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RESEARCH ARTICLE

Evaluation of the Routing Algorithms for NoC-Based MPSoC: A Fuzzy Multi-Criteria Decision-Making Approach

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This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by the Ethical Standards of the Institutional and/or National Research Committee and performed in line with the 1964 Helsinki Declaration.

ABSTRACT Routing algorithms play a crucial role in the performance of Network-on-Chip (NoC)-based Multi-Processor Systems-on-Chip (MPSoC). However, the selection of appropriate and effective routing algorithms poses a challenge for designers, given the multitude of assessment criteria, data fluctuations, and varying criteria importance. In this study, we propose a comprehensive assessment of various routing algorithms, aiming to identify the most suitable and effective routing algorithm that satisfies designers' system-level requirements and assessment criteria. This research integrates the Fuzzy-Weighted Zero-Inconsistency (FWZIC) method and the Fuzzy Decision by Opinion Score Method (FDOSM). The utilisation of the Z-Cloud Rough Numbers (ZCRNs) environment addresses the challenge of two types of uncertainty, providing a framework for managing ambiguity in the data and achieving a higher level of data freedom. Our methodology consists of two main phases. Firstly, the decision matrix is constructed based on the performance assessment criteria and routing algorithms. Secondly, we employ the ZCR-FWZIC method to derive the weights for each criterion and subsequently employ the ZCR-FDOSM-BM approach to rank the routing algorithms. The analysis reveals that Adaptive Dimensional Bubble Routing (ADBR), Message-based Congestion-Aware Routing (MCAR), and Dynamic and Adaptive Routing Algorithm (DyAd) are ranked as the top three routing algorithms, respectively. This research presents essential implications for designers and system engineers involved in NoC-based MPSoC, offering insights to enhance decision-making processes and facilitate the selection of an appropriate routing algorithm.

INDEX TERMS Z-number, ZCR-FDOSM-BM, ZCR-FWZIC-BM, multi-criteria decision-making, MPSoC.

I. INTRODUCTION

The Introduction section includes five sub-sections. Section I-A introduces the motivation behind the study. Section I-B provides an in-depth analysis of the problem statement and the associated challenges. Section I-C provides research gaps and contributions. Section I-D provides an exhaustive summary of the objectives. Section I-E presents the significance and Implications.

A. MOTIVATION

The field of computing heavily relies on MPSoC (see Figure 1) technology, which finds applications in diverse domains such as mobile computing, embedded systems, and personal computers like laptops and tablet PCs. With the continuous advancement of technology, MPSoCs in embedded

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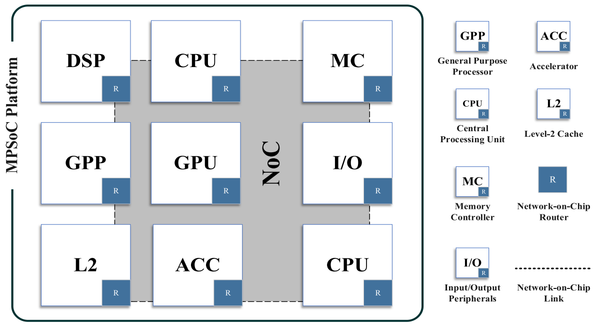

FIGURE 1. NoC-based MPSoC Platform with different IP cores, adopted from [3].

systems are becoming increasingly complex and larger in scale [1]. In response to these challenges, the concept of NoC has emerged as a promising solution for on-chip communication [2]. NoC provides a communication network that offers enhanced efficiency for MPSoCs. One of the most critical motives behind the routing algorithms ranking is that the routing algorithm in NoC-based MPSoC is an essential part of the development of communication architectures that are both efficient and capable of scaling effectively. Designers can achieve the development of high-performance, energy-efficient, and reliable MPSoC systems that are customised to meet specific application requirements by carefully considering factors such as performance, size topology, power consumption, fault tolerance, latency, and design complexity. This allows for a balanced approach that takes into account various trade-offs [4], [5].

B. PROBLEM STATEMENT AND CHALLENGES

The designers and system engineers of NoC-based MPSoC in the IoT domain have faced problems in evaluating the performance of the utilized routing algorithm to route the data packets among routers of NoC and prevent different traffic congestion, deadlock, and livelock issues, especially because no single routing technique is superior to the rest [6]. In addition, many routing algorithms and techniques lack routing efficiency and implementations [7]. The selection of routing techniques in on-chip communication in the context of MPSoCs poses several challenges that necessitate continuous attention to meet design requirements [3]. These challenges encompass complex evaluation criteria, diverse workload scenarios variation, conflicts in criteria, and the need for performance optimization [8]. The evaluation of routing algorithms requires consideration of multiple criteria simultaneously, which often have conflicting objectives. Moreover, the evaluation process becomes more intricate when faced with diverse workload scenarios that demand adaptable routing strategies [9]. To effectively address these challenges and enhance the selection of routing algorithms for NoC-based MPSoCs, MCDM methods provide a viable solution. MCDM methods offer a systematic and rigorous approach to evaluating routing algorithms by simultaneously considering multiple criteria [10], [11]. However, there are substantial hurdles to the precision and dependability of MCDM approaches posed by ambiguity in the decision-making process [12], [13]. Ambiguity in the criterion weights, imprecision in the decision-makers preferences, and a lack of knowledge or data are only a few of the causes of uncertainty in MCDM [14], [15], [16]. Since of these issues, it's tough to choose the optimal option since the outcomes may be unpredictable or inaccurate. Furthermore, the choice of the MCDM approach may alter the ultimate conclusion because of the variety of ways in which the methods manage ambiguity [17]. In order to get dependable and robust outcomes, it is essential to take into account the decision context and the causes of uncertainty while attempting to handle ambiguity in MCDM approaches. By addressing these challenges, researchers can contribute to the advancement of NoC-based MPSoC architecture and overcome the limitations of traditional bus-based systems. Ultimately, this progress will lead to improved performance, efficiency, and reliability in the design of MPSoCs.

