Volume: 14 Issue: 05 Pages: 5602 - 5608 (2023) ISSN: 0975-0290

PCA based Sugeno Defuzzification Method for Modelling Tacit Knowledge in Power Plants

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ABSTRACT

This paper highlights usability of PCA based Defuzzification for the improvement of Sugeno Defuzzification method for knowledge modeling. Research presents designing and implementation of an intelligent system for knowledge modeling, classification and defuzzification. Knowledge is the key to management of ecological innovations in electric utilities of power plants. However, knowledge in the process of information gathering has not been modeled in a formalized way. The system has been evaluated by a sub field of power systems domain of electricity marketing in power plants. Although Sugeno defuzzification method is considered to be the most computationally effective, there is uncertainty about the defuzzified output, since it generates a singleton fuzzy values objectively and not well evaluated. A methodology for PCA based Defuzzification for Sugeno type inference systems has been used directly integrated with the principal component analyzer, fuzzy inference engine, knowledge base and user interface. The PCA based defuzzification system has been tested for modelling tacit knowledge for electric utilities in power plants as per renewable energy. The electric utility assessment tool based on a questionnaire to classify electric utilities (wind, biomass, and hydro) in percentages and identify electric utility performance index in power plants. The project highlights usability of fuzzy logic for designing and implementation of an intelligent system by principal component analysis for renewable energy modeling, classification and defuzzification. The experiment was conducted to investigate performance of PCA based approach with the Sugeno type inference systems. The accuracy of the PCA defuzzification approach is 98 %.

Keywords – **Sugeno Defuzzification, Principal Component Analysis, Tacit Knowledge, Fuzzy logic, Power plants**

Date of Submission: January 15, 2023 Date of Acceptance: February 06, 2023

I. INTRODUCTION

The most popular defuzzification methods are the center of gravity method and the mean of maxima method, which are computationally inexpensive and easy to implement within fuzzy hardware chips although a full scientific reasoning has not been established. Many researchers have attempted to understand the logic of the defuzzification process. Yager and Filev contributed to the process of defuzzification from the perspective of invariant transformation between different uncertainty paradigms, including basic defuzzification distribution (Filev, etal., 1991; Yager, et al., 1994), semi-linear defuzzification (Yager, et al., 1993) and generalized level set defuzzification (Filev, et al., 1993). They all can be seen as an extension of the center of gravity method. Research has been also carried on the fast computation of the center of gravity defuzzification method (Wang, et al., 2000; Broekhoven, et al., 2006). It should be noted that with the developments of intelligent technologies, some adaptive and parameterized defuzzification methods that can include human knowledge have been proposed. (Saneifard Saneifard 2010) used neural networks for defuzzification. Since it is a more compact and computationally efficient representation than a Mamdani type fuzzy inference system, the Sugeno system lends itself to the use of adaptive techniques for constructing fuzzy models This is further explained as development of intelligent electric utility assessment system for power plants. It is mainly concerned with the development of electric utility assessment, model refinement, classification and defuzzification as features of the system for renewable electricity generation.

1.2 Problem statement

Although so many defuzzification methods have been proposed so far, no one method gives a right effective defuzzified output for commonsense knowledge modeling. The computational results of defuzzification methods often conflict, and they don’t have a uniform framework in theoretical view.Most of the existing defuzzification methods attempt to make the estimation of a fuzzy set in an objective way. However, an important aspect of the fuzzy set application is that it can represent the subjective knowledge of the decision maker; different decision makers may have different perception for the defuzzification results. Although Sugeno type inference system is considered as the most computationally effective, there is uncertainty about defuzzified output, because it generates singleton fuzzy values objectively and not well evaluated.

