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Statistical Fuzzy Inference System for Tacit knowledge modeling in Biomass Energy

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ABSTRACT

This paper highlights usability of statistical fuzzy inference systems based on PCA for tacit knowledge modeling in Biomass energy. Tacit knowledge is the key to management of ecological innovations in electric utilities of biomass power plants. However, tacit knowledge in the process of information gathering has not been implemented in a formalized way. Although the Sugeno defuzzification method is considered to be the most computationally effective, there is uncertainty about the defuzzified output, since it generates singleton fuzzy values objectively and is not well evaluated. A methodology enhancing the ability of statistical fuzzy inference systems for the improvement of tacit knowledge modeling. This has been exploited in the process of the new approach. The statistical inference system has been used directly integrated with the principal component analyzer, fuzzy inference engine, knowledge base and user interface. The system has been evaluated by a sub field of power systems domain of electricity marketing in biomass power plants. Approach evaluates performance of Biomass energy available for electricity generation. The has been built based on the proposed model and tacit data sets in electricity generation to be used to verify the accuracy of the model and the prototype. The electric utility assessment tool based on a questionnaire to classify electric utilities (agricultural residues, Forest waste, and Household waste) in percentages and identify electric utility performance index in biomass power plants. The experiments were conducted to investigate performance of PCA based Statistical Fuzzy Inference System based on a pilot survey. Output of the system is for computing biomass performance index based on fuzzy output values (agricultural residues, forest waste, household waste) has been generated by PCA based defuzzification process. The accuracy of the PCA based Statistical Fuzzy Inference System approach is 97%.

Keywords –**Fuzzy inference systems, Principal Component Analysis, Tacit Knowledge, Fuzzy logic, Biomass energy**

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I. INTRODUCTION

Statistical reasoning is a way of reasoning under partial information and, therefore, in presence of uncertainty. statistical reasoning is crucial for making informed decisions, solving problems, detecting biases, navigating uncertainty, and communicating effectively. It's a foundational skill in today's data-driven world. In particular, the pervasive expansion of the original theory of fuzzy sets (Zadeh, 1965) in the fields of Logic, Mathematics, and Engineering has provided fruitful ideas and new tools to statistical methodology. Starting from the late sixties, an increasing flow of contributions has enlarged the scope of statistical reasoning to encompass fuzzy information and fuzzy uncertainty [25]. Knowledge management efforts overlap with organizational learning, and may be distinguished from that by a greater focus on the management of knowledge as a strategic asset and a focus on encouraging the sharing of knowledge (Sanchez and Heene, 1997). Knowledge sharing remains a challenging issue for knowledge management, and while there are no clear agreement barriers may include time issues for knowledge works, the level of trust, lack of effective support technologies and culture [24]. Sugeno defuzzification method enhances computational effectiveness through analytical calculations, simplified rule evaluation, scalability in high-dimensional spaces, efficient rule base management, and improved interpretability. This paper highlights usability of statistical fuzzy inference system based on PCA for tacit knowledge modeling. Research presents designing and implementation of an intelligent system for data preprocessing, classification and reasoning. The system will be evaluated by a sub field of power systems domain of electricity generation in biomass energy power plants.

1.2 Problem statement

It is justified that tacit knowledge modeling in fuzzy inference systems is really a problem due to the defuzzification process and thereby fuzzy inference systems for tacit modeling knowledge are not properly addressed. Knowledge is the fundamental resource that enhances to function intelligently. Knowledge can be defined into two types such as explicit and tacit. Explicit knowledge can be presented formally and capable of effective (fast and good quality) communication of data to the user whereas tacit knowledge can be represented in an informal way and further modeling needed for gaining effective communication [4], [9].

