Adaptive Neuro-Belief Rule Based Diabetes Diagnosis System

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Abstract—**Diabetes is the most regular disease in medical science. It can affect the organs of the human body. Due to the handling both uncertain diabetic medical and clinical data to diabetes diagnosis system is a complex problem However, a computer-base diagnosis system for diabetes would help to enhance the accuracy of the diagnosis and reduce the time and cost. This paper describes an effective new approach "Adaptive Neuro-Belief Rule Based System (ANBRBS)" with Evidential Reasoning (ER) to diagnose diabetes, which can reduce the errors and medical uncertainties. This paper used the medical and clinical real data to implement and test of this proposed system. It has been observed that, this new adaptive methodology provides more reliable diabetes diagnosis result in percentage and recommendations.**

Keywords— Diabetes, Neural Network; Belief Rule Base; ER Algorithm, Neuro-BRB, Diagnosis

I. INTRODUCTION

Diabetes is a metabolic disease. 100 million people in the world are affected by diabetes [1] and it's the cause of 1.1 million deaths every year, 80% of which found in lower and middle income countries [2]. Now 32.7 million diabetic patients an estimated in India and this amount is expected to twice by 2025. Prevalence is expected to double worldwide in the next 20 years [3] and enlarged by 150% in lower and middle income countries [2][3][4].

A same situation having in other Asian countries [4][5]. The diabetic patient rate is enlarging from year to year. Diabetes disease is not diagnose and treated properly at an early stage of patients, it would affect people and lead to various diseases like cardiovascular disease, visual impairment, leg amputation and renal failure etc. However diabetes diagnosis at right time is a difficult to Physicians due to lack of subjective specialists or inexperience with the previous diabetic cases. The manual diabetes diagnosis system is does not sound due to the various types of uncertainty come from the medical and clinical diabetic data and knowledge. In general, the manual diabetes diagnosis system is time delay and expensive. An automated medical diagnosis system can enhance the accuracy of diagnosis and reduce the expenses of diagnosis.

There are numerous researches have been found in various methodologies such as Rule Based, ANN, Decision Tree and BRB for diabetes diagnosis. Artificial neural networks based Diabetes mellitus forecast [13] having the biggest challenge was the missing values in the data set. Rule base classification system for Diabetic Patient using Cascaded K-Means and Decision Tree cannot handle the various types of uncertainty from diabetic data. A Decision Support System to analyze elder diabetic patients using Decision Tree. This system does not consider younger patients [14]. A diabetes expert system [16] does not consider diabetes type 1. Belief Rule based (BRB) CDSS for Heart Failure Suspicion [17]. Diabetes diagnosis system by using OLAP and data dining integration can't handle the all types uncertainties [15].. Pima Indian Diabetes diagnosis system [18] is used the general regression neural networks to classify the patient as diabetic or not diabetic. It can't recommend any reliable value like a patient having the percentage of diabetes. The above survey highlights that the development of a diabetes diagnosis system, which aims to better diagnosis result than other existing systems by handling all types of uncertainties..

Therefore, it can be inferred that to handle the uncertainties of existing diabetes diagnosis and generate reliable results is needed to processed by using refined knowledge base schemata and inference system[6][7]. Hence, this research paper proposes to adopt a new adaptive methodology namely Adaptive Neuro-Belief Rule-Base (BRB) System with ER to the design and development of the diabetes diagnosis system. This methodology consists of two parts are neural network algorithm and BRB inference system with ER. BRB is the expanded form of the traditional IF-Then rule-base, which belief degree can handle. The ER approach [7] deals with MADA problems having both numeric and subjective attributes in the inference process.

This research paper is presents to develop an adaptive neuro-belief rule based system for diabetes diagnosis.. Pima Indian Diabetes dataset [9] has been used to development and test of this paper proposed system. It would find that the results of this proposed system are more accuracy than the other diabetes diagnosis systems.

This paper consists of five sections, including the preceding introduction. The second section presents an overview of the neural network and BRB system. The third section presents the design and implementation of the adaptive neuro-BRB system for diabetes diagnosis. Results and discussion are described in section four. Section five concludes with some final comments and suggestions for future researches.

II. NEURAL NETWORK AND BELIEF RULE BASE

Artificial neural networks used the back propagation algorithm using multi layer perceptions (MLA). This section presents the description of ANN and belief rule based (BRB) inference system.