C. RESEARCH GAP AND CONTRIBUTION

Many designers and system-level engineers consider routing algorithms as a key vital principle for enhancing the NoC-based MPSoC. However, the assessment and selection of routing algorithms is still a rising issue that needs to be intelligently solution. Also, previous studies have rarely provided reports on the evaluation and selection procedures employed for identifying the most appropriate routing algorithms using MCDM techniques, and this is considered a theoretical gap. Moreover, the ranking and weighting methods known as FDOSM and FWZIC have been identified as innovative, sophisticated, and resilient approaches [18], [19]. Nevertheless, it is important to acknowledge that FDOSM and FWZIC exhibit certain limitations. In the data-processing unit, the conversion of the opinion matrix into a fuzzy opinion decision matrix is constrained to the utilisation of a single fuzzy application in the first version, specifically, triangular Fuzzy [18], [20]. The alternative ranking results are aggregated and provided solely based on the direct aggregation operator [21], [22]. Unfortunately, previous research seldom takes into account both kinds of uncertainty (interpersonal, intrapersonal). Therefore, the aim of this study is to introduce a new extension known as Z-Cloud Rough Number Fuzzy Sets, which is integrated with FDOSM & FWZIC methods to facilitate decision-making under conditions of uncertainty. Specifically, the focus is on applying this approach to weight and rank routing techniques in the context of NoC-based MPSoC platforms. In summary, this article makes the following significant contributions:

1. This study fills the gap in evaluating the routing algorithms in the context of NoC-based MPSoC and selects the best routing approach.
2. This article proposes a new decision matrix for evaluating the routing algorithms based on a comprehensive

integration of the proposed routing aspects in the prior studies.
3. This study, for the first time, applies an MCDM approach to evaluate the NoC-based MPSoC performance aspects (routing algorithms).
4. This study develops a new formulation by combining the ZCR number with FDOSM named ZCR-FDOSM to solve the vagueness and uncertainty issues and rank routing algorithms.
5. This study develops a new formulation by combining the ZCR number with FWZIC named ZCR-FWZIC for weighting criteria.
6. Applied the new method as a group by using the Bonferroni operator (BM) to rank the routing algorithms to help designers and system engineers choose the appropriate alternatives.

D. OBJECTIVES

This article intends to achieve the following objectives:

1. Identifying the core metrics that routing algorithms are based on in the context of NoC-based MPSoC (decision metrics).
2. Developing a new version of FDOSM that integrates the ZCR technique to enhance the accuracy of ranking routing algorithms in a fuzzy environment.
3. Enhancing FWZIC by incorporating the ZCR number technique in order to provide a reliable weighting of criterion in an environment of uncertainty.
4. Expanding the abilities of ZCR-FDOSM through integrating a group of experts and integrating a new aggregation operator to enhance selecting the optimal routing algorithm for NoC-based MPSoC platforms in a cooperative fuzzy environment.
5. To validate the result of ZCR-FDOSM-BM & ZCR-FWZIC.

E. SIGNIFICANCE AND IMPLICATIONS

The significance and implications include four sub-sections. Section I-E1 why choose an efficient routing algorithm in an NoC-based MPSoC design. Section I-E2 why choose FWZIC to weight the criteria. Section I-E3 why choose FDOSM to rank the alternatives. Section I-E4 why work with Z- Cloud Rough numbers.

1) WHY CHOOSE AN EFFICIENT ROUTING ALGORITHM IN AN NoC-BASED MPSoC DESIGN?

Choosing an efficient routing algorithm in NoC-based MPSoC communication is crucial for several reasons: Performance Optimisation: The choice of a routing algorithm directly impacts the performance ofthe communication system within the MPSoC. An efficient routing algorithm can minimise latency, maximise throughput, and ensure reliable and timely delivery of data. By selecting an algorithm that effectively routes packets through the network, the overall performance of the MPSoC can be optimised, leading to improved system efficiency and responsiveness [23]. In addition, Resource Utilisation: Efficient routing algorithms can effectively utilise network resources such as links, routers, and buffers within the NoC. By intelligently selecting paths and avoiding congestion-prone routes, an efficient algorithm can prevent resource bottlenecks and enable better utilisation of the available resources [24]. This, in turn, can enhance the overall system performance and avoid unnecessary resource wastage. Moreover, Fault Tolerance: NoC-based MPSoCs are susceptible to faults and failures in the communication infrastructure. An efficient routing algorithm can incorporate fault-tolerant mechanisms to handle these failures. It can dynamically adapt the routing paths to avoid faulty components, reroute packets to alternative paths, and ensure uninterrupted communication in the presence of faults. This improves the reliability and robustness of the MPSoC system. Furthermore, Scalability: As the complexity and scale of MPSoCs increase, efficient routing algorithms become essential for maintaining scalability [25]. A well-designed algorithm can scale effectively with the growing number of processing elements and communication demands within the system. It can handle the increasing traffic load, prevent congestion, and ensure efficient communication across the expanding network. Besides. Energy Efficiency: Energy consumption is a critical consideration in MPSoC design. Efficient routing algorithms can optimise energy usage by minimising unnecessary data transfers, reducing idle time, and intelligently managing power consumption in network components. By selecting energy-efficient routing paths, the overall energy consumption of the MPSoC system can be minimised, leading to improved energy efficiency and extended battery life in mobile and embedded applications [26].

2) WHY CHOOSE FWZIC TO WEIGHT THE CRITERIA?

MCDM methods can be divided into two categories: Firstly, weighting methods, such as the Analytic Hierarchy Process (AHP), Best-Worst Method (BWM), and FWZIC. Secondly, the ranking approach such as FDOSM and TOPSIS [27]. FWZIC method is a recent advanced method for weighting criteria with zero inconsistency [20]. The use of FWZIC to weight criteria is not only effective, but it also offers several key advantages that make it a highly persuasive method for decision-makers [28]. One of the most notable benefits of FWZIC is its ability to handle inconsistencies within the decision-making process, which is a common challenge that can significantly impact the accuracy and reliability of decisions. By using fuzzy set theory and a zero-inconsistency approach, FWZIC is able to ensure that each criterion is weighted appropriately, even in the presence of inconsistencies. Another significant advantage of FWZIC is its ability to reduce the time and effort required to weight criteria [29], [30]. Unlike other methods that require direct comparisons between the criteria, FWZIC does not need such comparisons, which can be time-consuming. This means that

