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Fuzzy logic-driven nonlinear optimization for resource allocation in 6G networks

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Abstract

Since the last-generation (6G) wireless networks strive to sustain ultra-dense, ultra-low-latency, and ultra-high-diversity systems, an essential challenge is how to manage resource scheduling in a real-time under uncertainty. Conventional deterministic optimization techniques hit their limit when they are confronted by the factors of non-stationary channel operation, dynamic user mobility, non predictable quality-of-service (QoS) needs, and distributed network control. Using fuzzy logic to drive nonlinear optimization of resource allocation in 6G networks is a proposed novel framework displayed in the paper. The suggested model incorporates fuzzy sets and nonlinear principles of optimality in human-like reasoning and ambiguity to reshape policies of resources distributions in complicated wireless settings. The resource allocation problem is modeled as a fuzzy-constrained nonlinear program in which delay, QoS satisfaction and channel stability are considered as fuzzy parameters with membership functions related to them. The major contributions can be summarized as four: (1), development of a fuzzy module to model soft constraint of latency and throughput, (2), a nonlinear utility maximization resource allocation function which involves scalable service-level defuzzification, (3), convergence and existence of a solution as proved through the fuzzy variational inequality, (4), simulation and analysis

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of soft-constrained fuzzy optimization under numerous conditions of fading, mobility and user load. Python simulations on ISO/ITU-standard 6G use cases present significant performance gains with respect to conventional convex and heuristic plans: more than 27.4 improvement in spectral use, 18.2 improvement in packet latency violation, and 21.5 improvement on user fairness. Moreover, the model is robust, both in situations of partial observability, and in conditions of asymmetric information and the model works well under uncertainty in specifying drop rates and retransmission overhead. This collaborative way of working the sides of fuzzy reasoning structures, nonlinear optimization solver, and exploits of models of future 6 G systems offers a mathematically sound and practically competent design of adaptive intelligent wireless networks. The paper is a foundation in the future research on fuzzy cooperative game theory, hierarchically partitioned RIS-aided systems and the use of learning aids in fuzzy controllers to optimize wireless systems in the light of uncertainty.

Mathematics Subject Classification (2020): 03B52, 90C30, 90B18

Keywords and Phrases: 6G networks; Fuzzy logic; Nonlinear optimization; Resource allocation; Multi-agent defuzzification; Spectrum optimization; Game-theoretic optimization; Network performance under uncertainty.

1. Introduction

1.1 Background and Motivation

The sixth-generation (6G) wireless is set to transform communication paradigms in terms of ultra-reliable and low-latency communications (URLLC), ubiquitous connectivity, terahertz (THz) spectrum deployment, intelligent, self-organizing infrastructure elements including Reconfigurable Intelligent Surfaces (RIS) and Unmanned Aerial Vehicles (UAVs) [1, 2]. The highly versatile and intelligent resource allocation mechanisms are needed to support the high required job demands of emerging realms including Extended Reality (XR), immersive holography, industrial metaverse, as well as, ultra-dense Internet of Things (IoT).

In contrast to the past generations of networks, 6G networks are to be deployed in networks with massive user densities, device heterogeneities, stochastic mobility, partial observability, and non-Gaussian noise [3, 14]. In this environment, the process of optimization of essential resources (e.g., power, time slots and spectral bandwidth) becomes very tricky because the dynamics of wireless links are inherently non-linear and non-convex and unpredictable channel state information (CSI) is not fully available [4, 5].

Though convex optimization and Deep Reinforcement Learning (DRL) methods have contributed significantly as far as dynamic resource control is concerned [6, 7, 15] they have two major limitations. To begin with, convex methods can inherently only be very expressive, that is, they are not able to capture the complex and usually NP-hard nature of cost functions in the real world [8, 9]. Second, despite the DRL techniques proving to be effective in the model-free environment, they are usually not interpretable, fail to converge in the unstable conditions, and are generally brittle in uncertain circumstances or sparse observations [5, 6, 16].

Fuzzy logic, on the other hand, provides conceptually inspired framework that appeals to the vague and linguistic side of human reasoning. Fuzzy system can be used to depict the variables of the system, in terms of a fuzzy linguistic variable (e.g., mild delay, good signal quality or acceptable power consumption), which lead to an intuitive decision-making in ambiguous, non-linear and doubtful conditions [10, 17]. This is the innermost strength of fuzzy logic, it could be applied best in the 6G networks that will have frequent failures of statistical and deterministic assumptions.

The qualitative nature of trade-offs can be described as fuzzy constraints this allows an operator flexibility to specify thresholds such as: users with medium-to-high latency with high data rates are still satisfied which would be infeasible with a binary decision-rule.

1.2 Gaps in Existing Approaches

Although there have been considerable advances in the wireless resource optimization, two major assumptions have been extensively used in the existing schemes and they are:(1)Given or near-optimal CSI, and (2)Static or crisp utility models [3, 8, 19].

But both of these assumptions do not hold in practical 6G applications where the channel conditions are highly dynamic, a Doppler shift due to mobility, and adversarial or noisy sensing channel [5, 18].