A. *Artificial Neural Network (ANN)*

The construction of the neural network involves three different layers with feed forward architecture. This is the most popular network architecture in use today. The input layer of this network is a set of input units, which accept the elements of input feature vectors. The input units (neurons) are fully connected to the hidden layer with the hidden units. The hidden units (neurons) are also fully connected to the output layer. The output layer supplies the response of neural network to the activation pattern applied to the input layer. The information given to a neural net is propagated layer-by-layer from the input layer to output layer through (none) one or more hidden layers.

Important issues in Multi Layer Perceptions (MLP) design include specifications of the number of hidden layers and the number of units in these layers. The number of input and output units is defined by the problem the number of hidden units of use is far from clear. That is the amount of hidden layers and their neurons is more difficult to determine. A network with one hidden layer is sufficient to solve most tasks. In this paper, neural network used seven inputs in the input layer, one hidden layer and one node in the output layer.

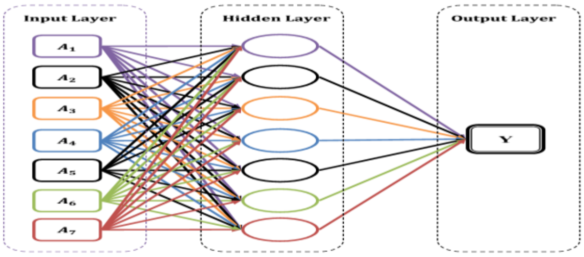

Figure 1. Artificial Neural network with Seven inputs, One hidden layer and one output

B. *Belief Rule Base (BRB) inference system*

The Belief Rules are the main components of a BRB that consists of three extra features such as belief degrees, rule weight and attributes weight. These belief degrees are the expanded form of general IF-THEN rules. The antecedent attributes of BRB takes referential values and consequent with belief degrees structure [20].

The Belief Rule Base (BRB) is used to represent the knowledge base schema of an expert system that allows handling of uncertain data. A belief rule can be elucidated as following way [7].

$$\mathrm{R_k}: \begin{cases} \mathrm{IF}\ (\mathrm{P}_1 \text{ is } \mathrm{A}_1^k) \cap (\mathrm{P}_2 \text{ is } \mathrm{A}_2^k) \cap \ldots\ldots\ldots \cap \mathrm{P}_{\mathrm{T_k}} \text{ is } \mathrm{A}_{\mathrm{T_k}}^k \\ \mathrm{THEN}\ \{(\mathrm{C}_1, \beta_{1k}), (\mathrm{C}_2, \beta_{2k}), \ldots\ldots\ldots, (\mathrm{C}_N, \beta_{Nk})\} \end{cases} \quad (1)$$

$$R_k : \left(\beta_{jk} \geq 0, \sum_{j=1}^{N} \beta_{jk} \leq 1\right) \text{with a rule weight } \theta_k, \text{attribute}$$

$$\text{weights } \delta_{k1}, \delta_{k2}, \delta_{k3}, \ldots\ldots, \delta_{kT_k} \quad k \in \{1, \ldots\ldots, L\}$$

Where the antecedent attributes of ***k***th rule are represent by P_1, P_2, P_3 ...P_{Tk}. $A_i^k (i = 1, \ldots\ldots, T_k, k = 1, \ldots\ldots, L)$ represents one of the referential values of the ***i***th antecedent attribute $\boldsymbol{P_i}$ in the ***k***th rule.C_j represents one of the consequent reference values of above belief rule. $\beta_{jk} (j = 1, \ldots\ldots, N,\ k = 1, \ldots\ldots, L)$is the belief degree of the consequent reference value C_j of BRB that believed to be true. If $\sum_{j=1}^{N} \beta_{jk} = 1$ the ***k***th rule is said to be complete, otherwise, it is incomplete. $\boldsymbol{T_k}$is presents the total number of antecedent attributes used in *k*th rule. ***L*** is considered the number of all belief rules in the BRB. ***N*** is the number of all possible referential values of consequents in a belief rule. An example of belief rule in the diabetes diagnosis system can be defined as follows-

$$R_k: \begin{cases} \textit{IF } A_1 \textit{ is High AND } A_2 \textit{ is High AND } A_3 \textit{ is High AND } A_4 \textit{ is High AND} \\ A_5 \textit{ is High AND } A_6 \textit{ is Medium} \\ \textit{THEN Diabetes is } \{(\textit{High}, (0.860)), (\textit{Medium}, (0.140), (\textit{Low}, (0.000))\} \end{cases} \quad (2)$$