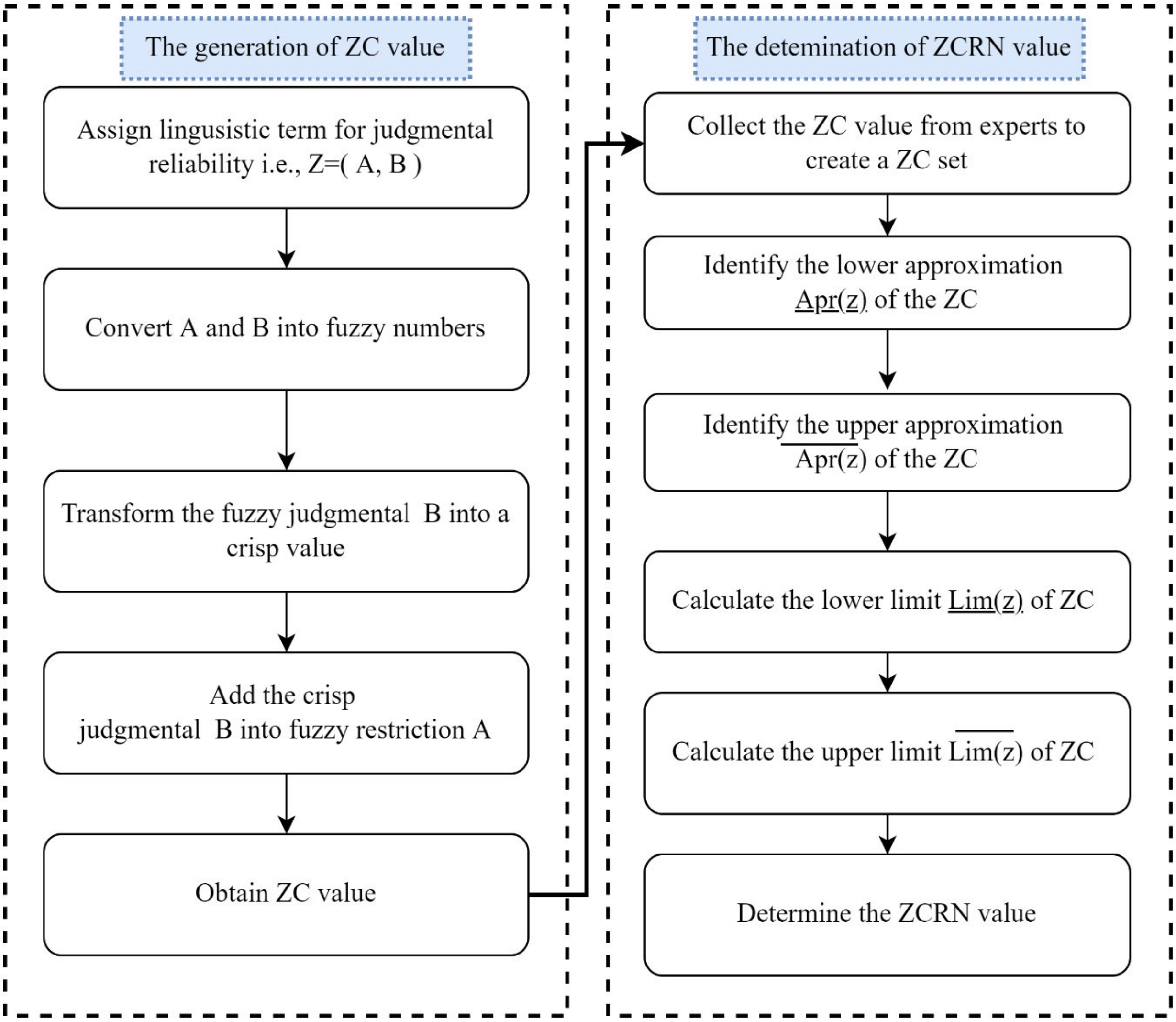

FIGURE 2. **The procedure for calculating ZCRNs.**

decision-makers can save significant resources and focus on other important aspects of the decision-making process. The multiple criteria weighted in FWZIC usually have no dependability, which means that adding or eliminating them doesn't need a new calculation [20]. Additionally, gathering feedback from specialists in FWZIC is an easy process. Furthermore, the iterative approach used by FWZIC ensures that the final weights are consistent, which can help increase the overall accuracy and reliability of the decision-making process [31]. This means that decision-makers can have greater confidence in the final decision, as it is based on a rigorous and consistent weighting of the criteria.

3) WHY CHOOSE FDOSM TO RANK THE ALTERNATIVES?

Due to the fact of the limitations of many MCDM methods at the level of consistency, comparisons, uncertainty, and ambiguity, the literature has developed several methods, such as FDOSM and FWZIC. FDOSM was proposed by Salih in 2020 [18]. FDOSM is an MCDM method that relies on a three-stage process, including data input, transformation, and processing. Under a fuzzy context, FDOSM presents a reliable and effective MCDM method. One of the key advantages of FDOSM is its ability to handle fuzzy data and uncertain information, which can be particularly useful in complex decision-making scenarios where data may be incomplete or imprecise [17]. In addition, by avoiding two preferences, FDOSM ensures that decision-makers do not express contradictory or conflicting preferences when evaluating alternatives [32]. FDOSM is based on ideal solutions, allowing decision-makers to identify the optimal solution and compare it against other values of alternatives based on the same criteria. This approach enables decision-makers to make informed choices and rank alternatives reliably and efficiently. In addition, FDOSM can be used in both individual and group decision-making contexts, making it a versatile approach that can be adapted to various decision-making scenarios. Combining FDOSM with uncertain techniques and competing criteria has shown promising results [15], [21], [32], [19], [33], [34], [35].

4) WHY WORK WITH Z-CLOUD ROUGH NUMBERS?

Many forms of fuzzy sets have been suggested in the literature since Zedeh [36] developed the concept of fuzzy sets to tackle the vagueness inherent in uncertain information. The reliability and validity of evaluations are impacted when a single intrapersonal or interpersonal uncertainty is applied. As a result, it is useful to use a systematic uncertainty manipulation model for an alternative assessment process that considers two forms of uncertainty. Consequently, the cloud model theory is a better fit for expressing and capturing experts' ambiguous preferences.

The cloud model theory has been successfully used in several sectors [37], [38]. However, it has two major drawbacks, namely (1) not having a mechanism to manage interpersonal data interaction connections and (2) not taking into account the validity of individual opinions. They both have an effect on how well the cloud model theory works [39]. Thereby, it's important to put effort into developing better theoretical frameworks for cloud models. Rough number theory is capable of dealing with restriction number (1) in the cloud model by employing higher and lower approximations. For this reason, it is possible to use a combination of the cloud model and rough number theories in order to address both individual and interpersonal uncertainty [39]. In addition, the Z-number theory [40] is a perfect method for overcoming restriction number (2) in the cloud model, as it allows experts to express their fuzzy preferences and judgment reliability in a single ordered pair (A, B) where A represents the vague amount of the assessed item and B indicates the fuzziness of the reliability of A [41]. Therefore, this study used ZCRNs, a model for manipulating uncertainty that considers the advantages of the cloud model, Z-numbers, and rough number theories all at once. Figure 2 is shown the procedure for calculating ZCRNs.

The subsequent sections of the paper are structured in the following manner. Section II comprises a comprehensive literature review. The methodology employed in this study is outlined in Section III. The findings and discussion are elaborated upon in Section IV. Section V provides validation for the proposed methods through the utilisation of objective validation, sensitivity analysis, and Spearman's rank correlation techniques. The evaluation and comparison with commonly used techniques are provided in Section VI. Finally, certain limitations, future directions, and final remarks are offered in Section VII.

II. LITERATURE REVIEW

The literature review section includes two sub-sections. In Section II-A, an overview of the studies conducted on the FDOSM and FWZIC is provided. Section II-B provides an overview of the study that was conducted on Z Cloud Rough Number.