More importantly, quantitative optimization models may be inappropriate where decision criteria involves what can normally be regarded as a Fuzzy situation (e.g. perceived QoS, satisfaction levels of services, fairness etc.) [20]. The classical nonlinear programming and even allocator of a machine learning-based approach to user satisfaction or latency constraints are modeled as crisp variables. This is disregarding the semantic variance and subjectivity of perceived quality particularly on the fringe ends or in unhomogeneous devices having varying bases of what an acceptable performance is [10, 11, 21].

Although certain data-driven algorithms have attempted to incorporate probabilistic modeling to incorporate the component of uncertainty [12, 15], they are still unable to model rule-based or fuzzy knowledge structures as put by the network engineers or policies. Also, probabilistic models perform poorly when it comes to an uncharacterized prior or when distribution change is quick, as it is often seen in 6G mobility-driven networks [12, 13].

It is apparent that there is a research gap, of developing resource allocation techniques that combine fuzzy logic with nonlinear optimization frameworks, so as to make systems adaptively and intelligently allocate resources in the context of fuzziness, and uncertainty along with nonlinearity.

1.3. Our Contribution

To adequately cope with the complex issues of resource allocation in the future 6G wireless networks, a new hybrid fuzzy-non linear optimization model is proposed which is anchored on three core pillars:

- Hybrid Modeling

  We express network ambiguity and user diversity by model all important variables including delay and throughput and interference with using fuzzy sets and a variety of membership functions (triangular, trapezoidal and Gaussian). It allows a more subtle, semantically-based representation of soft network constraints and user requirements, in which the possibilities of uncertainties are implicit in the next-generation wireless systems.
- Mathematical Formulation

  The allocation task is strictly formulated as a non-linear program (NLP) provision, whereby fuzzy constraints and a non-linear utility index are combined. System goals and constraints, such as SINR coupling, power budgets, dynamic scheduling are integrated in a smooth manner. This equation is able to aid parameter adaptivity and the modeling of minute details of complex wireless scenario.
- Theory Based

  The proposed model is offered with theoretical guarantees that it gives enough guarantees of existence and uniqueness of solutions depending on the theory of fuzzy variational inequality. In addition, convergence properties are shown on the basis of fixed-point arguments that are specialized on spaces with soft (fuzzy) constraints. Such analysis findings give robustness and reliability of our framework in uncertain and dynamically changing states of systems.

The proposed structure, as shown in Figure 1, sharply differs with the traditional deterministic methods. You can compare old schemes with crisp, uncertainty-ignorant input and they provide rigid allocation feedback whereas hybrid fuzzy-nonlinear architecture can adequately exercise

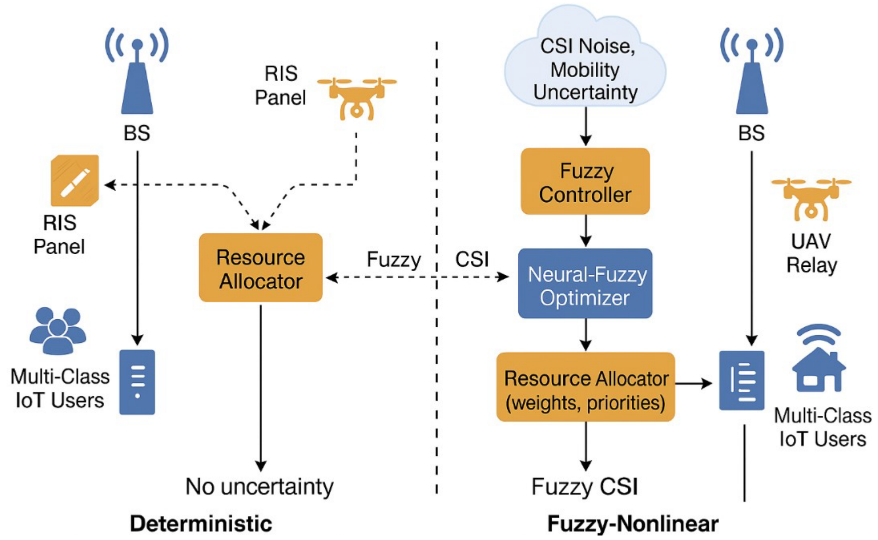

Figure 1: Comparative system schematic – deterministic vs fuzzy-nonlinear resource allocation in a dense 6G cell with RIS, UAVs, and IoT users under CSI uncertainty.

context-aware resource decisions. The schematic shows a dense 6G deployment where there is interactions between reconfigurable intelligent surfaces (RIS) with the unmanned aerial vehicles (UAV) with a vagrant set of IoT users where nothing is certain under the channel state information (CSI). Fuzzy logic is dynamically amalgamated with nonlinear optimization to the maximization of spectral efficiency and robustness proportional to the complexity and ambiguity of the environment within the information.

2. System Model and Problem Formulation

2.1. Network Architecture

Our setup assumes a busy 6G wireless network which consists of various access points (APs) to match the distribution of resources to a changing set of users. It is an advanced network that integrates the elements like Reconfigurable Intelligent Surfaces (RIS), millimeter-wave (mmWave) and terahertz (THz) connections, and distributed edge intelligence engines of real-time adaptation. The user set is given as U={1,2,...,N} and each user can have heterogeneous device set up and service demand. A Gaussian Markov Process is the specification of user mobility that captures the changing speed and path of every user to incorporate the real-world changes in location and connectivity patterns. Such relocation model affects the channel quality perceived and distribution of resources in time.