Where {(High, 0.860), (Medium, 0.140), (Low, 0.000)} is a belief degrees distribution with ”Diabetes” consequent of belief rule as present as in Eq. (2). “High”, “Medium” and “Low” are the referential values of consequent “Diabetes” in this research. The belief distribution present that the degree of belief of “High” is 84%, 16% degree of belief for “Medium”, while 0% degree of belief is considered with “Low”. In this belief rule, the total degree of belief is (0.860+0.140+0.000) = 1.000; hence, the rule is complete

The BRB inference system of this research methodology consists of input transformation, rule activation weight calculation, rule belief degree update, and aggregation by using ER algorithm [22] The inference engine of this system architecture works in the following ways [17] – i) First take the input data from the user by the interface layer, this input data are transformed in its attributes referential values of BRB’. ii) Calculate the activation weights of all BRB rules by the using (A.2) equation. iv) Update the belief degree of consequence in belief rules by using (A.3) and v) Finally aggregates all rules by using analytical ER algorithm (A.4). After all, system inference engine generates the overall inference result by using utility equation (A.5).

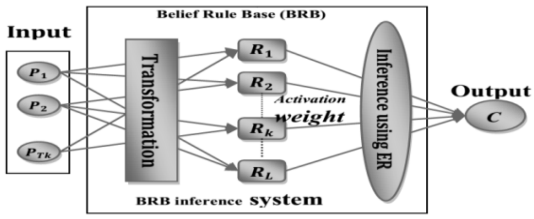

Figure 2. BRB Inference System

Figure 2 illustrates the BRB inference system, which consists of mention BRB, input transformation, activation weight calculation; update the belief rules and aggregation by using ER.

III. Adaptive Neuro-Belief Rule Base System for Diabetes Diagnosis

Adaptive Neuro-BRB system is a combination of neural network and belief rule based system. This expert system adapts the layered based system architecture that represents how its components consisting of inputs, process, and outputs are organized by using Adaptive Neuro-BRB and ER. This proposed adaptive neuro-Belief Rule Base system architecture consists of three basic layers namely interface layer, application processing layer and data management layer [30].This research considers a numerical multi-input single-output system, which can always be separated into a set of single-output systems [24]**.** The adaptive neuro-belief rule-based system with ER methodology is well adapted to develop a multi-input single-output system. The diabetes diagnosis system is a multi-input single-output system. Hence this approach employs to develop the diabetes diagnosis system.

The adaptive Neuro-BRB diabetes diagnosis system with ER consists of patient information and three layers system architecture. This section presents the diabetic information, factors, and system architecture along with design and implementation.

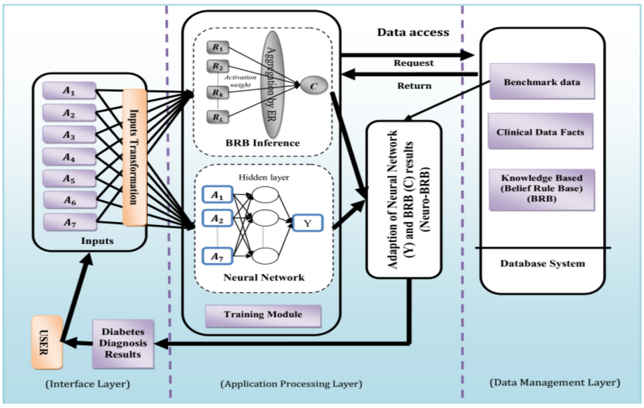

Figure 3. System Architecture of Neuro-BRB Diabetes Diagnosis System

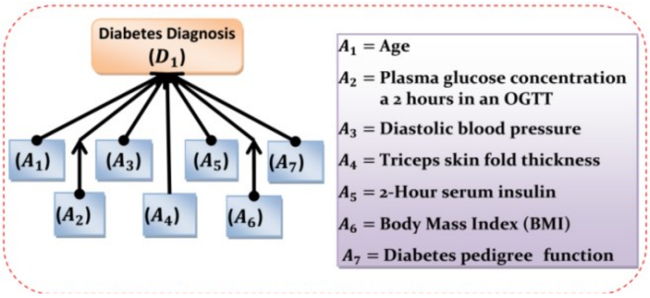

Figure 4. Hierarchical BRB Framework and antecedent attributes for diabetes Diagnosis System

Figure 3 illustrates the main components of the three-layered architecture of the adaptive Neuro-BRB diabetes diagnosis system along with the components as mentioned above.