2.0 REVIEW OF LITERATURE

Zhang [1] propose a novel approach to 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. The study by Eminli [2] propose fuzzy modeling algorithm to improve Takagi-Sugeno fuzzy model. This algorithm initially finds desirable number of rules at once, in advance, and then identifies the premise and consequent parameters separately by fixing 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. Chang [3] addresses one specific aspect of complexity reduction/interpretability improvement in fuzzy systems — how to limit the number of unique singletons in 0-th order Takagi-Sugeno (TS) systems, where the common practice is to assign a unique singleton to each rule. While abundance of free parameters makes 0-th order TS systems effective in data-driven identification, it also presents a computational load and an obstacle for interpretability and reliability of fuzzy rules. The developed reduction algorithm that utilizes singleton mapping matrix, subtractive clustering and least squares estimation algorithms, is able to bring the number of unique singletons down to the desired level without substantial accuracy loss. A research has been presented a new Tagaki-Sugeno (TS) type model whose membership functions (MFs) are characterized by linguistic modifiers. As a result, during adaptation, the trained local models tend to become the tangents of the global model, leading to good model interpretability. In order to prevent the global approximation ability from being degraded, an index of fuzziness is proposed to evaluate linguistic modification for MFs with adjustable crossover points. A new learning scheme is also developed, which uses the combination of global approximation error and the fuzziness index as its objective function. By minimizing the multiple objective performance measure, a tradeoff between the global approximation and local model interpretation can be achieved Zhou [3]. By analyzing above mentioned approaches, it is justified that knowledge modeling in Sugeno type fuzzy inference systems is really a problem due to defuzzification process and thereby fuzzy inference systems for 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 implicit. Commonsense knowledge is one type of in implicit knowledge [4]. Explicit knowledge can be presented formally and capable of effective (fast and good quality) communication of data to the user whereas implicit knowledge can be represented in informal way and further modeling needed for gaining effective communication [9]. Three ecological innovations are in the focus of the analysis electricity market restructuring: Biomass, hydro and wind Energy electric utilities are considered [5] [6].

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 most simple 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 Electricity supply

Electricity supply sector at present in Sri Lanka is mainly driven by two primary energy sources; petroleum based thermal power and hydroelectricity. Since most of the economical hydro potential in the county has been already harnessed, Sri Lanka will have to depend on petroleum based power generation during the next decade, until the next economical primary source, coal is introduced to Sri Lanka power sector.

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The different modes of grid connected electricity generation in Sri Lanka are listed below.
(i) CEB major hydro
(ii) CEB non-conventional: presently only wind power
(iii) CEB thermal: presently oil fired (Diesel, furnace oil and residual oil)
(iv) Independent Power Producers (IPPs): presently oil-fired thermal (Diesel & furnace oil)
(v) Small Power Producers (SPPs): presently small hydro and CHP, embedded in the distribution network [24]

2.2.1 Wind

Wind Power is one of the fastest-growing renewable energy technologies. Usage is on the rise worldwide, in part because costs are falling. Wind turbines first emerged more than a century ago. Following the invention of the electric generator in the 1830s, engineers started attempting to harness wind energy to produce electricity. Wind power generation took place in the United Kingdom and the United States in 1887 and 1888, but modern wind power is considered to have been first developed in Denmark, where horizontal-axis wind turbines were built in 1891 and a 22.8-metre wind turbine began operation in 1897. Wind is used to produce electricity using the kinetic energy created by air in motion. This is transformed into electrical energy using wind turbines or wind energy conversion systems. Wind first hits a turbine's blades, causing them to rotate and turn the turbine connected to them. That changes the kinetic energy to rotational energy, by moving a shaft which is connected to a generator, and thereby producing electrical energy through electromagnetism. The amount of power that can be harnessed from wind depends on the size of the turbine and the length of its blades. The output is proportional to the dimensions of the rotor and to the cube of the wind speed. Theoretically, when wind speed doubles, wind power potential increases by a factor of eight. Wind-turbine capacity has increased over time. In 1985, typical turbines had a rated capacity of 0.05 megawatts (MW) and a rotor diameter of 15 metres. Today's new wind power projects have turbine capacities of about 2 MW onshore and 3 - 5 MW offshore.

2.2.2Biomass

Biomass, also called Bioenergy, are fuels that is 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.