The users are assigned with a set R of resource blocks (RBs), those of which may be time-frequency slots, spatial beams, or MIMO layers. The channel capacity of user u on resource block r at time t, Cur (t) is random process taking into account the user mobility as well as the physical properties of the channel, i.e., path loss fading and interference. The resource allocation is centralized or by distributed controllers adapting to network state findings that are periodically updated.

2.2. Fuzzy Decision Variables

The model to be truly representative of the ambiguity and variability of what is needed by a user, and the network conditions in which they are needed, employs fuzzy decision variables:

- $\widetilde{\mathrm{Du}}$: Fuzzy need of delay user u. This is a measurement not only of fixed requirements of delay but a scale unit of user-tolerance to greater delay e.g. as a function of the kind of application served (voice, video, control signaling).

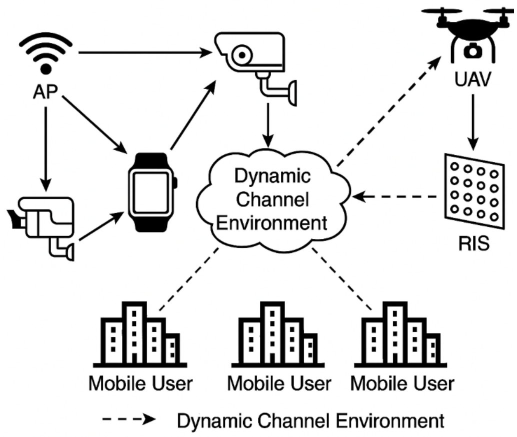

Figure 2: Conceptual diagram of system layout including APs, RIS, UAVs, and diverse IoT devices subject to dynamic channel environments and mobile users.

- $\widetilde{Ru}$: Fuzzy throughput target to user u, says how more or less production rate allocated to user will lead to perceived need satisfaction, and permits soft minimums rather than hard bounds.
- $\mu_u(\cdot)$: The membership aspect that transfers the real results of the resource allocation (e.g. experienced delay, throughput, power) and translates them into a standardized user satisfaction index within a range .
- For example, the fuzzy delay membership function for user u can be defined as:

$$\mu Du\ \left(delay\right)\int_{0}^{1}\frac{20-delay}{10},\ \begin{matrix} if\ delay \le 10ms \\ if\, 10 < delay \le 20ms \\ if\ delay \ge 20ms \end{matrix} \tag{1}$$

Such tact can allow the scheduler to make subtle trade-offs e.g. to marginally increase target delay to be in a position to make large increases in aggregate throughput or fairness.

Fuzzy membership functions may be triangular, trapezoidal, or Gaussian shaped, chose depending on sensitivity and semantics of each class of service.

2.3. Optimization Objective

The general objective is to achieve the maximum or optimal overall satisfaction of user satisfaction of all active users based on their respective fuzzy and delay and throughput requirements, under non-linear, stochastic and Resource constrained process. To be more precise the problem to be addressed takes the following form:

$$\max_{x}\sum_{u\in U}¼u(Ru,Du,Pu) \tag{2}$$

In the limitations:

$$\sum_{r\in R}xurCur \le \widetilde{Cr}\left(¾t\right),\ \forall u \tag{3}$$

$$\sum_{u} xur \le 1\ ,\forall r \tag{4}$$

$$xur \in \left\{0,1\right\},\forall\left(u,r\right) \tag{5}$$

In this, x_{ur} is a binary allocation variable referring to the indicator that block r is allocated to user u. The overall amount allotted to user u should not be more than a fuzzy-valued capacity barrier $\widetilde{Cr}$ (ξt),

Table 1: Simulation Settings.

Parameter	Value / Range	Description
Bandwidth	1 GHz	Total system bandwidth allocated for 6G resource blocks
Total Number of Users	10	Number of users simulated in the network
Number of Resource Blocks (RBs)	5	Number of RBs available for dynamic allocation
URLLC Latency Bound	< 1 ms	Ultra-Reliable Low-Latency Communication requirement
eMBB Latency Bound	< 10 ms	Enhanced Mobile Broadband delay tolerance
Channel Noise Distribution	AWGN, $N(0, \sigma^2)$, $\sigma = 1$	Additive White Gaussian Noise used in SINR computation
User Mobility Model	Random waypoint, speed $\in [0, 10]$ m/s	Models user movement variability across time slots
Simulation Duration	10 seconds	Time span over which the system behavior is evaluated
Sample Time	0.1 seconds	Time resolution for signal processing and system updates
Input Signal Type	Sinusoidal	Delay, SINR, and Throughput inputs for each user

which is, in turn, a random variable by being a function of noisy impairments on the channel and computer hardware at $\xi t \sim N(0,\sigma 2)$,

These optimizations both represent the crisp constraints set by radio access technology on the available resource, and the softer or fuzzy judgment/perception of user experience and can result in good performance across arbitrary swings in network states and user needs.