A. Diabetic Information and factors

The Age (A_1), plasma glucose concentration a 2 hours in an oral glucose tolerance test (OGTT) (A_2), diastolic blood pressure (A_3), Triceps skin fold thickness (A_4), 2Hour serum insulin (A_5), Body mass index (BMI) (A_6), and Diabetes pedigree function (A_7) that were taken from the patients are considered the input facts and input antecedent attributes for this proposed adaptive neuro-BRB diabetes diagnosis system. The input antecedent names along with their referential values present in Table A.I.

B. System Analysis Design, Architecture and its Implementation

The system architecture of adaptive Neuro-BRB diabetes diagnosis system consists of three layers mention in above. Figure 3 and 4 illustrates the BRB framework with input antecedent attributes and system architecture of the adaptive Neuro--BRB diabetes diagnosis System.

Interface layer - used to get the seven diabetes referential values from the patient or from the physician as inputs and to show the diabetes diagnosis outputs in percentage. It facilitates the acquiring of input (antecedent attributes of BRB) as diabetes clinical data, signs, symptoms and risk factors (BRB framework in Figure 1) This data are distributed over the referential values associated with each antecedent attribute by taking account of diabetes expert belief degree [26] and these seven diabetic data also input into the ANN component of application layer. The system interface also enables the displaying of the system results as the patient is diabetic or not with the recommendation in percentage.

Application layer- this layer having main components are BRB knowledge base and ER inference system, neural network and adoption process of BRB ER with ANN. it's also process to transform input, rule activation, rule update and rule aggregation by ER and generate neural network outcomes. Finally, adopt the neural network outcomes with BRB inference system output. The processing of this layer work as following way-

First, the knowledge base of the BRB inference system construct by using belief degree structured BRB which store and organized by data management layer. The BRB framework along with antecedents attributes of this research (by taking account of "Pima Indian Diabetes dataset) [9] have been developed and present in Figure 4. From this framework, it can be stated that input data of diabetes diagnosis include seven antecedent attribute (A_1-A_7) are mentioned previously. A BRB can be designed in many ways [28]. The initial BRB of this system have been constructed by the domain expert and benchmark dataset. This system BRB consists of only one consequent as "diabetes (D1)". All antecedent attributes consist of three referential values as high, medium and Low. Hence, this entire BRB system consists of 2187 (L) belief rules as illustrated in Table I. It is considered that all belief rules have equal rule weight and all antecedent attributes have equal weight that is 1.00.

An example belief rule of this BRB diabetes diagnosis system is given below-

R2: ***IF*** A_1 is High ***AND*** A_2 is High ***AND*** A_3 is High ***AND*** A_4 is High ***AND*** A_5 is High ***AND*** A_6 is High ***AND*** A_7 is Medium ***THEN*** Diabetes (D_1) is {High (0.86), Medium (0.14), Low (0.00)}

TABLE I. INITIAL BELIEF RULE BASE FOR NERO-BRB DIABETES DIAGNOSIS SYSTEM

Rule ID	Rule Weight	IF Antecedent attributes (A_1-A_7)							Then Consequent Diabetes (D_1)		
		A_1	A_2	A_3	A_4	A_5	A_6	A_7	High (H)	Medium (M)	Low (L)
R1	1.00	High	High	High	High	High	High	High	1.000	0.000	0.000
R2	1.00	High	High	High	High	High	High	Medium	0.860	0.140	0.000
R3	1.00	High	High	High	High	High	High	Low	0.860	0.000	0.140
.....	.....	.....	.....	.....	.....	.....	.....	.....	.....	.....	.....
R2186	1.00	Low	Low	Low	Low	Low	Low	Medium	0.000	0.140	0.860
R2187	1.00	Low	Low	Low	Low	Low	Low	Low	0.000	0.000	1.000

Above belief rule distributes the degrees of belief into the Diabetes (D1) consequent's referential values. Consequently, it can assign the initial degrees of belief to the diabetes consequent in the rule as "0.860" to "High", "0.140" to "Medium", "0.00" to "low" as shown in rule R2.

Second, The BRB inference system of this architecture of consists of a four step process such as take the input and its transformation in refential values of consequent, rule activation weight calculation by using (A.2), rule update by using (A.3), and aggregation of the rules of a BRB by using the analytical ER algorithm (A.4). . [27] .After that BRB inference system generate the BRB inference output (C_m) using utility equation (A.5).

Third, the seven inputs antecedent attributes used as inputs of the input layer of neural networks and it generates the one output (Y_m) in the outputs layer. This neural network of this system illustrate at Figure 1 and Figure 3. This network use only one hidden layer and one output layer. The diabetes diagnosis benchmark data (B_m) are used as target data on this network. The output of this network is also converted in to percentage value.