2.0 REVIEW OF LITERATURE

A novel approach is proposed by using an improved genetic algorithm (IGA) combined with the dynamic autoregressive with outside input (ARX) Takagi-Sugeno (T-S) fuzzy model. The IGA algorithm automatically generates the input variable, the appropriate fuzzy if-then rules, and the ARX structure to characterize the dynamic nonlinear feature of the oxygen content by processing the operation data from the industrial coke furnace [1]. This study proposed a fuzzy modeling algorithm to improve the Takagi-Sugeno fuzzy model [2]. This algorithm initially finds a desirable number of rules at once, in advance, and then identifies the premise and consequent parameters separately by fixing the number determined. The proposed algorithm consists of three stages: determination of the optimal number of fuzzy rules, coarse tuning of parameters and fine tuning of these parameters. To find the optimal number of rules, the new cluster validity algorithm that is based on the validity criterion Vsv adapted to the usage of FCRM-like clustering, is proposed. This paper discusses decentralized parallel distributed compensator design for Takagi-Sugeno fuzzy systems [7]. The fuzzy system is viewed as an interconnection of subsystems, some of which are strongly connected, while others are weakly connected. The necessary theory is developed so that one can associate this fuzzy system with another one in a higher dimensional space, the so-called expanded space, design decentralized parallel distributed compensators in the expanded space, then contract the solution for implementation on the original fuzzy system. A new approach uses arguments similar to those of traditional Lyapunov stability theory with positive and negative definite functions replaced by fuzzy positive definite and fuzzy negative definite functions, respectively [10]. It has been introduced the concept of the equivalent fuzzy system for a cascade of two fuzzy systems. It has been used in the cascade of a system and a fuzzy Lyapunov function candidate to derive new conditions for stability and asymptotic stability for type II and type III fuzzy systems. A new inference method based on a smoothing maximum function is propose a method to guarantee smoothness of the model output to a desired degree, boundedness of the output gradient at each point by the local gradients of the rule consequences and also improves the accuracy of the TS model improved inference for Takagi-Sugeno models [11]. A lot of investigations have been done to modify the systematic design of Takagi Sugeno fuzzy model. Besides what we discussed already, FLEXFIS algorithm is widely used to improve the learning process of Takagi Sugeno model [12].

Energy is defined as a vital input to our day-to-day life. Knowledge of how much energy is input to the economy and the quantities of different forms of energy. The indigenous primary sources such as biomass contribute a major part of the energy supply. Exploitation of biomass electricity generation is gaining a new momentum in Sri Lanka. It is important for the energy sector to have a historical collection of such data for future planning and decision-making. Three eclogical innovations in biomass energy such as Agricultural residues, Forest products and Household waste are considered [5] [6]. However tacit knowledge in the process of information gathering has not been modeled into a formalized way.

2.1 Fuzzy logic models in energy systems

Energy projects in developing countries have proved that renewable energy can directly contribute to poverty alleviation as well as provide for business and employment opportunities. However, electricity from renewable energy is argued to be intermittent and hence unreliable. On the one hand consumers need to be educated on the necessity of using non-polluting cleaner energy sources while the policy makers in the government must bring in legislations and reallocations in the budget spending so as to enhance renewable energy utilization to a greater extent. If realistic models are developed to provide reliable, environment friendly energy from homespun commercial and renewable energy sources it would aid the global community and leave behind a healthy environment for generations to come. Fuzzy logic helps in conceptualizing the fuzziness in the system into a crisp quantifiable parameter. Thus fuzzy logic based models can be adopted for effective energy planning to arrive at pragmatic solutions. Fuzzy logic deals with reality and it is a form of many valued logic. It deals with reasoning that is approximate having also linguistic values rather than crisp values. Fuzzy logic handles the concept of truth value that ranges between completely true and completely false (0–1). Fuzzy logic has been applied in many disciplines. Fuzzy logic and probability are different ways of expressing uncertainty. Fuzzy set theory used the concept of fuzzy set membership while probability theory uses the concept of subjective probability. The various types of membership functions normally used in fuzzy logic are ‘Λ’ triangular, ‘∏’ trapezoidal, ‘L’ function, ‘Γ’ function, ‘S’ function, Gaussian fuzzy set. All of these functions can be used in the modeling of energy systems. Fuzzy logic-based models in energy systems can range from the simplest to the most complex. They can be broadly classified as follows:

(a) fuzzy delphi
(b) fuzzy regression
(c) fuzzy grey prediction
(d) fuzzy AHP
(e) fuzzy ANP
(f) fuzzy clustering

(ii) Hybrid models
(a) neuro-fuzzy, adaptive neuro-fuzzy inference system (ANFIS)
(b) fuzzy genetic algorithm, neuro-fuzzy GA
(c) fuzzy expert system, neuro-fuzzy expert system
(d) fuzzy DSS
(e) fuzzy DEA, neuro-fuzzy DEA

(iii) Multi criteria decision models
(a) fuzzy VIKOR
(b) fuzzy TOPSIS
(c) fuzzy support vector machine
(d) fuzzy particle swarm optimization
(e) fuzzy honey bee optimization
(f) fuzzy cuckoo search optimization
(g) fuzzy quantum particle swarm optimization
(h) fuzzy ant colony optimization [20]

2.2 Biomass Energy

Biomass, also called Bioenergy, are fuels that are developed from organic materials. It is a renewable and sustainable source of energy used to supply mainly heat for various applications, while it is marginally used for power generation as well. Bioenergy use falls into two main categories: ’traditional and ’modern ‘. Traditional use refers to the combustion of biomass in such forms as wood, animal waste and traditional charcoal. Modern bioenergy technologies include liquid biofuels produced from bagasse and other plants; bio-refineries; biogas produced through anaerobic digestion of residues; wood pellet heating systems; and other technologies.