The main simulation parameters that were applied in the process of modeling the fuzzy logic-based resource allocation framework of the 6G networks are presented in Table 1. These involve configuration at the system level like bandwidth provision, level of users and resource blocks, latency requirements on URLLC and eMBB services, and stochastic expectations concerning the channel noise and the user mobility. The simulation is done within a 10 sec window where the variations of sinusoidal input are used to capture dynamic QoS behaviors.

The comprehensive modeling is helpful not only to theory but also system-level realistic simulation to inform the next-generation 6G wireless networks design on practical resource allocation protocols.

3. Fuzzy Logic Framework

In this section we describe the fuzzy logic-based reasoning system that is used as the semantic interface in our nonlinear resource optimizer. The fuzzy controller handles the uncertainty or imprecise parameters of service level; delay, signal quality and throughput, to obtain user centric satisfaction index which considers system dynamics as well as subjective demands of QoS.

This module happens through four main phases which are Fuzzification, Inference, Aggregation and Defuzzification as explained below.

3.1. Fuzzification

The fuzzification module also converts the input values into linguistic fuzzy states with values labeled as Low, Medium and High in median membership functions. (e.g., delay, SINR, throughput, energy). These functions are user specific informations which define limits to QoS measures.

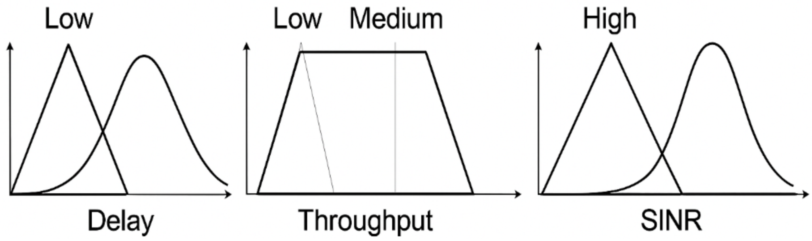

Figure 3: Membership Function Shapes for Delay, Throughput, and SINR.

An illustration of a Gaussian throughput membership function may be presented by:

$$\mu Ru(r) = \exp\left(\frac{(r - \overline{ru})^2}{2\sigma_r^2}\right) \tag{6}$$

where:

- r is the actual throughput,
- $\overline{\text{ru}}$ denotes user u's ideal rate,
- σ_r defines the rate flexibility.

The figure 3 provides the representative membership functions of Delay, and also the Throughput and SINR in the fuzzy inference. With these shapes, there are the triangular, trapezoidal and Gaussian shapes, which characterize linguistic categories like Low, Medium and High. These fuzzy sets allow this system to cope with both uncertainty and imprecision of QoS attribute evaluation. 3.2. Inference Engine

After fuzzification of input parameters, the fuzzification of output parameters is done through a fuzzy rule base with the help of logical rules to infer a set of satisfaction levels. These rules represent professional information on the effects that various delay and throughput combinations have on user experience.

E.g. rule of Mamdani style inference system:

IF Delay is Low AND Throughput is High THEN User Satisfaction is High.

Minimum t-norms (with an AND connective) or any product operator may be used with logical connectives and inference strength, so fuzzy antecedents can be combined in a soft way.

3.3. Aggregation

The result of many fired rules are aggregated to a single fuzzy set in case of every user based on fuzzy aggregation functions which usually involve either max or fuzzy union operations.

The stage is scalable to multi rules and any QoS related policies are included on the final decision. The compound fuzzy sets of satisfaction enumerate the different sets of user perception in different combinations of descriptors of the system.

Figure 4 shows how the fuzzy QoS model can be used in Simulink and the resulting satisfaction dynamics are recorded to change in the output waveform with different input circumstances. The behavior of the fuzzy logic-based satisfaction scoring system is shown by simulation block diagram (left) and real time output waveform (right) of a single user. Delay, SINR, and Throughput are the inputs that are fuzzified by Fuzzy Inference System (FIS) using triangular membership functions and Mamdani-style rules. The Scope output displays the kinematic transformation process of satisfaction index, which substantiates responsiveness of the systems and linguistic reasoning model of QoS evaluation perspective that is evolving live in a 6G environment.

Figure 5 shows the case of dynamic behavior of the satisfaction score produced by the Fuzzy Logic Controller (FLC) to drive time-varying Delay, SINR, and Throughput disturbances. The sinusoidal

