8.6	11.4	12.1
23	4.6	7.0	8.8	11.2	7.2	88	6.8	10.6	9.6		12.1
24 25	4.0 6.4	8.8	0.0 11.0	11.2	10.8	89	16.2		27.2	14.6 27.4	24.9
								18.4			
26	23.8	29.0	37.0	35.0	30.7	90	22.4	26.8	25.4	33.4	30.4
27	8.4	15.8	17.8	23.0	21.6	91	9.6	11.2	10.4	18.0	11.7
28	12.2	16.6	16.4	20.6	18.7	92	10.8	17.2	24.0	24.8	21.9
29	7.2	12.8	8.6	18.6	15.2	93	13.0	16.2	12.4	18.4	14.2
30	21.4	31.2	31.4	39.4	28.6	94	5.6	12.4	11.4	15.6	14.5
31	18.2	23.0	40.0	40.0	28.2	95	19.4	25.0	36.2	39.0	29.9
32	9.2	12.6	40.0	17.8	16.0	96	14.4	22.4	29.8	35.0	24.8
33	10.2	18.8	17.8	20.8	18.4	97	25.4	29.4	37.0	40.0	24.6
34	19.2	24.4	35.2	35.0	34.1	98	9.4	11.2	11.4	12.4	8.9
35	6.8	12.0	8.0	14.4	16.1	99	17.4	22.6	19.4	31.6	22.7
36	16.8	20.8	25.6	27.8	20.7	100	24.0	30.8	40.0	40.0	29.4
37	35.8	38.6	40.0	40.0	30.1	101	3.8	6.0	6.4	6.8	10.8
38	10.0	11.6	10.4	18.6	8.3	102	11.0	19.4	11.6	18.4	13.7
39	5.4	12.2	12.4	21.4	19.2	103	22.6	24.4	40.0	40.0	33.3
40	11.2	18.0	23.6	30.8	22.1	104	9.2	10.0	11.0	19.2	13.4
41	5.4	11.2	6.8	11.6	11.9	105	18.2	19.0	31.0	29.4	24.5
42	7.6	8.4	9.4	13.6	12.8	106	6.8	12.4	14.0	17.8	14.1
43	6.6	9.8	9.6	12.0	9.3	107	7.4	11.6	10.0	16.0	11.0
44	32.4	37.2	40.0	40.0	18.2	108	9.2	10.6	12.4	14.4	12.7
45	7.8	14.0	11.0	17.8	31.3	109	29.4	23.6	39.8	40.0	37.4
46	17.8	26.6	34.2	40.0	22.8	110	6.8	7.8	9.8	12.8	10.9
47	22.0	27.8	38.2	39.4	23.6	111	12.4	14.6	15.8	19.8	16.9
48	14.4	15.8	18.8	23.8	14.9	112	8.2	9.8	9.2	16.0	14.5
49	15.8	18.4	21.4	24.0	24.9	113	16.4	20.8	25.2	30.4	24.9
50	7.4	12.8	10.2	17.0	14.3	114	9.4	11.4	12.0	21.8	14.3
51	16.2	29.0	21.6	29.8	24.1	115	16.4	22.4	33.2	36.8	25.1
52	6.0	7.4	7.6	9.8	8.6	116	7.0	11.4	13.8	17.4	11.2
53	12.2	15.4	16.2	18.8	17.8	117	10.4	12.6	14.8	23.8	18.0
54	11.6	12.0	9.8	13.0	8.9	118	5.6	8.2	10.2	8.6	7.7
55	17.8	22.6	38.0	31.0	24.8	119	10.8	11.8	17.8	21.2	19.9
56	13.2	16.8	18.6	23.4	20.7	120	9.6	15.8	14.4	19.4	18.6
57	4.4	7.2	8.2	9.8	14.3	121	5.0	6.8	7.4	9.4	6.0
لننا											

58	16.2	21.8	28.2	32.6	27.2	122	9.8	12.2	12.4	15.4	13.5
59	11.4	19.4	28.8	32.8	22.3	123	13.8	18.0	16.4	21.0	19.3
60	11.2	13.0	18.8	22.6	21.9	124	8.8	12.8	9.8	11.8	13.3
61	8.6	11.4	7.2	10.2	7.5	125	15.8	21.0	35.4	39.8	27.3
61	20.4	26.2	31.0	32.8	25.8	126	10.8	16.6	15.6	23.2	16.5
63	7.0	8.8	11.6	9.4	12.0	127	9.0	10.6	10.0	16.8	11.9
64	14.6	17.4	12.8	16.8	14.7	128	8.8	12.4	10.0	10.8	11.3