About three-quarters of the world's renewable energy use involves bioenergy, with more than half of that consisting of traditional biomass use. Bioenergy accounted for about 10% of total final energy consumption and 1.4% of global power generation in 2015. Biomass has significant potential to boost energy supplies in populous nations with rising demand, such as Brazil, India and China. It can be directly burned for heating or power generation, or it can be converted into oil or gas substitutes. Liquid biofuels, a convenient renewable substitute for gasoline, are mostly used in the transport sector. Brazil is the leader in liquid biofuels and has the largest fleet of flexible-fuel vehicles, which can run on bioethanol - an alcohol mostly made by the fermentation of carbohydrates in sugar or starch crops, such as corn, sugarcane or sweet sorghum. In Sri Lanka, biomass still plays a dominant role in the supply of primary energy. Large quantities of firewood and other biomass resources are used for cooking in rural households and to a lesser extent, in urban households. Even though a large portion of energy needs of the rural population is fulfilled by firewood, there are possibilities to further increase the use of biomass for energy in the country, especially for thermal energy supply in the industrial sector.

2.2.1 Agricultural Residues

Anaerobic digestion is a widely adopted method for converting organic residues into biogas, primarily composed of methane (CH_4) and carbon dioxide (CO_2). This process occurs in oxygen-free environments, such as sealed digesters, where microorganisms break down organic matter. The resulting biogas can be utilized for electricity generation, heating, and even as a vehicle fuel when purified to biomethane standards. To enhance biogas yields, pretreatment methods like heat treatment, enzymatic processes, or co-digestion with nitrogen-rich materials (e.g., manure) are employed. Such strategies improve the carbon-to-nitrogen (C/N) ratio, optimizing microbial activity and gas production

Direct combustion of agricultural residues in biomass boilers or furnaces is a straightforward method for heat and electricity generation. While this approach is less complex than anaerobic digestion, it requires efficient combustion systems to minimize emissions and ensure energy efficiency. In regions like India, surplus agricultural biomass is being converted into pellets or briquettes for cleaner combustion in industrial boilers, reducing reliance on coal and mitigating air pollution.

2.2.2 Forest Waste

Forest waste, often termed forest residues, encompasses materials like tree tops, branches, sawdust, and other byproducts resulting from logging and forest management activities. These residues, once considered waste, are increasingly recognized as valuable sources of renewable energy.

Direct combustion involves burning forest residues to produce heat or electricity. This method is straightforward and widely used, especially in industrial settings. For instance, the Steven's Croft power station in Scotland utilizes wood waste to generate 44 MW of electricity, significantly reducing greenhouse gas emissions

Gasification converts biomass into a synthetic gas (syngas) through partial combustion at high temperatures. This syngas can then be used for electricity generation or as a chemical feedstock.

2.2.3 Household waste

Household waste, encompassing materials like food scraps, yard trimmings, paper, and plastics, can be transformed into valuable energy resources through various waste-to-energy (WTE) technologies. These methods not only reduce landfill dependence but also contribute to sustainable energy solutions.

This biological process decomposes organic waste in the absence of oxygen, producing biogas primarily composed of methane. Biogas can be utilized for electricity generation, heating, or as a vehicle fuel. Compact systems like SEaB Energy's Flexibuster have been implemented in urban settings, converting household waste into power and heat, effectively turning neighborhoods into self-sufficient energy producers.

Gasification is a thermochemical process that converts organic waste into syngas—a mixture of hydrogen, carbon monoxide, and other gases—through high-temperature decomposition. The syngas can be used to generate electricity or produce synthetic fuels.

3. METHODOLOGY

A new approach has been enhanced the ability of statistical fuzzy inference systems for the improvement of tacit knowledge modeling. This has been exploited in the process of the new approach in following steps. Approach evaluates performance of Biomass energy available for electricity generation. A prototype has been built based on the proposed model and tacit data sets in electricity generation to be used to verify the accuracy of the model and the prototype. It consists of the following modules.