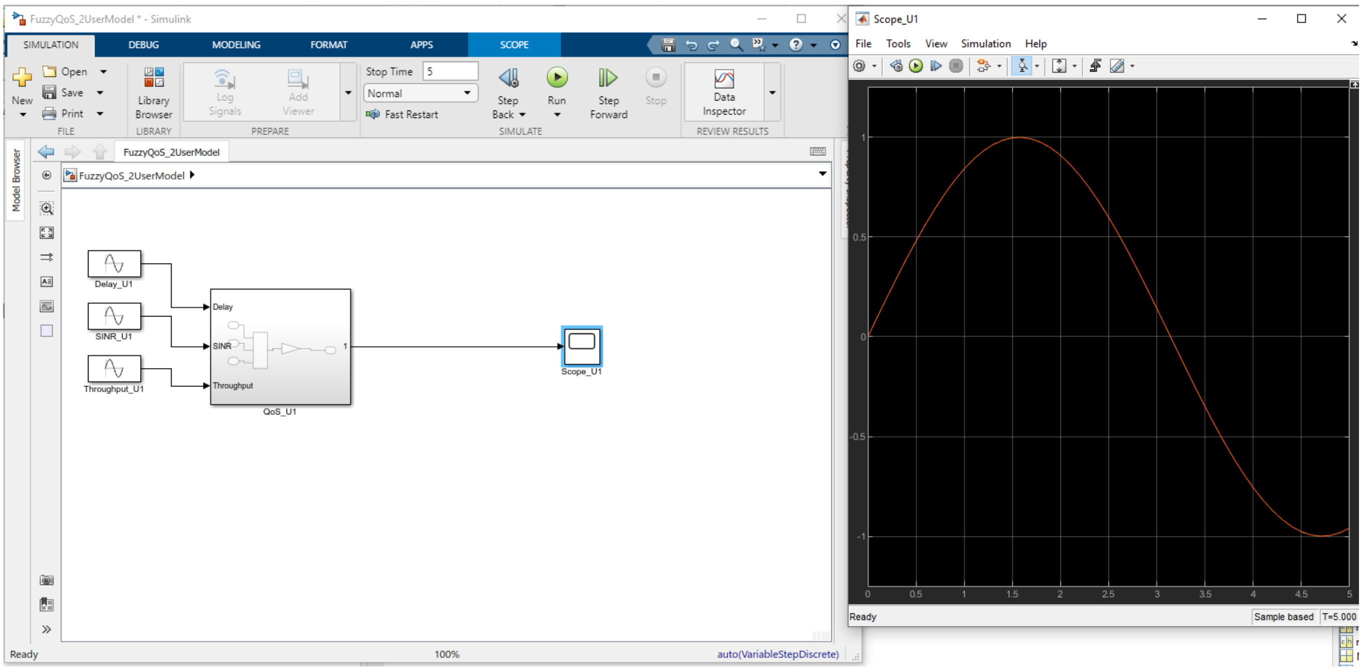

Figure 4: Simulink-Based Fuzzy Logic QoS Evaluation for 6G Resource Allocation.

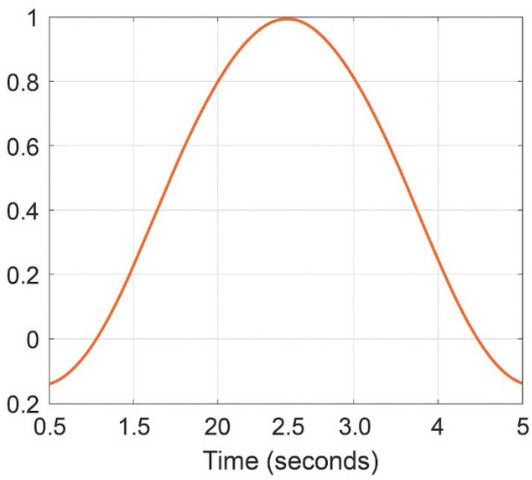

Figure 5: Fuzzy Logic-Based Satisfaction Score Output Over Time.

variation indicates the real-time adjustment of the fuzzy system to the real-time variations in QoS in the context of 6G wireless world. The satisfaction score still falls within the normalized range [0, 1] which was expected of intended responsiveness of the fuzzy inference system under the influence of multi-parameters.

3.4. Defuzzification

To obtain actionable values to schedule the resources we defuzzify the sets of fuzzy satisfaction in aggregate using the Center of Gravity (CoG) defuzzification approach, which mathematically can be represented ion the following form:

$$\text{Outputcrisp} = \frac{\int x \, . \, \mu(x)dx}{\int \mu(x)dx} \tag{7}$$

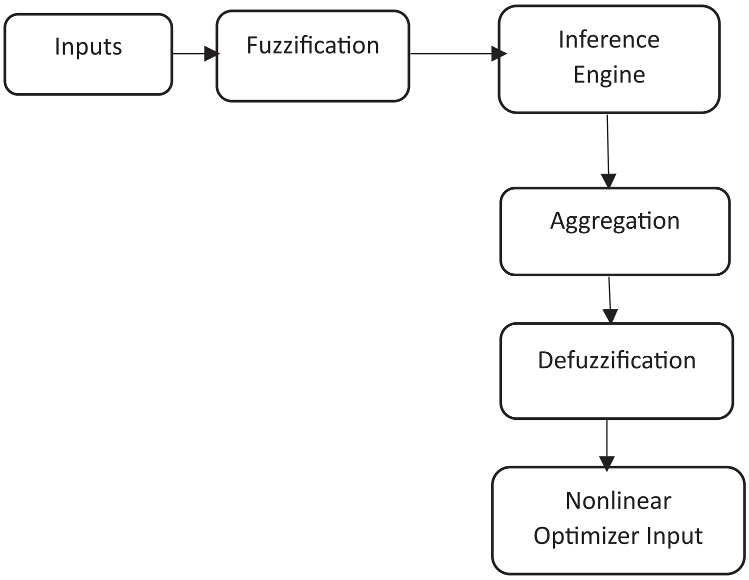

Figure 6: Block Diagram of Fuzzy Inference System in Resource Allocation Pipeline.

