IJRAR.ORG E-ISSN: 2348-1269, P-ISSN: 2349-5138

INTERNATIONAL JOURNAL OF RESEARCH AND ANALYTICAL REVIEWS (IJRAR) | IJRAR.ORG

An International Open Access, Peer-reviewed, Refereed Journal

Hybrid Fuzzy-Logic Decision Support Systems for Resource Constrained Scheduling in Complex Multi-Site Civil Engineering Projects

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Abstract

In recent times, fuzzy logic has become one of the very powerful techniques for dealing with analysis of hydrologic parameters and also in decision-making with respect to any water resources. The issues with hydrology deal with imprecision and vagueness that can readily be dealt with by fuzzy logic-based models. A wide variety of applications of fuzzy logic in hydrology and water resources is, therefore, briefly reviewed in this paper. So far, fuzzy logic-based hybrid models have been widely used in hydrologic applications. Additionally, this paper reviews the literature based on pure fuzzy logic applications and applications based on hybrid fuzzy modeling. This review indicates that hybrid fuzzy modeling has a wide range of applications in hydrology, much more than pure fuzzy logic modeling. The study of the Resource Constrained Project Scheduling Problem RCPSP took substantial interest, being one of the NP-hard problems in project management and operations research areas. The present work deals with the analysis of a new RCPSP extension in a multi-site environment with resource pooling between different sites, considering two types of resources: fixed and mobile ones. Novel constraints also consider transfer times of mobile resources and the decision on which job site to execute an activity. We propose a new solution based on a Particle Swarm Optimization paradigm to handle this variant of the RCPSP aiming at minimizing the total project Make span.

Its aim is to enable the circumvention of drawbacks posed by conventional decision support systems and promote adaptability to actual implementations characterized by uncertainty and complexity. The method thus consists of constructing a hybrid system with fuzzy logic rules and data classification algorithms. Imprecise information is modeled and processed in fuzzy logic, while data classification works on identifying the patterns and trends embedded in the data. The cooperative nature of the approach ensures all methods would reinforce one another, thus leading to a more powerful and effective decision support system. Results put forth demonstrate that the cooperative decision support system proposed yields better performance than using isolated conventional decision methods. This system was further capable of improved accuracy and adaptability, proving beneficial toward solving the problems posed by real-world datasets.

Keywords: Hybrid Fuzzy Logic, Decision Support Systems (DSS), Resource-Constrained Project Scheduling (RCPSP), Multi-Site Scheduling, Civil Engineering Project, Fuzzy Inference Systems, Project Makespan Minimization, Fuzzy Logic Controller (FLC), Hybrid Fuzzy Logic Decision Support Systems (HFL-DSS)

1. INTRODUCTION

1.1. Background of the study

In essence, scheduling refers to the arrangement of time-bound activities, tasks, and/or events in an organized manner towards ensuring that they get done effectively and efficiently. Scheduling, however, is important in practical terms: it becomes critical for the success of a project or an operation in focusing resources in the most effective manner possible. A typical project scheduling problem is that of assigning a list of interrelated project activities, accompanied by an estimate of each activity duration, the consumable and renewable resources that are required for each activity, and in terms of precedence relationships amongst the different activities. The next step is to determine an initial plan regarding the starting point and the end of every task, the resources allocated to it, and the tasks involved according to the existing dependencies of these tasks. Some downfalls of effective project schedule can be delayed completion, budget overrun and poor quality work. Essentially, it is categorized mainly into Resource Constrained Project Scheduling Problems (RCPSPs) and Time-Crunch Project Scheduling Problems (TCPSPs). The TCPSP is a well-known problem even in the literature of project management which comprises scheduling a set of tasks or activities on the basis of precedence relations and time constraints imposed on these activities. Then, the objective becomes executing all tasks of the project within an agreed-upon deadline (say, handover date of the project), all the meanwhile achieving a smooth utilization profile of the resources during the life span of the project (in what commonly is referred to as the resource levelling problem)

In principle, the resource smoothing/leveling problem specifically addresses the problematic issue of resource allocation among all resources to minimize fluctuation in usage over time. It is NP-hard, even in the single-resource case, and is known to be quite difficult. However, RCPSP would be an actual case statement of project management, wherein the scheduling of activities has some limitations in resources with respect to availabilities. In other words, in RCPSP, some limited resources in terms of equipment, personnel, or funds can be assigned to a set of activities that compose a project at a time. The objective of RCPSP will be to schedule all activities such that the little amount of resources will be optimally utilized and the overall duration of the project will be minimized. The RCPSP has been focused on for a few decades now, and it is widely known as a NP-hard optimization problem. In time, additional versions of this problem have been produced, such as multi-mode RCPSP, RCPSP with time windows and multi-skilled RCPSP, the last one being the specific topic from this paper. Recently, Laurent et al. (2017) addressed the multi-site resource-constrained project scheduling problem, or short multi-site RCPSP, which allows understanding the execution of a project's activities at several sites and sharing.