A. STUDIES ON FDOSM AND FWZIC

The FDOSM and FWZIC are new MCDM techniques for ranking and weighting, respectively [20]. Multiple important papers have used them as an acceptable alternative to traditional MCDM methods, leading to usage in various studies. FDOSM and FWZIC were based on fuzzy triangular sets. The problem is that TFN is limited in dealing with ambiguity and uncertainty [19]. When confronted with real-world challenges, the complexities lie in their inherent vagueness, indeterminacy, and ambiguity, thereby amplifying the intricacies of decision-making [28], [42]. Fuzzy decision support models, such as FDOSM and FWZIC, need to be improved and expanded into a new fuzzy type to address the challenges of uncertainty and collect extra useful information under uncertain and imprecise settings. Firstly, the authors in [43] evaluated the benchmarking process of active queue management approaches, which analyse an MCDM issue using multidimensional criteria, where the authors expanded FDOSM to four kinds of aggregation techniques utilised in the direct aggregation approach. In addition, reflecting on the privilege of the T-spherical fuzzy sets in their ability to handle the uncertainty in information, a group of researchers expanded the FDOSM and FWZIC into the T-spherical environment to be used in the distribution of COVID-19 vaccines [35]. Moreover, extending FDOSM & FWZIC under q-ROFS was done because of its benefits and flexibility, where the goal was to use q-RO_FDOSM & q-RO_FWZIC to distribute COVID-19 vaccination doses fairly [32]. Furthermore, in 2022, M. E. Alqaysi et al. [28] introduced basic FDOSM & FWZIC as an assessment methodology for evaluating the most effective hybrid diagnostic models for autism patient classification. Next, based on the benefits of Cubic Pythagorean fuzzy sets, one of the most advanced fuzzy environments lately is provided to tackle the uncertainty issue. Alamoodi et al. [31] suggested extending it with FWZIC and FDOSM to solve the issues related to Sign language. Furthermore, authors of [44] integrated Spherical fuzzy rough sets with FDOSM & FWZIC to select the best smart e-tourism app due to multiple criteria. Besides, authors in ref. [45] utilised Fermatean probabilistic hesitant fuzzy sets and FDOSM techniques to effectively address uncertainty and evaluate the performance of supply chains in Agri-Food. Finally, the palm oil industry encounters significant competition and sustainability obstacles, which require adherence to industry norms and the integration of Industry 4.0 techniques within a system of circular economies and sustainable practices (I4.0-in-a-CE-and-SPs). In order to ascertain the most practical application of Industry 4.0 within a Circular Economy and Sustainable Production context, the FWZIC method is employed alongside an interval-valued Pythagorean fuzzy rough set. The applications are then ranked using the evaluation EDAS method [46].

Previous authors recommended that the uncertainty issue still be considered an open challenge. Also, they recommended combining various fuzzy set techniques with FDOSM & FWZIC to explore the suitability of these forms in trying to solve the uncertainty issue; however, none of these versions has considered the ZCR-number, although its ability to deal with two types of uncertainty.

B. STUDIES ON Z CLOUD ROUGH NUMBER

Previous studies have extensively explored the integration of Z-numbers in various decision-making contexts. In one study, the ZBWM method was introduced as a way to address a supplier development problem within the framework of MCDM [47]. This method combines the best-worst method (BWM) with Z-numbers. In addition, a research team [48] presented a framework for assessing and prioritising smart mining strategies by leveraging Z-number theory and VIseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR). They demonstrated how Z-numbers can be used to enhance decision-making in this context. Another study proposed a rough-Z-number-enhanced MCDM approach for evaluating design concepts. This approach integrates Z-numbers with the analytical hierarchy process (AHP) and attributive border approximation area comparison (MABAC) [49]. Moreover, a novel approach was introduced in another paper, which integrates rough Z-numbers with BWM and TODIM. The objective was to evaluate the performance of technological service platforms. This approach offers a more comprehensive evaluation method that considers both roughness and imprecision in decision-making [50]. In addition, actual mathematical strategies commonly neglect the combination of uncertainties in experts' decisions, including variety, randomness, and ambiguity. In order to tackle this issue, a novel linguistic assessment model known as rough fuzzy integrated clouds was proposed. This model combines rough fuzzy numbers with cloud model theory, thereby enhancing its ability to effectively handle uncertain information [51]. Besides, fuzzy rough and soft sets are mathematical constructs specifically developed to effectively manage and address situations involving inherent uncertainty. Their paper introduced a novel matrix known as the generalised Z-fuzzy soft-covering-based rough matrix. AHP with Z rough set is employed to determine the optimal candidate for an assistant professor position within an academic institution [52]. Moreover, a study focused on developing a MADM method specifically designed to handle decision problems with fuzzy numbers represented by uncertain linguistic variables. The researchers [53] introduced dual uncertain Z-numbers with fuzzy cloud concepts to represent fuzzy numbers and addressed the challenges associated with uncertainty in decision-making. In a similar vein, another study [54] proposed a novel MCDM method that incorporates information description, fusion, and measures to address practical decision problems. The method introduced uncertain Z-numbers to represent evaluation information and information reliability. Cloud models were utilised to process the uncertain Z-number information, employing a concept known as Z-trapezium-normal clouds. Finally, an assessment model for design alternatives in product development was introduced to account for subjective perceptions, preferences of experts, and various types of uncertainties. Existing studies often overlook certain uncertainties, limiting their effectiveness. To bridge this gap, the proposed model integrates ZCRNs, BWM, and MABAC [39]. The concept of ZCRN is introduced to handle different uncertainties, combining the strengths of cloud models, Z-numbers, and rough numbers.