2.2.3 Hydroelectric Energy

Hydropower is energy derived from falling water. More than 2,000 years ago, the ancient Greeks used waterpower to run wheels for grinding grain; today it is among the most cost-effective means of generating electricity and is often the preferred method where available. The world's largest hydropower plant is the 22.5-gigawatt - Three Gorges Dam in China. It produces 80 to 100 terawatt-hours per year, enough to supply between 70 million and 80 million households. Small-scale micro-hydropower projects can make a big difference to communities in remote locations. The basic principle of hydropower is using water to drive turbines. Hydropower plants consist of two basic configurations: with dams and reservoirs, or without. Hydropower dams with a large reservoir can store water over short or long periods to meet peak demand. The facilities can also be divided into smaller dams for different purposes, such as night or day use, seasonal storage, or pumped-storage reversible plants, for both pumping and electricity generation. Hydropower without dams and reservoirs means producing at a smaller scale, typically from a facility designed to operate in a river without interfering in its flow. It is also called "run-of-the-river" projects. Many consider small-scale hydro a more environmentally-friendly option. Hydro power is a key energy source used for electricity generation in Sri Lanka, which provided almost all the electricity until early 1990s. A large share of the major hydro potential has already been developed and delivers valuable low-cost electricity to the country. Currently, hydro power stations are operated to supply both peaking and base electricity generation requirements. A substantial number of small hydro power plants which operate under the Standardized Power Purchase Agreement (SPPA) and more are expected to join the fleet during the next few years.

3. METHODOLOGY

I will postulate a new approach enhancing the ability of PCA based Defuzzification for the improvement of Sugeno Defuzzification method for knowledge modeling. This will be exploited the process of the new approach in following steps. Approach will evaluate performance index for electric utilities available for electricity generation by using PCA based Defuzzification method. Although Sugeno defuzzification method is considered to be the most computationally effective, there is uncertainty about the defuzzified output, since it generates a singleton fuzzy values objectively and not well evaluated. To solve the problem in electricity generation domain, which contain explicit knowledge, following model is proposed. A prototype will be built based on the proposed model and explicit data sets in electricity generation to be used to verify the accuracy of the model and the prototype. It consists of following modules.

3.1 Principal Components Analyzer

The process will be carried out with data sets. In the first instance of knowledge acquisition, a pilot survey has been done for the purpose of extracting Principal components [8]. 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 I should analyze the knowledge for finding dependencies. The datasets will be analyzed using principal component analysis to find dependencies. In the first instance data will be mapped knowledge regarding to analysis of electric utilities available for electricity generation

3.2 Fuzzy inference engine

The fuzzy inference engine carries out the functions of fuzzifier and defuzzifier whereby the fuzzy inference system reaches a solution. The principal component analyzer is integrated with the fuzzy inference engine.

3.3 Fuzzifier

Membership functions will be constructed by using output of model refinement. Membership functions for Biomass, hydropower and wind will be constructed using the out puts of principal component analyzer.

3.4 Defuzzifier

In the case of defuzzification process, finding the singleton values is considered as an automated process by the principal component analyzer. The zero-order analyzer takes only one singleton value from fixed values of the Classifier which defines Singleton values. Calculation of singleton values take the proportion of uncertainty values based on Upper Bound/ Lower Bound method.

3.5 Knowledge base

The knowledge base consists of fuzzy membership functions, fuzzy rules and fuzzy logic operators. Fine tuning analysis for output generated by the fuzzy inference system will be processed using Fuzzy membership functions, fuzzy rules and fuzzy logic operators in the knowledge base. The knowledge will be implemented using VB 6.

3.6 Database

Extracted principal components will store in MS Access database, which integrated with the Principal Component Analyzer through the developer interface. The questionnaire is consisted of commonsense knowledge stored in the database that is integrated with the user interface

I postulated a new approach enhancing the ability of classifying lands using an intelligent system based on principal component analysis and Fuzzy logic. This exploits the process of the new approach in following steps. The approach has been evaluated using land selection in archaeological sites.