1.2. Multi-site Resource Constrained project Scheduling Problem

The multi-site RCPSP—similar to the single-site RCPSP consists of allocating individual units of some renewable resources over time to the execution of the activities of a project such that the project duration is minimized while taking into account a prescribed set of completion-start precedence relationships between pairs of activities. In addition, in the single-site RCPSP, it is assumed that all activities are executed at the same site and, consequently, that all resources are located at this site. In the multi-site RCPSP, in contrast, a specific site for the execution of each activity must be selected. Moreover, the spatial distance between the sites gives rise to two different types of transportation times that must be considered in the project schedule. First, during the transport of a resource unit between the sites, the resource unit cannot be allocated to the execution of an activity. Second, if two activities that are interrelated by a precedence relationship are executed at different sites, then a minimum time lag between the completion of the first activity and the start of the second activity must be taken into account, which corresponds to the time required to transport the first activity's output between the respective sites. Hereafter, we refer to the first type of transport as resource transport and to the second type of transport as output transport

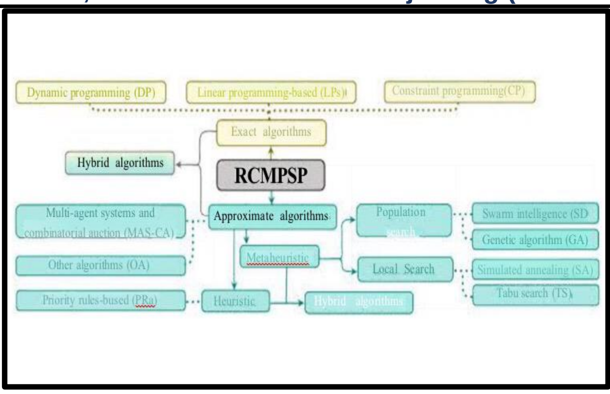

FIG 1: MS-RCPSP ALGORITHM

From what we know, the binary linear programming approach and four different metaheuristics developed by Laurent et al. (2017) appear to be the only ones described in the literature for multi-site RCPSP. The linear programming formulation characterizes discrete-time models; that is, the planning horizon is split into a series of periods of equal length with the assumption that an activity is only permitted to be started at the beginning of a given period. In an experimental analysis, Laurent et al. (2017), using CPLEX on a set of 192 instances, where the number of activities was varied between five and thirty, had occurred that none of the instances comprising 30 activities could be solved to optimality within a fixed time limit of 3600 s of running time. The four metaheuristics are based on representing feasible solutions using an activity list and a site list and then apply the search strategies of local search, simulated annealing, and iterated local search. In a different experimental analysis conducted by Laurent et al. (2017) from instances of 30 to 120 activities, it was established that the iterated local search and simulated annealing metaheuristics were superior to the rest. For years, various studies have been performed to enhance precision in fuzzy systems and the ultimate inference is that fuzzy hybrid modeling is capable of optimizing the accuracy of fuzzy system modeling. Since the initial application of fuzzy logic in hydrology many different researches have been done and now fuzzy logic holds a large place in the analysis of hydrology and decision-making concern to water resources. In this paper, the principal application areas in hydrology and water resources are presented.