C. STUDIES ON NoC ROUTING ALGORITHMS

Due to the adapting of NoCs as communication infrastructures in the context of MPSoC of IoT, designers are forced to consider the routing techniques amongst accommodated IP cores in their MPSoC platforms. For example, authors of [55] proposed new logic-based routing algorithms called Repetitive Turn Model (RTM) for 2D mesh-based NoC. By distributing prohibited turns repetitively, the RTM algorithms are designed and outperform existing ones. Through extensive simulations on 2D mesh topologies ranging from 6×6 to 15×15, RTM achieves up to 51% performance improvement over the traditional Odd-Even routing algorithm, with smaller routing pressures. In addition, authors of [56] proposed a congestion-aware routing method for NoC to enhance network performance. The method combines both local and non-local network information to determine the best path for packet forwarding. This approach aims to balance traffic load and alleviate congestion in NoCs effectively. Moreover, the authors of [57] proposed a unique non-local adaptive routing strategy for NoC dubbed FreeRider. Unlike previous techniques that employ a separate Congestion Propagation Network (CPN), which incurs additional cabling and power expenses, FreeRider uses spare bits in existing packet head flits to transport and broadcast rich congestion information without adding more wires or flits. The experimental results show that FreeRider beats a state-of-the-art adaptive routing approach with CPN in terms of throughput, latency, and power consumption. Furthermore, to address power and area constraints, the authors of [58] proposed a bufferless routing method for NoC in the deep submicron regime. Based on the idea of making a stop (MaS), the technique provides deadlock and livelock freedom in wormhole-switched NoCs. The suggested routing method beats a current bufferless routing technique in simulation, achieving up to a 10% improvement in average latency, a 9% reduction in power usage, and an 80% reduction in area overhead. The authors of reference [59] presented Dynamic XY (EDXY), an adaptive routing system for two-dimensional mesh NoCs. EDXY is more resilient to connection failures and congestion than the DyXY algorithm. On SPLASH-2 benchmarks running on a 49-core CMP, simulation results show that EDXY delivers lower latency than alternative adaptive routing algorithms across varied workloads, with an average and maximum latency decrease of 20% and 30%, respectively. Finally, authors of [60] suggested Chameleon, a unique heterogeneous multi-NoC design for energy-efficient NoC architectures. Chameleon utilises a fine-grained power-gating algorithm that simultaneously leverages power-saving possibilities at several levels of granularity, with the goal of reducing leakage power, which accounts for a major portion of NoC power. Chameleon surpasses Catnap, the best available solution, with an average of 2.61% greater performance and a 27.75% lower power consumption, according to experimental findings on simulated and real workloads. Previous investigations on this topic have been limited in their ability to undertake extensive evaluations of routing algorithms based on several parameters such as topology, packet size, power dissipation, latency, and throughput. A comprehensive assessment of routing algorithms based on several design and performance metrics is critical for acquiring deeper insights into their efficiency and scalability.

III. METHODOLOGY

The proposed methodology, as illustrated in Figure 3, consists of two primary phases, each comprising two stages. In Phase 1, the stages involve Decision Matrix (DM) criteria identification, while Stage 2 focuses on DM alternatives identification through the consideration of various routing algorithms within the context of NoC-based MPSoC. In terms of Phase 2, the stages are as follows: Stage 1 utilises the ZCR-FWZIC MCDM method for DM criteria weighting, and Stage 2 employs the ZCR-FDOSM MCDM method for DM alternatives ranking.

A. PHASE 1: IDENTIFICATION OF DECISION MATRIX

This section provides an overview of Phase 1 of our methodology. It begins with an explanation of the Decision Matrix (DM) (Table 1), which is constructed by considering the crossover of routing algorithms, criteria, and their alternatives within the context of NoC-based MPSoC. The subsequent section delves into a detailed explanation of the routing algorithms and their specific characteristics. Furthermore, Phase 1 encompasses Stage 1 and Stage 2, which are dedicated to identifying the DM criteria and alternatives, respectively.

1) STAGE 1: IDENTIFICATION OF DM CRITERIA

In this section, we provide an in-depth analysis of the criteria used in the DM and the various alternatives considered within the MCDM benchmarking approach. These evaluations aim to assess the routing algorithms for NoC-based MPSoC in order to determine the optimal system design solution.

1) Size: Size refers to the physical dimensions or area occupied by the NoC. It represents the size of the chip or the network fabric used to interconnect the IP cores in the MPSoC [61].
2) Topology: Topology defines the interconnection structure or arrangement of the network nodes in the NoC. It determines how the IPs are connected and how the communication paths are established between them. Examples of NoC topologies include mesh, torus, ring, tree, and so on [62].
3) Routing Type: Routing type refers to the mechanism used to determine the path or route taken by the packets or flits (flow control units) through the NoC. It can be deterministic or adaptive. Deterministic routing follows predefined rules, while adaptive routing dynamically selects routes based on the network conditions [63].
4) Routing Characteristics: Routing characteristics describe the properties or features of the routing algorithm used in the NoC. These characteristics may include deadlock avoidance, fault tolerance, load balancing, minimal latency, minimal power consumption, and so on [63].
5) Packet Flit Size: Flit size represents the size of the smallest unit of data that can be transmitted over the NoC. In NoCs, data is typically divided into small units called flits (flow control units). Flit size is usually measured in bits and determines the granularity of data transmission in the network [64].
6) Power Dissipation (W): Power dissipation refers to the amount of power consumed by the NoC or its components, such as switches and links. It is measured in watts (W) and represents the energy consumed during the operation of the NoC. Minimising power dissipation is crucial for efficient and energy-aware MPSoC designs [65].
7) Number of Bits: The number of bits represents the size of data or information that can be transmitted in a single flit or packet. It indicates the width of the data bus in the NoC and affects the data bandwidth and communication capacity of the network.
8) Latency (Cycle): Latency refers to the time taken for a packet or flit to traverse the NoC from the source IP to the destination IP core. It is measured in cycles and represents the delay or the time it takes for a communication request to complete.
9) Throughput (flit/cycle): Throughput represents the rate of data transfer or the number of flits transmitted per cycle in the NoC. It measures the efficiency and performance of the network and indicates how much data can be processed within a given time frame. Higher throughput values indicate better network performance [66].

2) STAGE 2: IDENTIFICATION OF DM ALTERNATIVES

In this section, we will discuss the alternatives (routing algorithms) used in the DM within the context of NoC-based MPSoC. We will explore the characteristics associated with these routing algorithms and their relevance to the design of MPSoC systems based on NoC architectures.

FIGURE 3. Research methodology.

1) OE (Odd-Even): OE routing algorithm is a deterministic routing scheme that divides the network into odd and even layers. It ensures that packets or flits traverse odd layers and even layers alternately. This algorithm is simple and easy to implement but may suffer from congestion in certain network scenarios [67].
2) CATRA (Congestion Aware Trapezoid-based Routing Algorithm): CATRA is an adaptive routing algorithm that utilises compressed address information to determine the routing path. It reduces the routing overhead by encoding the address information into a compact format. CATRA aims to provide efficient routing with reduced packet latency and improved throughput [56].
3) ADBR (Adaptive Dimensional Bubble Routing): ADBR is an adaptive routing algorithm designed to avoid deadlock and livelock situations in the NoC. It uses a bubble flow control mechanism to prevent deadlock by introducing special control flits called "bubbles." ADBR dynamically adjusts the routes

TABLE 1. DM of routing algorithms in NoC-based MPSoC.