3.1 Data preprocessing

The process will be carried out with data sets. In the first instance of knowledge acquisition, a pilot survey based on questionnaire has been done for the purpose of extracting Principal components. The SPSS statistical package is used for conducting the functions of Principal components extracting. So PCA is mainly used to reduce dependencies among the variables in the datasets constructed for acquired knowledge. Once knowledge has been acquired then it should be analyzed the knowledge for finding dependencies. The datasets has been analyzed by using principal component analysis to find dependencies. In the first instance data will be mapped knowledge regarding to analysis of biomass energy for electricity generation.

3.2 Fuzzy inference system

Fuzzy inference system is consisted modules of fuzzication, fuzzy inference and defuzzification. The sub-phase of Fuzzification, it is basically analysis of the fuzzy set and membership function based on output of principal components analyzer. Sugeno defuzzication method based on output of principal component analyzer has been conducted in defuzzification module. Fuzzy inference engine has been used for fuzzification and defuzzification directly integrated with the fuzzy inference system. The defuzzification process has been implemented by computing singleton fuzzy values integrated with extracted principal components. The knowledge base has been used to represent domain knowledge in terms of fuzzy rules, fuzzy operators and membership functions.

4. RESULT & DISCUSSION

This project presents a novel statistical fuzzy inference system, which is incorporated in the modeling knowledge in the electric utilities in power plants on a modified version of Sugeno defuzzification technique. Biomass in power plants are classified as agricultural residues, forest waste, and household waste. These electric utilities have been used as an input for the intelligent biomass assessment system.

Here Principal Component Analysis has been used to reduce dependencies of variables in the dataset. The datasets have been classified for the purpose of analysis of the biomass energy power plants for computing electric utility types (agricultural residues, forest waste and household waste) available in Sri Lanka.

4.1 Constructing the questionnaire

Tacit knowledge of biomass energy has been acquired via questionnaire and informal interviews with energy experts. The knowledge extracted from energy experts has been mapped into a questionnaire consisting of 45 numbers of questions based on Likert scale. This knowledge has been entered into the system using the *developer mode* of the system. Using the questionnaire editor, each question of the questionnaire and the marks-range using Likert Scale has been stored into the database.

1. Using agricultural residues for biomass energy reduces greenhouse gas emissions.
2. Biomass energy from agricultural residues is a sustainable alternative to fossil fuels.
3. The environmental benefits of using agricultural residues for energy outweigh the potential drawbacks.
4.Investing in biomass energy from agricultural residues is economically beneficial for farmers
5.The cost of converting agricultural residues into biomass energy is justified by the energy produced
6. Government incentives for biomass energy from agricultural residues are sufficient to encourage adoption
7.Current technology is adequate for efficiently converting agricultural residues into biomass energy
8.Research and development in biomass energy from agricultural residues should be a priority
9. The infrastructure for biomass energy from agricultural residues is well-developed in my region
10. Biomass energy from agricultural residues provides a reliable source of energy
11. The energy yield from agricultural residues is competitive with other renewable energy sources
12.The efficiency of biomass energy systems from agricultural residues meets industry standards
13. Biomass energy projects using agricultural residues create job opportunities in rural areas
14. Community awareness and support for biomass energy from agricultural residues is high.
15. Local communities benefit economically from the use of agricultural residues for energy.
16. Biomass energy from forest products (Snags, Sawdust) is an effective way to reduce greenhouse gas emissions
17. Using forest products for biomass energy contributes to deforestation
18. The environmental benefits of biomass energy from forest products outweigh the potential ecological risks
19. Biomass energy from forest products is a cost-effective energy source compared to fossil fuels.
20. The biomass energy industry creates significant economic opportunities in rural areas.