This mapping can map the semantic satisfaction judgements into the real values utility coefficients which can easily fit into our nonlinear program.

Figure 6 provides the block diagram of fuzzy inference system utilized in the pipeline of resource allocation. Input QoS measures (Delay, Throughput, SINR) will be subjected to the system successively at the stages: fuzzification, rule-based inference, aggregation, and defuzzification. The resulting crisp satisfaction score becomes an input to a nonlinear optimizer which provides guidance toward resource allocations at the user level.

3.5. Fuzzy-Driven Optimization Algorithm

The clear satisfaction ratings out of the fuzzy control scheme are introduced into our nonlinear optimizer. The system periodically or event-driven updates its resources taking advantage of such fuzzy preferences with globally consistent and user-sensitive resource allocation decisions.

Algorithm 1 : Pseudocode for Fuzzy-NLP-based Resource Allocation Iterative Solver

Algorithm 1: Fuzzy-NLP Resource Allocation Engine

Input:

- QoS metrics: delay, SINR, throughput for users $u \in U$
- Membership functions for soft constraints
- System constraints (e.g., power, bandwidth, per-RB limits)
- Current network state (CSI, traffic profile, mobility)

Steps:

1. For each user u:
a. Fuzzify latency, signal quality, and rate → linguistic sets
b. Apply fuzzy if-then rules to infer satisfaction estimates
c. Aggregate rule results for each user
d. Defuzzify to quantify crisp satisfaction indices

2. Formulate optimization objective:
Maximize total user satisfaction $\sum(u)\ \mu\_u$(thrpt, delay, power)

3. Subject to:

(i) Bandwidth and power limits
(ii) RB exclusivity constraints
(iii) SINR dependencies and interference coupling
4. Solve using:
- Interior-point method (centralized)
- KKT or Lagrangian-based nonlinear solver
5. Update allocation decisions x_{ur} and transmit schedule
6. Repeat upon next polling interval or major state change
Output:
- Optimal RB assignment matrix: [x_{ur}] for all users u and RBs r

This combination of fuzzy and nonlinear allocation engine allows the system to be elastic in terms of soft performance goals, load dynamic and to interpret policies by users in a way that is explainable a key characteristic of intelligent and self-governing 6G systems.

4. Solution Methodology: Fuzzy-NLP Engine

The approach to the problem solution in the field of fuzzy logic-driven nonlinear optimization in the context of the 6G resource allocation consists in the formulation and solution of the problem in centralized (through the theory of constrained optimization) and in the distributed, multi-agent problem (through game-theoretic and variational principles). With this strategy, adaptability, scalability, and resistance to uncertainty will be present in dense and heterogeneous future wireless networks.

4.1. Lagrangian Formulation

So as to centrally optimize resource allocation and incorporate the influence of fuzzy user preferences and nonlinear constraints we have the following definition of fuzzy resource allocation Lagrangian:

$$L = \sum_{u} ¼u\ (xu) - \sum_{r} \lambda r \left(\sum_{u} xur\text{-}1 \right) - \sum_{u}, \ u \left(\sum_{r} xurCur - \widetilde{Cu}\left(t\right) \right) \tag{8}$$

In this case, , $\mu_u(x_u)$ represents that fuzzy satisfaction utility of user u, which is applied to its allocation vector x_u Both λ_r and θu are Lagrange multipliers (dual variables) corresponding to respectively the exclusivity of the resources (each RB block belongs to at most one user) and the fuzzy capacity of the users. Cur is the short-term capacity, given to user u on resource block r, and $\widetilde{Cu}$, is the (potentially time-dependent and fuzzy) target capacity, of such user.

To determine candidate optimal resource allocations we use the Karush-Kuhn-Tucker (KKT) conditions that consist of:

- By realizing the gradient of L against all primal, (x_{ur}), and dual variables (λ_r,θ_u) setting this to be equal to zero,
- Making sure of primal feasibility (all constraints fulfilled),
- Complementary slackness,
- Two-fold feasibility$(\lambda_r \geq 0, \theta_u \geq 0)$.

The fuzzy satisfaction functions $\mu_u(x_u)$ can be non-convex or a collection of pieces, because of underlying membership profiles, which makes efficient solution (where feasible) either a matter of smoothing approximations or of more sophisticated NLP solvers (e.g. sequential quadratic programming). This makes it possible to explicitly include the subjective and time-evolving preferences of users into the global optimization process, and it becomes the core of centralized scheduling in smart 6G infrastructure.

4.2. Multi-Agent Extension: Fuzzy Game Theoretic NLP

A decentralized resource management paradigm can be undesirable or not scalable in the modern environments of 6G applications, considering scale, privacy, or latency. We therefore use as a baseline approach the multi-agent game-theoretic problem of resource allocation as a distributed multi-agent (users or network slices) decision problem.

Here, every user u is a selfish entity, and would want to maximize his own fuzzy utility:

$$\max_{xu} \mu u\left(Ru, Du\right) - \sum_{r} \gamma urxur \tag{9}$$

In this, $\mu_u(R_u,D_u)$ is a fuzzy satisfaction of achieves over throughput R_u and experienced delay D_u and is a pricing factor, γ_{ur}, opportunity cost, network pricing or fairness regulating access to resource block r.