Routing Algorithm (Alternative)	Criteria								
	Design Metrics					Performance Metrics			
	Size	Topology	Routing Type	Routing Characteristics	Packet Flit Size	Power Dissipation (w) (pir:0.2/flit/cycle)	Number of Bits	Latency (cycle)	Throughput (flit/cycle)
OE	15x1	mesh	Partial Adaptive	Deadlock free	7	6.1	100	100	0.128
CATRA	8x8	Tours	Adaptative	Congestion Aware	5	2.5	100	200	0.135
ADBR	8x8	mesh	Fully Adaptive	Flow Control	12	3.5	64	98	0.240
Free Rider	16x1	mesh	Adaptive	Congestion Aware	5	4	128	45	0.144
MaS Routing	10x1	mesh	Bufferless	Livelock free	8	6.5	128	53	0.157
EDXY	7x7	mesh	Deterministic	Congestion Aware	10	26.1	120	100	0.172
DyAD	6x6	mesh	Deterministic/ Adaptive	Fault/ Congestion	5	2.5	100	195	0.125
Traffic Allocation	6x6	mesh	Adaptive	Fault Aware	1	3.7	160	89	0.123
MCAR	8x8	mesh	Adaptive	Congestion Aware	7	7.85	75	95	0.120
Zigzag	5x5	mesh	Deterministic	Fault Aware	8	62.69	100	46	0.88

based on the network conditions and avoids congestion [68].

4) Free Rider: Free Rider is a routing algorithm that exploits the underutilised resources in the NoC. It identifies and utilises lightly loaded or idle paths to transmit packets or flits, thereby reducing congestion and improving overall network performance. Free Rider aims to balance the traffic distribution and enhance the throughput of the NoC [57].

5) MaS (Making-a-Stop) Routing: is a concept used in the design of routing algorithms for wormhole-switched NoC systems. The goal of MaS is to ensure freedom from deadlocks and lovelock within the NoC. It involves strategically introducing specific routing behaviors that allow packets to make controlled stops at certain points during their traversal through the network. By carefully managing these stops, the MaS-based routing algorithm aims to enhance the overall performance and efficiency of the NoC system [58].

6) EDXY (Enhanced-Dynamic-XY): EDXY is an adaptive routing algorithm for 2D mesh NoCs. It improves DyXY with congestion awareness and link failure tolerance. It avoids congestion by adding wires between cores and considers alternative paths. Simulation results show EDXY achieves lower latency compared to other algorithms [59].

7) DyAD (Dynamic and Adaptive Routing Algorithm): DyAD is a routing scheme that combines deterministic and adaptive routing approaches to optimise network performance. It dynamically switches between these routing modes based on the congestion levels in the network. Simulation results demonstrate the effectiveness of DyAD compared to purely deterministic and adaptive routing schemes across various traffic patterns. A prototype router based on the DyAD concept has been designed and evaluated, showing improved performance with minimal overhead compared to purely adaptive routers (less than 7% overhead) [69].
8) Traffic Allocation: Traffic Allocation is a routing algorithm that involves distributing the network traffic across multiple paths or channels in a balanced manner. It aims to evenly distribute the communication load to prevent congestion and maximise the utilisation of network resources. Traffic Allocation helps improve throughput and reduce latency in the NoC [70].
9) MCAR (Message-based Congestion-Aware Routing): MCAR is a non-local adaptive routing algorithm designed for NoC systems. Congestion in NoCs can be mitigated by considering congestion information from both local and distant links. Existing non-local adaptive routing algorithms use additional wires/clusters or embed congestion information in packet headers to propagate this information. In contrast, MCAR introduces two special types of messages to propagate congestion information without the need for extra wires/clusters. This approach improves the timeliness of congestion information. MCAR efficiently utilises this information to determine the output link selection [71].
10) ZigZag Routing: ZigZag is a deterministic routing algorithm that uses a diagonal routing pattern in a 2D mesh NoC. It directs packets or flits diagonally through the network to reduce the average hop count and improve overall performance. ZigZag aims to provide efficient routing with reduced latency and improved throughput in mesh-based NoCs [72].

B. PHASE 2: DEVELOPMENT OF MCDM APPROACH

This section includes a description of the processes for developing decision-making methods in order to shed light and address the problems of the NoC-based MPSoC in terms of decision-support systems.

1) STAGE1: ZCR-FWZIC

This section describes the ZCR-FWZIC method for assigning weights. Then this method was described in five vital steps.

Step 1: Determine the criteria

The first stage is to determine the criteria that will be used to evaluate the performance. The predetermined group of evaluation criteria is investigated and displayed. The gathered criteria and sub-criteria are divided into several groups. The suggested model unifies the stated and chosen criteria.

Step 2: Structured Expert Judgement (SEJ)

The expert panel members are selected from the community of study to assess and describe the degree of significance of the criteria defined in the previous step. In this investigation, we focus on members of the MPSoC community. After a community of possible experts has been uncovered, the selection and nomination process can begin. The SEJ committee has been formed. Finally, we convert the language scale to its equivalent numerical scale, as given in Table 2, and create an evaluation form to capture the consensus of all SEJ panelists per criterion.

1- Identify experts: Uses the term "expert" to describe people who have been or are now active in the case study's subject matter and are widely recognised as an authority. Literature experts may alternatively be called "domain" experts or "practical" experts. The existing research relies on data analysis of all researchers in the literature to determine an expert panel.
2- Choice experts: The case study experts are chosen when the expert identification process is complete [20]. This step requires the involvement of a minimum of 4 specialists. In order to confirm their accessibility and desire to be regarded as possible experts for the panel, the author emailed all of the experts from the previous round.
3- Use the evaluation form: The assessment form should be completed due to its relevance as a tool for gathering agreement among experts. Each expert from the previous phase reviews the document before finalising the evaluation form in order to ensure its trustworthiness and reliability.
4- In this stage, the 5 experts chosen will use a 5-point Likert scale to define the importance of each criterion. There is no theoretical impediment to using a response scale of varying lengths. It has been scientifically proven that when the number of scale points for Likert items (and related rating scales) drops below five or climbs above seven, the reliability of the data they produce declines dramatically. Research has shown that five-point scales are more effective than seven-point ones, although these studies do not explain why [73].
5- Making a numerical scale-out of linguistic scale: For the sake of the study, all preference values are numerically translated from their original subjective form. For each criterion, the Likert scale used by each expert is transformed into a numerical scale, as shown in Table 2.
6- The linguistic scale used in the assignment of (importance or difference) assists in the evaluation criteria procedure. The scale of the degree of importance begins from the smallest importance level to the very important level. However, without converting language scores into numerical values, it is difficult to extract any relevant information when conducting further analysis

TABLE 2. The numerical and linguistic scoring scale.

A Linguistic scoring scale	Numerical scoring scale	B Linguistic scoring scale
Not important / No difference (ND)	1	Very small (VS)
Slight important / Slight difference (SD)	2	Small (S)
Moderately important / Difference (D)	3	Medium (M)
Important / Big difference (BD)	4	High (H)
Very important / Huge difference (HD)	5	Very high (VH)

TABLE 3. EDM.