4. INTELLIGENT ELCTRIC UTILITY ASSESEMENT SYSTEM

This project presents a novel intelligent electric utility assessment system, which is incorporated in the modeling knowledge in the electric utilities in power plants on a modified version of Sugeno defuzzification technique. Electric utilities in power plants are classified as wind, biomass and hydro power. These electric utilities have been used as an input for the intelligent electric utility 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 renewable energy power plants for computing electric utility types (wind, biomass, and hydro) available in Sri Lanka.

4.1 Constructing the questionnaire

Commonsense knowledge of electric utilities has been acquired via questionnaire and informal interviews with energy experts. The knowledge extracted from energy experts has been mapped in to questionnaire consisted of 30 number of questions. This knowledge has been entered to 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 in to the database.

4.2 Principal component analysis for reducing dependencies

A survey using 16 numbers of participants including energy experts have been conducted for the principal component analysis. Extracted principal components (9 nos.) have been used for reducing dependencies of the data set.

4.3 Autonomous generating fuzzy membership functions

In this sub phase of Fuzzification, it is basically analysis the fuzzy set and membership function for commonsense knowledge modeling in power plants. Membership functions has been constructed by using output of model refinement. Membership functions for wind, biomass and hydro have been constructed by using the out puts of principal component analyzer.

Fuzzy membership for wind, biomass and hydro (input fuzzy values of input fuzzy variable of (EUtilitywind, EUtilityBiomass , EUtilityHydro) have been constructed. For defining the fuzzy membership function, lower bound and upper bound values have been obtained by using Likert scale (*LS*).

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4.4 Fuzzy rule base

The fuzzy output variable (Electric utility performance index (EUPI)) is based on fuzzy output vlaues (Wind-Biomass, Wind-Hydro, Biomass-Hydro) of Electric utility in power plants. However fuzzy output values have been considered as singleton functions. Computaion of fuzzy input variables ($EUtility_{wind}$,$EUtility_{Biomass}$, $EUtility_{Hydro}$) has been achieved by computing fuzzy input values (Wind, Biomass, Hydro) based on PCA with Fuzzy logic integration.

4.5 Defuzzification

Singleton fuzzy output values has been defined for fuzzy output variable (EUPI) for singleton fuzzy membership functions (*WIND-BIOMASSS, WIND-HYDRO, and BIOMASS-HYDRO*).

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 (EUPI) for singleton fuzzy membership functions (*WIND-BIOMASSS, WIND-HYDRO, BIOMASS-HYDRO*).

$$EUPI = \frac{(Max(\mu_{BIOMASS}(y), \mu_{WIND}(x)))*K_1 + (Max(\mu_{WIND}(x), \mu_{HYDRO}(z)))*k_2 + (Max(\mu_{BIOMASS}(X_2), \mu_{HYDRO}(X_3)))*K_3}{Max(\mu_{WIND}(x), \mu_{BIOMASS}(y)) + Max(\mu_{WIND}(x), \mu_{HYDRO}(y)) + Max(\mu_{BIOMASS}(y), \mu_{HYDRO}(z))}$$

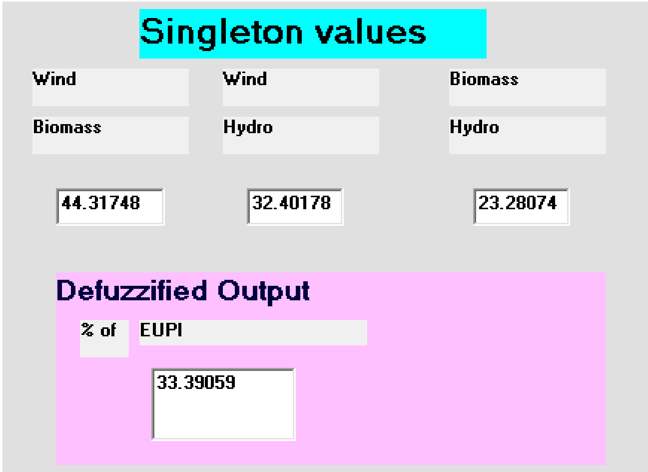

Fig.1: Defuzzification window

4.6 Experiments

The electric utilities in power plants data set has been applied to the proposed system for evaluation and testing. The experiments are carried out in in power plants to enable the Sugeno defuzzification with PCA as given below.