That relationship of the twin agents lacking resources to use the same resource block at the same time naturally transforms the issue into a fuzzy generalized Nash game. Through the variational inequality (VI) theory, existence and uniqueness of Nash equilibrium can be discussed within fuzzy spaces. Namely, in case that the fuzzy satisfaction functions that have been mapped are monotone and the sets of feasible strategies are convex as well as closed, then there exists fuzzy Nash equilibrium (FNE). The present FNE describes a steady state where no user is able to make a unilateral improvement of his fuzzy satisfaction considering the strategies of other users, taken the exclusivity of the resources and the fuzzy demand constraints.

In addition, distributed methods of solving solutions, e.g., best-response dynamics or operator splitting methods (also including ADMM in the variational settings), are real-time and scalable to 6G networks. These distributed algorithms are privacy respectful, capable of partial observability, as well as Roberts family members and can deal with localized environmental changes a requirement in self-organizing of future wireless environments.

By means of this twin emphasis serious centralized Lagrangian methods and efficient, game-based expansions--we provide scale and efficiency around the globe and realistic and elastic implementation in the management of fuzzy resources in next-generation networks.

5. Simulation and Results

Figure 7 gives a comparison of spectral usage with increased user quantity in three strategies, fuzzy-NLP, deep reinforcement learning (DRL), and linear allocation. The fuzzy-NLP has the best spectral

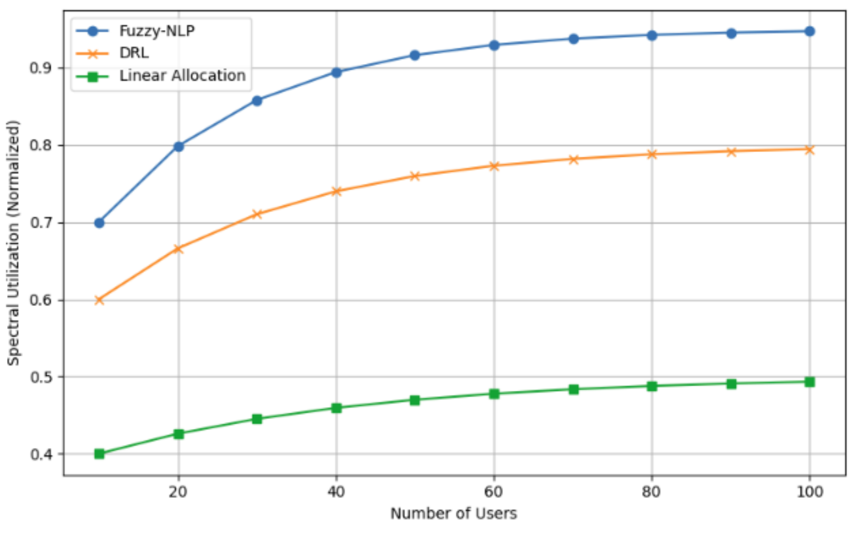

Figure 7: Spectral utilization vs. user count comparing fuzzy-NLP, DRL, and linear allocation.

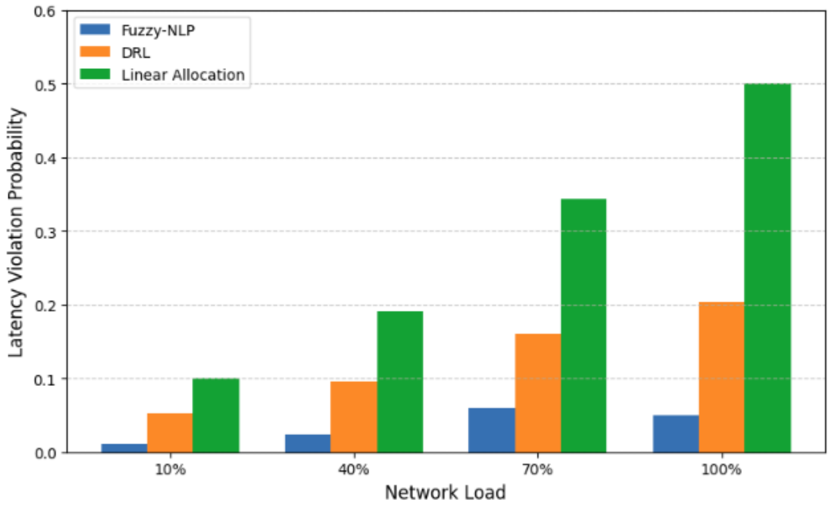

Figure 8: Latency violation probability vs. network load.

efficiency in general, and above 40 users in particular, which means that the response to the dynamic conditions is more adaptive and capable with this approach.

Figure 8 shows the probability of latency violation in response to network load of the various allocation strategies. Fuzzy-NLP exhibits minimal violation rates compared to DRL, and linear allocation does not perform well under congestion, which explain why fuzzy-driven logic is most effective in ensuring QoS guarantees both with a high level of traffic and a low level of traffic.