1.3. Related Work

Many researchers have applied fuzzy logic to decision-support systems and exhibited its efficiency in drowning imprecise and vague information. Fuzzy logic literally is employed in modeling as well as representing uncertainty, lending itself to more robust decision-making processes.This has dwelt on the strength and limitation of various classification approaches, even emphasizing their use in unearthing patterns and trends within datasets. Various studies have been conducted into fuzzy logic and data classification individually, but only a few of the integrated kinds have been conducted on them as decision support systems. This area of investigating is scant with existing techniques tending not to have a holistic and cooperative framework but hence the need for a more unified method. Big data has been discussed in much literature concerning its volume, velocity, and variety. Studies have also highlighted the shortcomings of traditional decision support systems in tackling the complexities and uncertainties found in modern datasets, laying the roadmap for new initiative endeavors. Research on hybrid intelligent systems has attracted attention, bringing forth a new trend whereby different strategies are combined for improved performance. Although there have been various efforts to integrate fuzzy logic with machine learning, fuzzy logic and data classification collaboration for decision support has not been much discussed and therefore calls for more elaborative research. A section of research is focused on the scalability and performance of decision support system development when dealing with large and dynamic databases. They deal with the need to have such systems adaptable to changing data landscapes; hence, the necessity of intelligent and flexible approaches.

This overview will highlight the current trends concerning fuzzy logic-based channel selection and their application in CRNs. However, there is a large room for improvement in terms of direction towards reducing the sensing errors, uncertain results, and better usage of spectrum. A fuzzy logic-based spectrum was suspected sharing procedure in which mobile network operators will share their availability of spectrum information among other potential users that would purchase such licenses of spectrum for their communication needs. With the proposed scheme, operators will be able to choose the best licensed channel that would serve their transmissions requirements. The appropriate channel selection is done taking into account the parameters such as LSA spectrum efficiency, interference, load trend, user mobility, and co-primary spectrum efficiency.

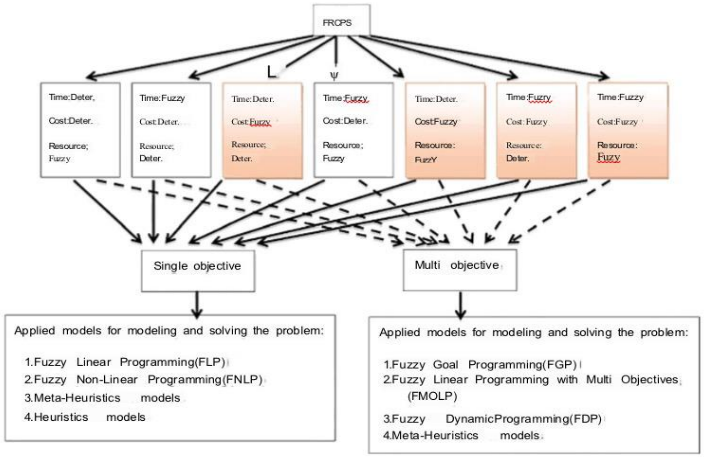

FIG 2: FUZZY LOGIC BASED SCHEME

Hence, a fuzzy logic-based scheme was devised in to make better and more efficient channel handoff decisions.

2. Literature Review

Real civil engineering projects become infinitely more complex than the project scheduling problems in terms of inter-site dependencies, multi-skilled labor requirements, timelines for material delivery or variable environmental and operational conditions as far as resource constraints are concerned: they form an interdependent task with limited resources and huge logistical challenges. Traditional scheduling techniques, therefore, accept the boundaries of dynamic and vague environments. This, therefore, requires the generation of intelligent and adaptable planning tools. This is a growing tendency witnessed by many scholars in handling the scheduling complexity posed by multi-site projects. For instance, Bahroun et al. (2024) present systematic-as of now-the Multi-skilled Resource-Constrained Project Scheduling Problem (MS-RCPSP) because construction plans become increasingly complicated. They plead for decision-making models that can withstand multi-skilled workforce deployment and cross-site co-acting and varying constraints for resources. Bigler et al. (2024) took this a step further by proposing MIP-based approaches but specific for multi-site scheduling problems in addition to noting that these had computational limitations in large-scale real-time scenarios. Such a framework would be used by Petri et al. (2017) as federated cloud computing platforms to outsource multi-site constructions projects. Their writing leaned heavily on the provision of real-time scheduling, resource tracking, and inter-site communication essential features that make for successful complex project execution. According to Stiti and Driss (2019), computational models for multi-site RCPSPs provide the same perspective: emphasizing the necessity of digital tools in managing decentralized project constraints. That is where Decision Support Systems were shaped up to be highly important tools as they collect pieces of information from various sources and analyze in real-time to support the evaluation of different alternative scheduling strategies. Lohmer and Lasch (2021) introduced this in their review of production planning in the context of multi-factory networks. They illustrated the transfer of principles derived from industrial scheduling for construction by treating individual construction sites as networked production nodes. This promotes adaptive tools that would be able to deal with spatial dispersion, logistical uncertainty, and coordination inefficiencies.