4.6.1 Calculation of Predicted Value

c1 =Max (wind, biomass, hydro)

c2 = Min (wind, biomass, hydro)

Predicted value = (c1 + c2) / 2

4.6.2 Calculation of Error

Error= Predicted value- Actual value

7. RESULT & DISCUSSION

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

quest-id	Wind	Biomass	Hydro	expected output	actual (defuzzified)	error
1	32.730	32.099	35.170	33.634	33.07329	0.561590
2	31.75716	34.18274	34.0601	32.96995	33.33445	0.3645029
3	32.55424	34.20447	33.24128	33.37936	33.34216	0.03719902
4	31.64601	38.29867	30.05532	34.17699	33.39059	0.7864094
5	42.03994	38.62689	19.33317	30.68655	33.61294	2.926387
6	35.25331	34.23647	30.51022	32.88177	33.43092	0.5491581
7	30.74616	26.72419	42.52966	34.62692	32.21567	2.411255
8	31.47714	28.0929	40.42996	34.26143	32.45794	1.803493
9	26.71892	28.4901	44.79098	35.75495	31.81688	3.938075
10	32.38631	32.49216	35.12153	33.75392	33.05221	0.7017117
11	29.96866	21.34334	48.688	35.01567	31.71869	3.296979
12	34.65739	23.53956	41.80305	32.6713	32.66965	0.001649857
13	34.25558	29.3289	36.41553	32.87221	33.11178	0.2395706
14	34.63979	37.05791	28.30231	32.68011	33.35405	0.6739397
15	26.38321	34.76167	38.85512	32.61917	32.93356	0.3143921
16	34.37756	24.73784	40.88459	32.81122	32.71796	0.09326172

Fig. 2: Analysis of electric utilities of power plants

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

Accuracy has been considered for knowledge modeling in electric utilities of power plants. Here accuracy of PCA based Defuzzification in Sugeno defuzzification method has been considered

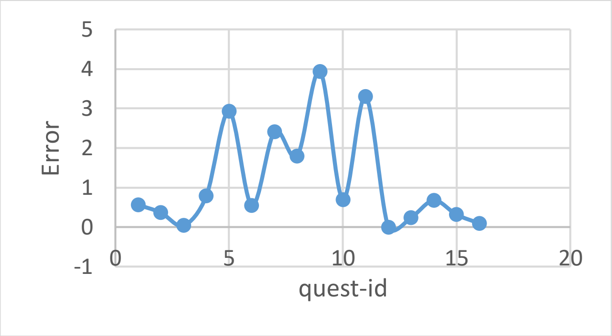

Fig. 3: Error in electric utilities of power plants

It is shown that error (difference between expected outputs an actual output) is minimized by 2% of the average error made by defuzzification by principal component analysis. It can be conclude that this has happened due to defuzzification by principal component analysis.

8. CONCLUSIONS, RECOMMENDATIONS & LIMITATIONS

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

The project highlights usability of PCA based Defuzzification for the improvement of Sugeno Defuzzification method for knowledge modeling. Research presents designing and implementation of an intelligent system for knowledge modeling, classification and defuzzification. The system has been evaluated by a sub field of power systems domain of electric utilities in power plants. The system based on datasets to classify and compute performance index for electric utilities in power plants available for electricity generation. This enable a guide understand, instrumental values, operating values, and weak values of electric utilities.

The overall system facilitates for a user in modeling explicit/implicit 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 a data sets such as electric utilities in power plants. It has been examined whether the system was capable of exploring the effects of tacit/explicit 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 Sugeno type inference system. This leads to reducing inconsistency and able to extract conclusions in higher level of accuracy of defuzzification process.

The output result for computing electric utility performance index based on fuzzy output values (wind-biomass, wind-hydro, and biomass-hydro) has been generated by PCA based defuzzification process. This autonomous process has been achieved by integrating PCA with Fuzzy logic.