Fourth (optional), The second part of this layer is to build the BRB training module to learn the initial belief rule base (BRB) of the data management layer. Its aim to find optimal BRB parameters set $\left(\boldsymbol{\theta}_{\mathbf{k}}, \boldsymbol{\delta}_{\mathbf{i}}, \boldsymbol{\beta}_{\mathbf{jk}}\right)$ by minimizing the discrepancy between the system results and the sampled data by using (A.6). [30].

Finally, the output of the BRB inference system and neural network are adopted in a single value output by using following algorithm 1.

Algorithm 1: Special Rule Based Algorithm
Input : BRB inference output(C_m) and Neural network output (Y_m)
Output: Final Neuro-BRB system result $\mathrm{O}((\mathrm{A}_{1\ldots7})_\mathrm{m})_\mathrm{m}$

BEGIN
BRB inference output:= (C_m);
Neural Network $\coloneqq (Y_m)$
Diabetes diagnosis Benchmark value $B_m \coloneqq \{0,1\}$
IF $C_m > Y_m$
THEN $\mathrm{O}((\mathrm{A}_{1\ldots7})_\mathrm{m})_\mathrm{m} = {}^1\!/_2\,(\mathrm{Y_m} + \mathrm{C_m}) + \{{}^1\!/_2\,(\mathrm{C_m} - \mathrm{Y_m})\}B_m$
ELSE
$\mathrm{O}((\mathrm{A}_{1\ldots7})_\mathrm{m})_\mathrm{m} = {}^1\!/_2\,(\mathrm{Y_m} + \mathrm{C_m}) + \{{}^1\!/_2\,(\mathrm{Y_m} - \mathrm{C_m})\}B_m$
END
RETURN Neuro-BRB system result $\mathrm{O}((\mathrm{A}_{1\ldots7})_\mathrm{m})_\mathrm{m}$
END

Data management layer – manage the initial Belief Rule-Base (BRB) and diabetes diagnosis facts including clinical data and actual benchmark data of diabetes diagnosis.

IV. Result and Decision

This research proposed system input antecedent's data in the BRB framework (Figures 2 and 3) and ANN have been collected from the female patients of Pima Indian heritage [14]. There are seven input attributes of diabetes data have been used in this adaptive Neuro-BRB diabetes diagnosis system to diagnose the diabetes in percentage. The input data form same data set are used to generate the diabetes diagnosis results in manual system and BRB expert system (BRBES) are also shown in Table II.

TABLE II. Diabetes Diagnosis Result By BRB, Expert and Neuro-BRB System

ID	Age	Plasma glucose concentration a 2 hours in an OGTT	diastolic blood pressure (mm Hg)	Triceps skin fold thickness (mm)	2 Hour serum insulin (mu U/ml)	Body mass index (BMI)	Diabetes pedigree function	Actual Diabetes Diagnosis Outcome (Benchmark)	Diabetes Diagnosis using BRBES	Expert Opinion	Diabetes Diagnosis using Neuro-BRB (This system)
P1	50	148	72	35	0	33.60	0.627	1	76.41%	70%	78.10%
P2	31	85	66	29	0	26.60	0.351	0	32.12%	30%	35.04%
P3	32	183	64	0	0	23.30	0.672	1	85.40%	80%	90.00%
P4	21	89	66	23	94	28.10	0.167	0	43.31%	45%	42.45%
P5	33	137	40	35	168	43.10	2.288	1	91.85%	90%	94.00%

We have considered the actual diabetes diagnosis results as the benchmark data to compare the adaptive Neuro-BRB diabetes diagnosis system results with other diabetes diagnosis tools and train this proposed system. This benchmark data are one (1) or zero (0). The data one represents the patient having diabetes and zero data represent the patient non-diabetic as shown in Table II. The data set consists of 768 samples. For simplicity only five patients data set are presented in Table II.

The column 12 of Table II illustrates this adaptive Neuro-BRB diabetes diagnosis system results in percentage and column 10 presents the BRBES' generated output in percentages. The column 11 gives the expert opinion (known as manual system) on diabetes diagnosis also in percentage. It is observed that the Adaptive BRB diabetes diagnosis system results are more realisable than other system tools like manual system and BRBES.