In the construction of major and expensive structures, DSS must solve automated solutions through advanced AI and logic systems. An experimental study conducted by Smith and Wong (2022) investigated AI-based DSS models on sustainable construction with respect to the intelligence with which these systems work to optimize traditional return performance measures-cost and time-to include additional performance measures relating to sustainability and specification. In addition, Ossei-Bremang and Kemausuor (2021) demonstrated DSS paradigms to incorporate multi-dimensional criteria decision-making for renewable energy projects and direct applicability to civil infrastructures project competing goals and limited resources. At the heart of intelligent DSS, fuzzy logic-defined reasoning meaning it evaluates ambiguity and imprecision very close to human reasoning. Construction scheduling is a case where you do not guarantee definite input data: hence, fuzzy logic works federally on degrees of truth rather than binary specification. Kambalimath and Deka (2020) describe their application of fuzzy logic amidst other strategies for concerns-over-water resource management in modeling nonlinear relationships and uncertain parameters. These results are in the same spirit for the application to construction-like dubious weather, irregular labor, and delivery late. According to this, a cooperative permitted fuzzy logic system is put forward to intelligent decision-making regarding learning and adaptation to new input conditions. Hence Mahmoudi et al. (2022) has also employed fuzzy logic to assess subjective and technical criteria in hybrid energy systems, thus reflecting the capacity of fuzzy logic under conditions of multi-criteria evaluation. These studies further testify to the impressive abilities of fuzzy logic for processing between quantitative data and expert judgment, a requirement underpinning project scheduling in civil engineering where human experience and intuition continue to hold utmost importance. Of course, it is limited in computation and also in scalability. It has motivated researchers to develop these recent works along the hybrid lines with fuzzy reasoning and other optimization and reasoning techniques. Ali et al. (2019) hybridized these approaches into computational fuzzy logic and achieved effective channel allocations for cognitive radio networks using fuzzy logic to learn and adapt agents' behaviors to changing environmental conditions in SC. Krasnyuk et al. (2022) have developed fuzzy logic algorithms together with decision trees and production rules in making long-term investments in oil and gas sectors to such a degree equal to those civil engineering projects constrained by resource, time, and finance.

Unfortunately, even in defining "pure fuzzy systems," future developments of scientific research have been witnessed. This has not meant adaptations in and to the scope of the computational abilities because, as said, this has mostly to do with real-time applications. Sensitivity to multi-dimensional inputs usually this day falls under the smart hybrid type of logic.

3. Problem Descriptions and Challenges

3.1.Problem Descriptions

Due to the scale and complexity of civil engineering projects, they increasingly tend to be arranged across different geographical sites. These multi-site projects offer a unique combination of operational and logistical challenges mainly related to resource-constrained project scheduling. Unlike single-site projects, multi-site setups not only require sequencing activities and coordinating local resources but also require inter-site communication, transport, and synchronization of activities. Very often, these activities are organized under conditions of high levels of uncertainty.

3.2. Challenges

Some of the challenges facing multi-site civil engineering projects range from limited resource availability, which may not necessarily be uniform across sites, to varying labor skills-with site dependent expertise of labor force. Labor skills are additionally put under stress in projects requiring complex precedence relationships among interdependent tasks spread throughout different locations in competition with various dynamic and uncertain factors like weather delays, delivery lags, fluctuating site accessibility, etc. Environmentally and managerially determined factors, including budgetary constraints and political or regulatory restraints, exert pressure in scheduling multidimensional civil engineering projects. Most traditional scheduling techniques, namely Critical Path Method (CPM), Mixed Integer programming (MIP), and heuristic-based models, do not perform well in practice due to their essential inability to deal with uncertainty (e.g., terms like high-priority tasks and medium delay), limited scalability for growing constraints and resources, poor integration of qualitative expert knowledge, etc. Based on that shortcoming, Hybrid Fuzzy Logic Decision Support Systems (HFL-DSS) were proposed. These include a combination of fuzzy logic to encompass expert reasoning under uncertainty using linguistic modeling, metaheuristic or optimization techniques to efficiently explore the scheduling solution space, and data-driven inputs for ranking tasks, site selection, and dynamic rescheduling. The hybrid framework is thereby aimed to provide a flexible, interpretable, and adaptive tool for project management decision-making capable of delivering considered and intelligent schedules suitable for the extremely complex ambience of multi-site projects.