Table. 1: Part of the questionnaire

4.2 Principal component analysis for reducing dependencies

A survey using 13 numbers of participants including energy experts have been conducted for the principal component analysis. Extracted principal components (8 nos.) have been used for reducing dependencies of the data set.

questions	Pc1	Pc2	Pc3	Pc4	Field6	Field7	Field8	Field9
VAR00001	0.907156	-0.03299	0.067376	0.017978	0.126606	0.247725	-0.1544	0.244465
VAR00002	0.838004	0.109069	0.369604	-0.00882	-0.04957	0.232123	-0.10144	0.037446
VAR00003	0.941055	0.061803	0.116028	0.142687	0.13138	-0.07272	-0.06122	0.09077
VAR00004	0.916734	0.025978	-0.23626	0.146265	-0.08305	0.072505	0.106535	0.174194
VAR00005	0.723415	0.098113	0.264346	0.174132	0.22394	0.451286	0.036401	0.193266
VAR00006	-0.82298	0.031873	0.232254	0.202283	0.257578	0.187195	-0.05664	0.326814
VAR00007	-0.06939	0.281957	-0.36438	0.116538	0.452364	0.495483	0.446791	-0.02729
VAR00008	0.902396	-0.06849	-0.00797	0.070769	0.089389	-0.1492	0.152832	-0.14331
VAR00009	-0.84935	0.298636	0.094283	0.109334	-0.11551	0.27769	-0.12888	-0.12633
VAR00010	0.238028	0.816703	-0.05068	-0.1277	-0.24014	0.077021	-0.04091	-0.13661
VAR00011	0.081382	0.753339	0.310718	-0.45715	0.219631	-0.04074	-0.07704	0.070412
VAR00012	-0.17704	0.615885	-0.48845	-0.12879	-0.23343	0.210548	-0.29052	0.294301
VAR00013	0.828392	0.323722	0.300703	-0.07491	0.15237	0.127073	-0.09261	0.113668
VAR00014	-0.096	0.013333	0.729165	0.265828	0.106435	0.313254	-0.15371	-0.31565
VAR00015	0.578539	0.425012	0.39349	0.032756	-0.04718	0.254434	-0.05067	-0.4675
VAR00016	-0.04779	0.429989	0.250572	-0.71919	-0.08976	-0.09339	0.334774	0.256698
VAR00017	0.749468	0.34252	0.379762	0.129054	0.010889	0.025874	-0.25016	-0.02376
VAR00018	-0.00167	0.647433	-0.35536	-0.2913	0.46026	-0.17201	-0.12709	0.031254
VAR00019	0.108218	0.454283	-0.47546	0.016493	0.443803	-0.55432	-0.15563	-0.0135
VAR00020	0.879555	0.379753	0.183927	0.035623	-0.01846	0.093789	0.120068	0.018891
VAR00021	-0.22962	0.05143	0.879946	-0.04796	-0.20174	-0.20775	-0.05525	-0.09541
VAR00022	-0.67891	0.469242	-0.02536	0.350228	0.034535	-0.11305	0.306102	-0.04386
VAR00023	-0.55754	0.313277	0.422225	0.084801	0.519725	-0.14525	-0.22607	0.006943
VAR00024	-0.82182	0.155072	-0.06106	-0.11949	0.128613	0.263484	0.227672	-0.1531

Table. 2: Part of the principal components' matrix

4.3 Autonomous generating fuzzy membership functions

In this sub-phase of Fuzzification, it is basically analysis of the fuzzy set and membership function for tacit knowledge modeling in power plants. Membership functions have been constructed by using output of model refinement. Fuzzy membership functions for agricultural residues, forest waste and household have been constructed by using the outputs of principal component analyzer.

4.4 Fuzzy rule base

The fuzzy output variable (biomass performance index (BPI)) is based on fuzzy output values (agricultural residues-forest waste, agricultural residues-household waste, forest waste-household waste) of electric utility in power plants.

4.5 Defuzzification

Singleton fuzzy output values have been defined as a fuzzy output variable (BPI) for singleton fuzzy membership functions (agricultural residues-forest waste, agricultural residues-household waste, forest waste-household waste).

The Upper Bound / Lower Bound Method is a way to get a rough estimate of the uncertainty in a calculated quantity. The basic procedure is to calculate the fuzzy value, take the average of the upper and lower bound (Coppia 2014; Renato 2006)

Here k_1, k_2 and k_3 are defined as singleton fuzzy output values defined for fuzzy output variable (BPI) for singleton fuzzy membership functions (agrires-forest, agrires-housew, forest-housew).

$$BPI = \frac{(Max(\mu_{agrires}(y), \mu_{forest}(x))) * K_1 + (Max(\mu_{agrires}(x), \mu_{housew}(z))) * k_2 + (Max(\mu_{forset}(X_2), \mu_{housew}(X_3))) * K_3}{Max(\mu_{agrires}(x), \mu_{forest}(y)) + Max(\mu_{agrires}(x), \mu_{housew}(y)) + Max(\mu_{forest}(y), \mu_{nousew}(z))}$$

Fig.1: Defuzzification window

4.6 Experiments

The biomass energy in power plants data set has been applied to the proposed system for evaluation and testing.