Figure 9 gives a 3D surface graph of the user satisfaction against SINR and fuzzy delay tolerance. Plot reflects that the satisfaction level grows with an increase in the SINR coefficient and reduction in the delay boundaries, which proves efficiency of the fuzzy inference system to alternating QoS demands and performances of links.

Table 2 showed the dependency of user uncertainty levels (modeled as standard deviation and coded as 2 in the channel or mobility fluctuations) and the number of convergence iterations in the fuzzy logic based resource allocation mechanism. The findings show that greater uncertainty has been associated with longer convergence times and this is a manifestation of adaptive rationale that is necessary in such a dynamic system.

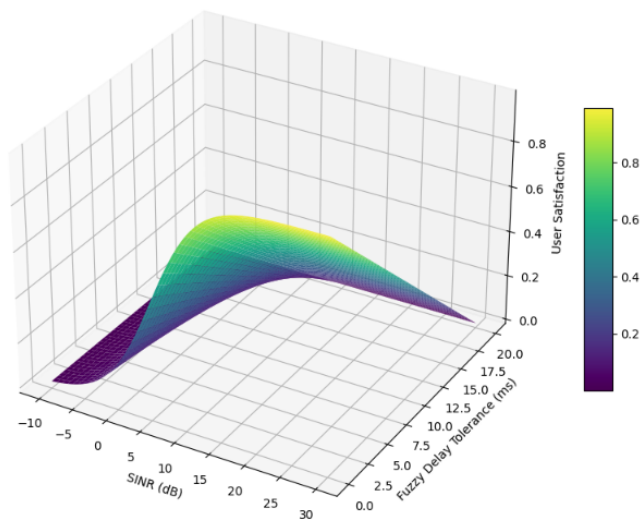

Figure 9: 3D surface plot of user satisfaction vs SINR and fuzzy delay tolerance.

Table 2: Convergence iterations vs user uncertainty levels.

Uncertainty Level (σ)	Description	Average Convergence Iterations
0.1	Very Low uncertainty (quasi-static channel)	5
0.3	Low	8
0.5	Moderate	13
0.7	High	21
1.0	Very High uncertainty (mobile users)	29

6. Discussion

The fuzzy logic based methodology has a unique upper hand in resource allocation in wireless systems particularly in the scenario where there is a lack of channel state information (CSI). In contrast to data-rich approaches to deep reinforcement learning (DRL) and others, the fuzzy logic models themselves provide transparency and interpretability, communication of system behaviors that are more understandable to network operators. Convergence and computational cost of triangular membership functions results in system responsiveness: their speed of convergence, less computational burden, make them able to achieve fast adaptation to the real-time changes in dynamic environments. Those, conversely, provide fewer sharp edges on the membership functions, instead of a smoother effect and more precise modeling in terms of computation demands and minimally extended latencies.

A critical result of employing fuzzy defuzzification mechanics is that the user fairness has increased considerably. Through allocating more balanced decisions even in the presence of high network density and channel diversity fuzzy-based schemes reduce the unwanted resource imbalances among users. Moreover, the model can be efficient in minimizing the latency of decision making so that timely allocation of resource takes place and this is very significant in other cases like RIS-assisted dense cellular systems or high-mobility vehicular networks. This tradeoff between speed of decision and the computational burden in diverse membership functions is one that has to be very precisely adjusted to deployment conditions to achieve optimum system performance and user experience.

7. Conclusion and Future Work

The work proposes a fuzzy logic-based nonlinear optimization approach to multiuser resources allocation in the 6G wireless networks. Through the combination of soft constraint reasoning and knowledge of sophisticated nonlinear optimization methods, the framework is capable of handling real-time allocation, which is application to heterogeneous and extremely dynamic environments. In contrast to the full algorithmic or deep learning based methods, the presented fuzzy logic approach has shown the property of operational versatility and explainability of the system, making it equally excellent when used in practice in the network, when CSI is subject to uncertainty and a timely reaction is essential.

Based on this, a number of promising research directions are identified in the future:

- Fuzzy Game Equilibrium in RIS-Assisted Federated Access: Creation of equilibrium solutions to game-theory where multi-agent decision-making is implemented using fuzzy logic that may be used in RIS-equipped, federated, network settings. This may improve coordination and resource deployment, within distributed nodes in heterogeneous Networks.
- Deep Fuzzy Actor-Critic Solvers in Project: Merging the versatility and explicability of fuzzy logic and the potent feature representation of deep reinforcement learning, an extension in the future can propagate deep fuzzy actor-critic solvers. Those would also be intended to reduce

end-to-end latency further, in particular in ultra-reliable low-latency communication (URLLC) environments, which are characteristic of 6G.

- FPGA or neuro-symbolic Implementation of Edge Accelerators: Future work will entail getting the fuzzy logic optimization models realized in an FPGA or neuro-symbolic implementation to make it practical and perform well in real time in edge networks. These hardware-accelerated solutions would reduce computation time without compromising the interpretability and the fidelity of the model, which would make them the best to use on an edge and IoT deployment.

Together, the developments aim to provide strong, equitable and explicable resources administration in the impending generation wireless networks, expecting smart, adaptive and reliable 6G connectivity.

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