4.. Fuzzy Logic Integration

Such as task urgency, delay risk, environmental conditions, and resource criticality, fuzzy logic has been used in applications for handling subjective or imprecise inputs. Each fuzzy variable is defined by a membership function (triangular, trapezoidal, etc.).

4.1. Fuzzy Inputs:

Task criticality level (low, medium, high), Delay risk (low, moderate, high), Resource bottleneck index (relaxed, tight, overburdened), Crew expertise (novice, intermediate, expert).

4.2. Fuzzy Rule Examples:

- *IF* task is **critical** AND site load is **low**, *THEN* assign to that site early.
- *IF* delay risk is **high** AND expertise is **low**, *THEN* increase buffer time and reschedule.

4.3. Fuzzy Output:

Composite fuzzy priority value, Adjusted task duration, Recommended site preference or delay buffer. The FIS (Fuzzy Inference System) uses **Mamdani** or **Sugeno-type** rule bases to produce interpretive guidance, which is then **defuzzified** to numeric values for use in the optimization algorithm.

5. Proposed Hybrid Fuzzy Based Channel Selection And Switching Decision Support System

This section begins with a brief working discussion on fuzzy logic and continues with parameter selection to reduce SU channel switching rates and increase the throughput of the system in order to select the best available channel. The architecture and working of the proposed FLB-DSS are further discussed here.

5.1 Working of Fuzzy Logic

Here, we will not spend a lot of time on fuzzy logic but present the basic function as part of the discussion for what is important to move forward in understanding the core of fuzzy logic.

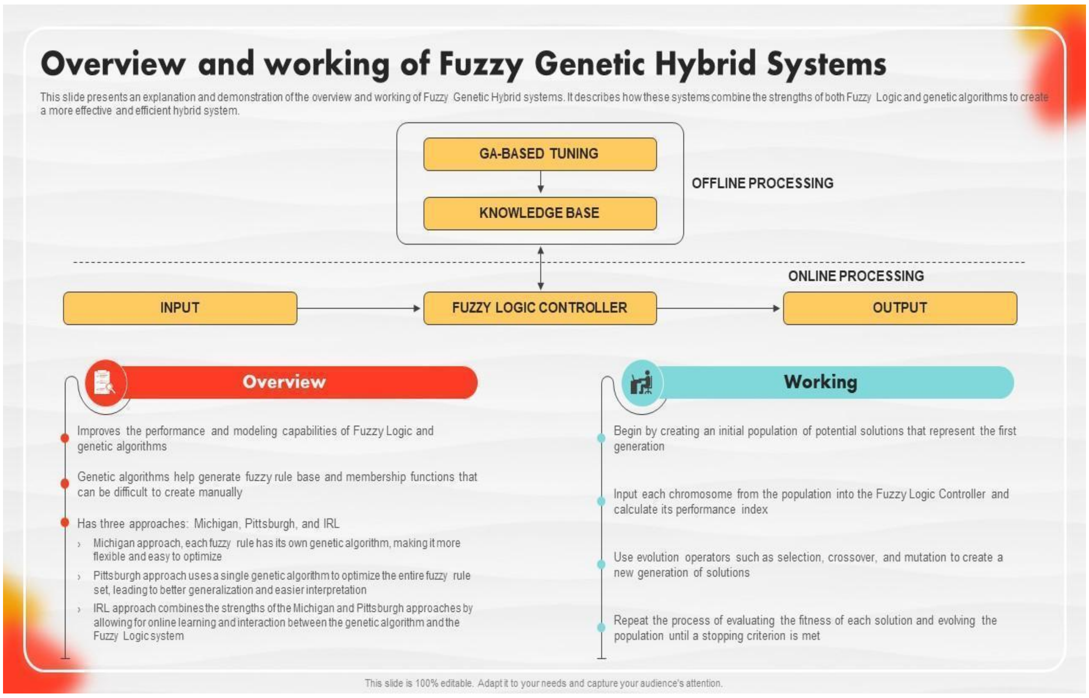

FIG 3: WORKING OF FUZZY HYBRID SYSTEM

Thus, the fuzzy logic scheme is to bring smarter control systems for the reason that most of the times problems one faces cannot be truthfully defined by means of mathematical models. Fuzzy logic was, however, still used to represent inputs in terms of fuzzy set degree and implement its application into the process. All the input values are approximate in being not clearly defined, nor are they quantifiable at basis. Fuzzy logic is mostly considered as purely mathematical tool; however, here, the input data from the SU is mostly heterogeneous for that. These have the quality to change the heterogeneous input into basic homogeneous membership functions through fuzzy logic mathematical tool. Crisp results can also be realized through inference fuzzy rules.