The experiments are carried out in power plants to enable the Sugeno defuzzification with PCA as given below.

4.6.1 Calculation of Predicted Value

c1 =Max (agricultural residues, forest waste, household waste)

c2 = Min (agricultural residues, forest waste, household waste)

Predicted value = (c1 + c2) / 2

4.6.2 Calculation of Error

Error= Predicted value- Actual value

Error has been computed with defuzzification by PCA for tacit knowledge modeling in biomass energy of power plants.

quest-id	Agricultural Residues	Forest Waste	Household Waste	expected output	actual (Biomass performance index)	error
1	43.07781	35.21274	21.70945	32.39363	33.14697	0.753334
1	32.9207	34.04835	33.03096	33.48452	33.23307	0.2514534
2	74.6599	16.24626	9.093843	41.87687	37.15488	4.72199
3	32.87474	31.18411	35.94114	33.56263	33.30799	0.2546339
4	25.87353	34.9995	39.12697	32.50025	33.30179	0.8015404
5	70.75675	-30.69453	59.93777	20.03111	33.91505	13.88394
6	33.72291	28.41634	37.86075	33.13855	33.30061	0.1620607
7	33.45868	35.26635	31.27497	33.27066	33.1601	0.1105633
8	49.00446	23.91469	27.08085	36.45958	35.23173	1.227849
9	30.44096	34.02552	35.53352	32.98724	33.32091	0.3336735
10	30.67383	38.65694	30.66922	34.66308	32.59658	2.066502
11	31.3326	28.94088	39.72652	34.3337	33.26775	1.06595
12	36.76477	23.08721	40.14801	31.61761	33.30832	1.690701
13	80.2223	9.403094	10.37461	44.81269	37.76239	7.050302

Table. 3: Analysis of biomass energy

Accuracy has been considered for knowledge modeling in biomass energy. Here accuracy of PCA based Defuzzification in Sugeno defuzzification method has been considered

Fig. 2: Error in biomass energy analysis

It is shown that error (difference between expected outputs and actual output) is minimized by 3% of the average error made by Sugeno defuzzification by principal component analysis. It can be concluded that this has happened due to improvement of Sugeno defuzzification method based on output of principal component analysis in the system (Table.3). The proposed approach involves developing a Statistical Fuzzy Inference System that incorporates expert knowledge, historical data, and statistical analysis to model and manage tacit knowledge in biomass energy systems. This system would utilize fuzzy logic to handle uncertainty and imprecision in expert knowledge and statistical methods to analyze and interpret data patterns.to compute biomass performance index (BPI).

5. CONCLUSIONS, RECOMMENDATIONS & LIMITATIONS

It has been developed as an approach to model tacit knowledge by PCA based defuzzification for enhancing the ability of Sugeno type fuzzy inference systems. Here, singleton values in the Sugeno defuzzification method have been computed by using an integrated principal components analysis approach. In this approach it has been encouraged by the domain experts to present their knowledge to construct a more useful questionnaire. However, different experts may propose different questionnaires since their emphasis on domain knowledge is different. At present our system is based on one expert view of domain knowledge. Eventually Principal Component analysis has been done on that knowledge and generates the appropriate fuzzy membership functions for classifying knowledge. Defuzzification for classified knowledge has been achieved by the fuzzy inference system where defuzzification is done with principal component analysis.

The overall statistical fuzzy inference system facilitates for a user in modeling tacit knowledge that has not been modeled in existing mechanism of defuzzification method of Sugeno type inference system. The evaluation of the PCA based defuzzification for domains with tacit knowledge was done by testing of the system with data sets such as electric utilities in power plants. It has been examined whether the system was capable of exploring the effects of tacit knowledge modelling, with the conclusion that it minimized the error of 2 % by PCA based defuzzification. This is considered as an automated way of computing singleton fuzzy values with minimum error in the statistical fuzzy inference system. This leads to reducing inconsistency and being able to extract conclusions in higher levels of accuracy of the defuzzification process.in statistical fuzzy inference system.

The output result for computing biomass index performance index based on fuzzy output values (agricultural residues, forest waste, household waste) has been generated by PCA based Sugeno defuzzification process. This autonomous process has been achieved by integrating PCA with Fuzzy logic in the statistical fuzzy inference system.

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