Criteria	$C1$	...	Cn
E_1	I($E\_1/C1$)	...	I(E_1/Cn)
E_2	I($E\_2/C1$	...	I(E_2/Cn)
E_3	I($E\_3/C1$)	...	I(E_3/Cn)
…	...	...	...
E_m	I($E\_n/C1$)	...	I(E_m/Cn)

*(I) denotes the importance level

of the scores provided by experts. When the relative significance of the routing algorithms criteria can be quantified, a number value has been provided alongside each linguistic phrase.

Step 3: Constructing the Expert Decision Matrix (EDM)

The EDM is built during this stage. Table 3 illustrates the essential components of the EDM, including the evaluation criteria and the alternatives under consideration.

Step 4: Implementation of a fuzzy member function

Z-number represents an ordered pair of fuzzy numbers that appear as Z=(A, B) [40]. Z-number represents an ordered pair of fuzzy numbers that appear as Z= (A, B). The computational complexity of Z-numbers may be reduced in practice by converting them to regular fuzzy numbers [41], [74]. The ZC model was created with the primary intention of incorporating the Z-second number's component (i.e., reliability) into the first (i.e., the fuzzy constraint) [39]. The Z number is converted to ZC using the equations below:

Step 1: Convert the reliability $\tilde{B}$ of the element $\tilde{A}$ into a real number.

$$\tilde{\alpha} = \frac{\int x\varphi_B(x)dx}{\int \varphi_B(y)dx} \tag{1}$$

where $\int$ denotes an integration in algebra.

Step 2: The weighted Z-number is provided by first converting the value of judging reliability $\tilde{B}$ into the fuzzy restriction $\tilde{A}$ [75].

$$\tilde{Z}^{\tilde{\alpha}} = \left\{ \left\langle x, _{\tilde{A}^{\sim}}(x) \right\rangle \mid \mu_{\tilde{\tilde{A}}}(x) = \tilde{\alpha}\mu_{\tilde{A}}(x), x \in X \right\} \tag{2}$$

For ease of use, the Z number is indicated by the symbol $\tilde{Z}^{\tilde{\alpha}}=(\tilde{A}, \tilde{\alpha})$.

Step 3: Convert the irregular cloud number into a traditional cloud value number.

$$\tilde{Z} = \left\{ \left\langle x, \mu_{\tilde{Z}}(x) \right\rangle \mid \mu_{\tilde{Z}}(x) = \mu \left(\frac{x}{\sqrt{\tilde{\alpha}}} \right), x \in X \right\} \tag{3}$$

As a result, the ordinary Z-number set $Z = \left\{ \left\langle x, \tilde{A}_{\mu(x)}, \tilde{B}_{\varphi(x)} \right\rangle \mid x \in X \right\}$ is converted into a matching ZC set $\tilde{Z}$ that has the shape of the standard cloud value, which can greatly reduce the complexity of handling evaluation difficulties utilising z numbers.

As was previously said, the ZC model is able to regulate intrapersonal uncertainty well but struggles with interpersonal uncertainty due to the wide range of experience, knowledge, cultural norms, and preferences across people. In this situation, a rough number is an efficient tool for controlling interpersonal ambiguity [76]. It begins by sorting all items into k groups in order of ascending. Furthermore, it employs lower and higher approximations to characterise the ordered groups of all items in the collection. Lastly, based on the higher and lower approximations of every group, the higher and lower limits of the corresponding group are determined to overcome the ambiguity of every group's assessment. Generally, the larger the gap between the group's lowest and the highest, the greater the group ambiguity of the mentioned group, and the lower the general agreement scale between many experts in that group. Next, the steps below involve outlining the primary methods for converting ZC numbers to ZC rough numbers [39].

Let $\tilde{Z}_i^{Ex} = \left\{ \tilde{E}x_1, \tilde{E}x_2, \ldots, \tilde{E}x_n \right\}, \tilde{Z}_i^{En} = \left\{ \tilde{E}n_1, \tilde{E}n_2, \ldots, \tilde{E}n_n \right\}$, and $\tilde{Z}_i^{He} = \left\{ \tilde{H}e_1, \tilde{H}e_2, \ldots, \tilde{H}e_n \right\}$. Then, the lower approximation $\underline{Apr}\left(\tilde{Z}_i\right)$ of $\tilde{Z}_i$ can be identified as:

$$\underline{Apr}\left(\tilde{E}x_i\right) = \cup \left\{ \tilde{E}x_j \in \tilde{Z}_i^{Ex} \middle| \tilde{E}x_j \leqslant \tilde{E}x_i \right\} \tag{4}$$

$$\underline{Apr}\left(\tilde{E}n_i\right) = \cup \left\{ \tilde{E}n_j \in \tilde{Z}_i^{En} \middle| \tilde{E}n_j \leqslant \tilde{E}n_i \right\} \tag{5}$$

$$\underline{Apr}\left(\tilde{H}e_i\right) = \cup \left\{ \tilde{H}e_j \in \tilde{Z}_i^{He} \middle| \tilde{H}e_j \leqslant \tilde{H}e_i \right\} \tag{6}$$

wher $\left(Ex_i, \tilde{E}n_i, \tilde{H}e_i\right)$ *are elements in* $\left(\tilde{Z}_i^{Ex}, \tilde{Z}_i^{En}, \tilde{Z}_i^{He}\right)$ *respectively*; 1 i, j k *The lower approximation* $\underline{Apr}\left(\tilde{E}x_i\right)$ of $\tilde{E}x_i$ *includes all elements in* $\tilde{Z}_i^{Ex}$ *that have class values equal to and less than* $\tilde{E}x_i$. *A nd likewise for the rest.*

Likewise the upper approximation Apr $\left(\tilde{Z}_i\right)$ of $\tilde{Z}_i$ can be identified as:

$$\overline{\text{Apr}}\left(\tilde{E}x_i\right) = \cup\left\{\tilde{E}x_j \in \tilde{Z}_i^{Ex}|\tilde{E}x_j \geqslant \tilde{E}x_i\right\} \tag{7}$$

$$\overline{Apr}\left(\tilde{E}n_i\right) = \cup\left\{\tilde{E}n_j \in \tilde{Z}_i^{En}|\tilde{E}n_j \geqslant \tilde{E}n_i\right\} \tag{8}$$

$$\overline{Apr}\left(\tilde{H}e_i\right) = \cup\left\{\tilde{H}e_j \in \tilde{Z}_i^{He}|\tilde{H}e_j \geqslant \tilde{H}e_i\right\} \tag{9}$$