References

[1]. Zhang, Ridong, (2016) Industrial and Engineering Chemistry Research, v. 55, (22), p. 6465-6474

[2]. Eminli, Mübariz, Guler, Nevin ,(2010), An improved Takagi-Sugeno fuzzy model with multidimensional fuzzy set, , Journal of Intelligent & Fuzzy Systems, vol. 21, no. 5, pp. 277-287,Expert Systems, vol. 19, no. 1, pp. 34-45.

[3]. Chang Su Lee (2009), A Framework of Adaptive T-S type Rough-Fuzzy Inference Systems (ARFIS),Doctor of Philosophy of Engineering, School of Electrical, Electronic and Computer Engineering of The University of Western Australia

[4]. Debbie Richards and Peter Busch, Acquiring and Applying Contextualized Tacit Knowledge, Journal of Information & Knowledge Management Vol. 02, No. 02, pp. 179-190 (2003)

[5]. Johansson, T.B., Kelly, H., Reddy, A.K.N., and Williams, R.H. Renewable energy: Sources for fuels and electricity. United States: N. p., 1993.

[6]. Robert L. Bradley (1998) Renewable Energy: Not Cheap, Not Green?, Strategic Planning for Energy and the Environment, 17:3, 15-21.

[7]. Akar M, (2000), Decentralized techniques for the analysis and control of Takagi-Sugeno fuzzy systems, IEEE Transactions on Fuzzy Systems (Volume: 8, Issue: 6, Dec 2000, pp. 691 – 704

[8]. Chatfied C, (1996), Introduction to Multivariate Analysis, Chapman and Hall

[9]. Richards D, Bush P, (2003). Measuring, Formalizing and Modeling Tacit Knowledge, IEEE/Web Intelligence Conference (WI-2003), Bejing, Internet publication.

Volume: 14 Issue: 05 Pages: 5602 - 5608 (2023) ISSN: 0975-0290

[10]. YAGER,R.R.and .P.FILEV(1993).SLIDE:a simple adaptive defuzzification method. IEEE Transactions on Fuzzy Systems 1(1), pp.69–78
[11]. en.wikipedia.org/wiki/Renewable energy.
[12]. REN21. Renewables 2010. Global status report.
[13]. UNEP, Bloomberg, Frankfurt School, Global trends in renewable energy investment; 011.
[14]. Groscurth HM, Kress KP. Fuzzy data compression for energy optimization models. Energy 1998; 23(1):1–9.
[15]. Cai YP, Huang GH, Yang ZF, Tan Q. Identification of optimal strategies for energy management systems planning under multiple uncertainties. Appl. Energy 2009; 86:480–95.
[16]. Ludwig B. On the sustainability of future energy systems. Energy Convers Manag 1997; 38(15–17):1765–76.
[17]. Kaminaris SD, Tsoutsos TD, Agoris D, Machias AV. Assessing renewables-to electricity systems: a fuzzy expert system model. Energy Policy 2006; 34:1357–66.
[18]. Kyriakarakos G, Patlitzianas K, Damasiotis M, Papastefanakis D. A fuzzy cognitive maps decision support system for renewables local planning.
[19]. Renew Sustain Energy Rev 2014; 39:209–22.
[20]. Mamlook R, Akash BA, Mohsen MS. A neuro-fuzzy program approach for evaluating electric power generation systems. Energy 2001; 26:619–32.
[21]. Agrawal RK, Singh SP. Energy allocations for cooking in UP households (India): a fuzzy multi-objective analysis. Energy Convers Manag 2001; 42:2139–54.
[22]. Sunny Thukra, Jatinder Singh Bal, Medical Applications on Fuzzy Logic Inference System: A Review Int. J. Advanced Networking and Applications Volume: 10 Issue: 04 Pages: 3944-3950 (2019) ISSN: 0975-0290
[23]. K. Kalaiselvi, J. Abdul Samath, Survey on Electricity Consumption using Data Mining Techniques, Int. J. Advanced Networking and Applications Volume: 10 Issue: 04 Pages: 3974-3980 (2019) ISSN: 0975-0290
[24]. https://www.energy.gov.lk/images/energy-balance/energy-balance-2017.pdf

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