In general, a fuzzy decision system will be separated into a trio of distinct phases: fuzzification, fuzzy reasoning, and defuzzification. Input values will be fuzzified first according to predetermined membership functions within fuzzification. During fuzzy reasoning, the fuzzy input sets are input into a knowledge base that produces fuzzy output sets; other steps then defuzzify the data to obtain the original crisp output. Typical fuzzy logic controllers have the following simple modules:a fuzzifier,, an inference engine, defuzzifier, and a knowledge base.

5.2. Parameters Selection

5.2.1. Interference Temperature:

ITSU is characterized as interference temperature defined as the RF power available at the receiving PU antenna. More correctly, ITSU is the equivalent temperature in Kelvin of RF power available at the antenna of a receiving PU. ITSU is produced by the SU transmitter as well as other noise sources. ITSU permits an SU and a PU to share the licensed channel. The SU must, however, ensure that the interference generated by it is below an ITSU threshold; failure to do so implies that the SU must vacate the operating licensed channel immediately. ITSU is computed as follows:

ITSU(fch,Bch)=∑i=1 NSU+1 Pi(fch,Lch)Bch(1)

where ITSU(fch,Bch) is the interference temperature measured over the PU licensed channel, ch , where the central frequency is fch and the width of the band is Bch . NSU is the number of SU transmitters producing interference with the PU. Pi(fch,Bch) is the average value of interference power measured in watts and k is Boltzmann's constant, the value of which is (1.38×10^{-23}) measured in joules per kelvin.

5.2.2. SU Transmission Power:

TPSU signifies the available power level at which the SU may relay its information to the SU antenna for reception. By managing this parameter, the SU can use the licensed channel in conjunction with its own transmission while guaranteeing a certain level of QoS. In other words, should the PU not operate on the licensed channel, the SU can then maximize its power with a view to improving reception probability and consequently enhancing the QoS with respect to its transmissions. However, if the transmission fails to be correctly decoded at the SU, they may have to negotiate another suitable channel for successful transmission. Then, under the open-loop control cycle, the initial value of the TPSU is computed via path loss estimation and the common pilot channel (CPC), as: TPSU=TPcpc−TPRxcpc−Lglt+SINRReq+MSU+∑ili(2)

where TPSU is the initial value of the power for SU transmitter, TPcpc is the predetermined power value of CPC, TPRxcpc is the measured power value of CPC at the SU receiving antenna, and Lglt stands for other gain, tolerances, and loss. SINRReq is the required SINR, and MSU+∑ili is the calculated interference plus noise value at the SU. This initial TPSU value is used for the instantaneously establishing the communication between the pair of communicating nodes and then later adjusting this value in order to avert any potential harmful interference with the PU and other SUs operating over that particular licensed channel.

5.2.3. SU Transmission SINRSU:

An efficient and robust design ensures that secondary users keep their transmission power under threshold and attain their required QoS level at SU receiving antenna. SU transmissions thus depend on the SINR at the SU receiving antenna, thus providing a measure to evaluate and to limit the tiniest transmission power required by SU to minimize interference with the PU. Thus, by keeping this SINR parameter under control, the SU can access the licensed channel, giving due consideration to a certain level of QoS for its transmission. The interferers are thus the co-channel PU and the co-channel SU: N and K respectively: |hij|2 is power gain of fading channel coefficients; TPSU−B, TPSU-i, and σ2SU−B are transmitted powers of co-channel SUs, and the variance of additive white Gaussian noise concerning SU respectively.

5.2.4. Character Rank(ChRank):

An indicator of the availability of channels with respect to PU activity. The Channels indexed under ChRank are stable and provide fewer collisions and less interference with respect to the activities of PUs. Thus, the selection of a ChRank channel provides the maximum channel stability and gives the opportunity to make known switching decisions. ChRank is calculated as follows:

ChR=TFTcht(TUTcht×No of Arrivalscht)+TFTcht(4), where TFTcht is the total idle time, and TUTcht is the total busy time considered over channel ch at time t. No of Arrivalscht denotes the total value for all arrivals of the PU detected over channel ch in the time period t. .