V. Conclusion

This paper has been proposed new adaptive methodology as adaptive neuro-BRB system with ER approach and explained the design, development and application of proposed system methodology for diabetes diagnosis to account of signs, symptoms, risk factors and data of diabetes. This diabetes diagnosis system can handle the various types of uncertainties found in diabetes medical and clinical data. This system is the adaption of BRB inference system and artificial neural network. Hence, adaptive Neuro-BRB with ER can be considered as a robust method, which can be utilized in the diabetes diagnosis system. The system will facilitate the diabetic patient to diagnose their improvement of diabetes level as well. In this research, the system provides the results as a percentage of diabetes diagnosis of patient (Diabetic) that it's more informative and reliable than from the traditional expert's opinion. This system result is cost effective and time consumes to diagnose diabetes. The outputs of this adaptive Neuro-BRB diabetes diagnosis system have been compared to other diabetes diagnosis tools like traditional expert opinion and BRBES etc, this system results founded as more reliable than outputs on patient having diabetes. Further, this system methodology will train and use to implement for other disease diagnosis system.

APPENDIX

TABLE A.1 THE INPUTS FACTORS WITH REFERENTIAL VALUES

Sl. No.	Input Antecedent	Input	Referential Values
A1	Age	20-34	Low
		35-46	Medium
		>46	High
A2	plasma glucose concentration a 2 hours in an OGTT	< 95,	Low
		95-150	Medium
		>150	High
A3	diastolic blood pressure	>100	High
		70-100	Medium
		<70	Low
A4	Triceps skin fold thickness (mm)	> 40	High
		21-40	Medium
		<21	Low
A5	2-Hour serum insulin (mu U/ml)	>200	High
		140-200	Medium
		140>	Low
A6	Body mass index (BMI)	>29	High
		23-29	Medium
		23>	Low
A7	-Diabetes pedigree function	>0.8	High
		0.4-0.8	Medium
		0.4>	Low

$$\alpha_k = \prod_{i=1}^{T_k} \left(\alpha_i^k\right)^{\overline{\delta_{ki}}} \quad \textbf{(A.1)}$$

$$\omega_k = \frac{\theta_k \alpha_k}{\sum_{j=1}^{L} \theta_j \alpha_j} = \frac{\theta_k \prod_{i=1}^{T_k} \left(\alpha_i^k\right)^{\overline{\delta_{ki}}}}{\sum_{j=1}^{L} \theta_j \left[\prod_{l=1}^{T_k} \left(\alpha_l^j\right)^{\overline{\delta_{jl}}}\right]} \text{ And } \overline{\delta_{ki}} = \frac{\delta_{ki}}{max_{i=1,\dots,T_k}\{\delta_{ki}\}} \quad \textbf{(A.2)}$$

$$\beta_{ik} = \overline{\beta_{ik}} \frac{\sum_{t=1}^{T_k} \left(\tau(t,k) \sum_{j=1}^{J_t} \alpha_{tj}\right)}{\sum_{t=1}^{T_k} \tau(t,k)} \quad \textbf{(A.3)}$$

Where, $(t,k) = \begin{cases} 1, & if\ P_i\ is\ used\ in\ defining\ R_k (t = 1, \dots, T_k) \\ 0, & otherwise \end{cases}$

Here $\overline{\beta_{ik}}$ is the original belief degree and β_{ik} is the updated belief degree

$$\beta_j = \frac{\mu \times \left[\prod_{k=1}^{L} \left(\left(\omega_k \beta_{jk} + 1 - \omega_k \sum_{j=1}^{N} \beta_{jk}\right)\right) - \prod_{k=1}^{L} \left(1 - \omega_k \sum_{j=1}^{N} \beta_{jk}\right)\right]}{1 - \mu \times \left[\prod_{k=1}^{L} 1 - \omega_k\right]} \quad (\boldsymbol{A.4})$$

With

$$\mu = \left[\sum_{j=1}^{N} \prod_{k=1}^{L} \left(\omega_k \beta_{jk} + 1 - \omega_k \sum_{j=1}^{N} \beta_{jk}\right) - (N-1) \times \prod_{k=1}^{n} \left(1 - \omega_k \sum_{j=1}^{N} \beta_{jk}\right)\right]^{-1}$$

$$C_m = H(A^*) = \sum_{j=1}^{N} u(C_j)\, B_j \quad \textbf{(A.5)}$$

$$\zeta(\mathrm{P}) = {}^{1}/_{\mathrm{M}} \sum_{\mathrm{m}=1}^{\mathrm{M}} (\mathrm{y_m} - \hat{\mathrm{y}}_{\mathrm{m}})^2 \quad \textbf{(A.6)}$$

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