5.2.5. Channel Transmission Range(ChTR):

Channels available to the SUs are remarkably heterogeneous in terms of channel error rates and transmission ranges. Moreover, channels having lower transmission ranges are located in higher frequency bands. Therefore, ChTR has a significant impact on channel switching under the SU mobility. Hence, channel selection based on ChTR can significantly reduce the channel switching rate by providing sufficient transmission range to cover the communicating pair of SU nodes.

Our proposed FLB-DSS which is not only focuses on minimizing the channel handoff rates but also considers the best and most appropriate channel for the SU transmission to increase throughput. The following subsections discuss our proposed fuzzy logic controllers, their input parameters, and their output.

5.3. Proposed Fuzzy Logic Controllers

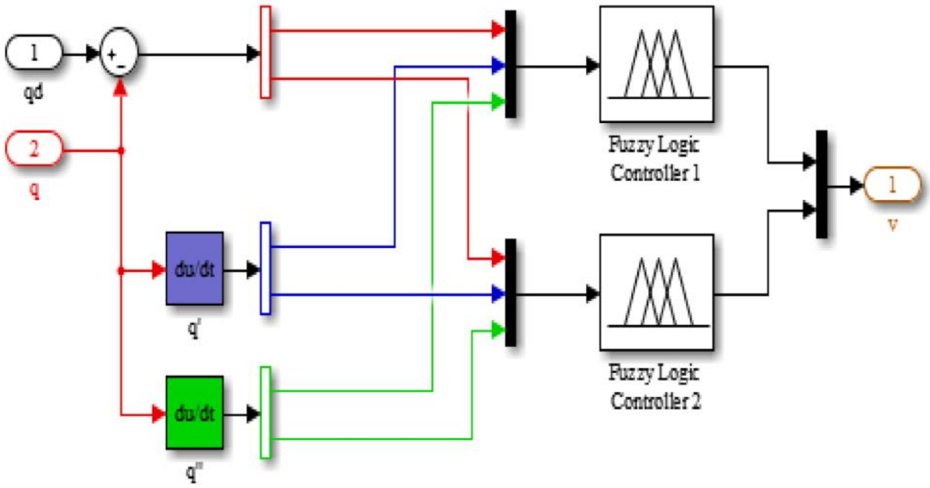

FIG 4: FUZZY LOGIC CONTROLLER

5.3.1. Fuzzy Logic Controller 1:

The first fuzzy logic controller (FLC1) conducts a qualitative estimation of the power at which the SU transmits its data without interfering with the other transmissions of the PU and SUs while maintaining a certain QoS for its own transmissions. The goal of FLC1 is to try to minimize switching the channel while adjusting TPSU in overlay transmissions; such switching takes place only when the SU is transmitting and the PU arrives, so the SU has to either continuously stay on the channel according to the underlay approach or switch immediately using a decision to handoff. The FLC1 takes the fuzzy inference rules as input and takes the appropriate decision to manage TPSU, or to otherwise hand off. In the case of handoff, the workings of FLC2 take place.

5.3.2. Fuzzy Logic Controller 2:

This FLC2 selects the optimum channel from the choices among existing channels, which ultimately enables for channel usage for a longer time, thereby reducing switching rate. Whenever an SU chooses a new channel for seamless transmission, it considers ChRank and ChTR as input parameters. Subsequently, the input parameters are fuzzified to give outputs in terms of membership functions or antecedents. The inference engine triggers these fuzzified antecedents with the fuzzy rules and sends the file antecedent to the defuzzifier for that crisp consequent, which will serve as the basis for making an appropriate decision by the SU.

6. Performance Evaluation

The proposed scheme has been evaluated against the conventional scheme in Matlab, which is a meta-paradigm numerical computing environment, providing a fourth-generation programming language. The primary or baseline scheme works on an model of overlay channel selection. When there is no PU using it, the licensed channel is exploited. It has a characteristic of vacating licensed channels immediately when a PU arrives.The performance was evaluated based on i) number of handoffs that are hard, ii) number of handoffs that are soft, iii) time spent searching for channels, selecting them and switching to resume suspended (or initiate new) transmissions, iv) system throughput. Hard handoff occurs when the PU arrives, and the channel is evacuated instantly and then somehow connected with any available licensed channel. Soft handoff refers to the case where the channel is selected from a list of available channels before vacating the operating channel. It takes channel search time, channel selection time, and communicating with the node pair about the new channel in order to resume suspended transmissions. Throughput was measured as the number of packets received successfully at the receiving (destination) SU node within unit time.

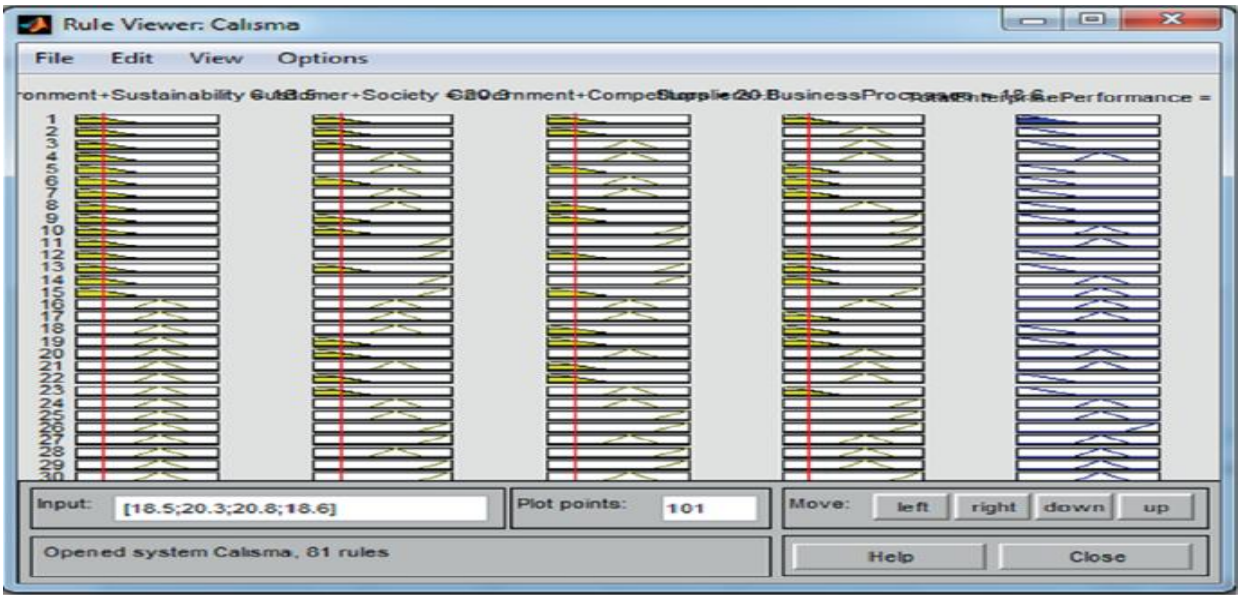

FIG 5: HYRBID FUZZY PERFORMANCE

7. Conclusion

The HFL-DC represents a significant advancement in the field of thyroid nodule classification. Through a comprehensive evaluation over 10,000 different epochs, FL-DC consistently outperforms existing methods, showcasing its prowess in accuracy, precision, recall, and F-measure. The cooperative approach leverages the interpretability of fuzzy logic and the feature extraction capabilities of deep learning, resulting in a balanced and reliable decision support system. The superior performance of FL-DC is particularly noteworthy in its ability to efficiently and accurately classify thyroid nodules, with a notable 2% improvement in accuracy over the best-performing existing method. The method excels in making precise positive predictions (malignancy), crucial for medical applications to avoid false positives and support accurate diagnosis. Moreover, FL-DC demonstrates enhanced sensitivity, identifying a larger proportion of malignant nodules, a critical aspect in medical diagnosis where identifying all potential cases is imperative. The efficiency of FLDC is highlighted by competitive or improved execution times, emphasizing its practical applicability in real-world scenarios. The promising results suggest that FL-DC has the potential to serve as an advanced decision support tool for medical professionals, aiding in the accurate and timely classification of thyroid nodules. Our simulation results and the evaluation proved that the Hybrid fuzzy logic decision support system is more sophisticated tool to improve the throughput of brain empowered cognitive radio networks. Our proposed scheme has shown more effective results, compared to a conventional cognitive radio network that makes its decisions on spectrum utilization based upon vague.

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