The lower approximation $\underline{\text{Apr}}\left(\tilde{E}x_i\right)$ of $\tilde{E}x_i$ contains all objects in the set $\tilde{Z}_i^{Ex}\tilde{E}x_i$. Next, the lower limit $\underline{\text{Lim}}\left(\tilde{Z}_i\right)$ of $\tilde{Z}_i$ is calculated as:

$$\underline{\text{Lim}}\left(\tilde{E}x_i\right) = \frac{1}{\vartheta_L^{Ex}}\sum_{j=1}^{v_L^{Ex}}\tilde{E}x_j \mid \tilde{E}x_j{\in}\underline{\text{Apr}}\left(\tilde{E}x_i\right) \tag{10}$$

$$\underline{\text{Lim}}\left(\tilde{E}n_i\right) = \sqrt{\frac{1}{\vartheta_L^{En}}\sum_{j=1}^{v_L^{En}}(\tilde{E}n_j)^2|\tilde{E}n_j \in \underline{\text{Apr}}\left(\tilde{E}n_i\right)} \tag{11}$$

$$\underline{\text{Lim}}\left(\tilde{E}h_i\right) = \sqrt{\frac{1}{\vartheta_L^{He}}\sum_{j=1}^{v_L^{He}}(\tilde{H}e_j)^2|\tilde{H}e_j \in \underline{\text{Apr}}\left(\tilde{H}e_i\right)} \tag{12}$$

where ϑ_L^{Ex}, ϑ_L^{En}, and ϑ_L^{He} represent the total numbers of elements in $\underline{Apr}\left(\tilde{E}x_i\right)$, $\underline{\text{Apr}}\left(\tilde{E}n_i\right)$, and $\underline{Apr}\left(\tilde{H}e_i\right)$, respectively. For convenience, $\underline{\text{Lim}}\left(\tilde{E}x_i\right)$, Lim $\left(\tilde{E}n_i\right)$, and $\underline{\text{Lim}}\left(\tilde{H}e_i\right)$ are expressed as $\tilde{E}x_i^L$, $\tilde{E}n_i^L$, and $\tilde{H}e_i^L$ in subsequent contents, respectively. Briefly the lower limit of a class ZC value is the average value of the classes included in its lower approximal Similarly, the upper limit Lim $\left(\tilde{Z}_i\right)$ of $\tilde{Z}_i$ is determined as:

$$\overline{\text{Lim}}\left(\tilde{E}x_i\right) = \frac{1}{\vartheta_U^{Ex}}\sum_{j=1}^{\vartheta_U^{Ex}}\tilde{E}x_j \mid \tilde{E}x_j{\in}\ \overline{Apr}\left(\tilde{E}x_i\right) \tag{13}$$

$$\overline{\text{Lim}}\left(\tilde{E}n_i\right) = \sqrt{\frac{1}{\vartheta_U^{En}}\sum_{j=1}^{\vartheta_U^{En}}(\tilde{E}n_j)^2 \mid \tilde{E}x_j \in \overline{Apr}\left(\tilde{E}n_i\right)} \tag{14}$$

$$\overline{\text{Lim}}\left(\tilde{H}e_i\right) = \sqrt{\frac{1}{\vartheta_U^{He}}\sum_{j=1}^{\vartheta_U^{He}}(\tilde{H}e_j)^2 \mid \tilde{E}x_j \in \overline{Apr}\left(\tilde{H}e_i\right)} \tag{15}$$

where ϑ_U^{Ex}, ϑ_U^{En}, and ϑ_U^{He} refer to the total number of elements in $\overline{Apr}\left(\tilde{E}x_i\right)$, $\overline{Apr}\left(\tilde{E}n_i\right)$, and $\overline{Apr}\left(\tilde{H}e_i\right)$, respectively. For simplicity, Lim $\left(\tilde{E}x_i\right)$, Lim $\left(\tilde{E}n_i\right)$, and Lim $\left(\tilde{H}e_i\right)$ are expressed as $\tilde{E}x_i^U$, $\tilde{E}n_i^U$, and $\tilde{H}e_i^U$ in the subsequent contents, respectively. The upper limit of a class ZC value is the average value of the classes included in its upper approximation. Once the lower limit $\underline{\text{Lim}}\left(\tilde{Z}_i\right)$ and the upper limit Lim $\left(\tilde{Z}_i\right)$ for an arbitrary Z-cloud class $\tilde{Z}_i$ have been established, the ZCRN value ZCRN $\left(\tilde{Z}_i\right)$ of $\tilde{Z}_i$ can be defined as follows:

$$\left[\tilde{Z}_i\right] = \left[\tilde{Z}_i^L, \tilde{Z}_i^U\right]\left[\left(\tilde{E}x_i^L, \tilde{E}n_i^L, \tilde{H}e_i^L\right), \left(\tilde{E}x_i^U, \tilde{E}n_i^U, \tilde{H}e_i^U\right)\right] \tag{16}$$

where $\left[\tilde{Z}_i\right]$, $\tilde{Z}_i^L$, and $\tilde{Z}_i^U$ represent the $ZCR\left(\tilde{Z}_i\right)$, the lower limit $\underline{\text{Lim}}\left(\tilde{Z}_i\right)$, and the upper limit Lim $\left(\tilde{Z}_i\right)$, respectively.

To get to the final weight, the aggregation operator must be used. In this part, the arithmetic operation of ZCRNs is described for processing extensive data using the sources [38], [39]. Table 4 demonstrates the rate of every linguistic term using ZC.

Suppose $\left[\tilde{Z}_i\right] = \left[\tilde{Z}_i^L, \tilde{Z}_i^U\right] = \left[\left(\tilde{E}x_i^L, \tilde{E}n_i^L, \tilde{H}e_i^L\right), \left(\tilde{E}x_i^U, \tilde{E}n_i^U, \tilde{H}e_i^U\right)\right]$ $(i = 1, 2, \ldots, n)$ are $nZCRNs$. The arithmetic operation of ZCRNs is defined as (17), shown at the bottom of the next page.

Step 5: Calculation of the final weights of the evaluation criteria

In this stage, the last values of the weight coefficients of the assessment criteria are determined based on the fuzzification data for the criterion in the previous step, as shown below.

1- Calculate the ratio of fuzzification details employing the formula (18) Table 5 shows that

$$\frac{Imp(\widetilde{E1}/C1)}{\sum_{j=1}^{n} Imp(\widetilde{E1}/C_{1j})} \tag{18}$$

where $Imp(\widetilde{E1}/C1)$ denote the fuzzy number of Imp (E1/C1) and $\sum_{j=1}^{n} Imp(\widetilde{E1}/C_{1j})$ is the summation of all fuzzy number values of the significance given by the expert per criterion [33].

After the Fuzzy EDM is employed, formula 17 to calculate the value of every criterion. In order to get the final weight, defuzzify the criterion weights by using centroid method and formula 19 is used. Keep in mind that the summation of the final weight must be 1.

$$\widetilde{W}_J = \left(\sum_{i=1}^{m}\frac{\text{Imp}\overline{\left(E_{tj}/C_{tj}\right)}}{\sum_{j=1}^{n}\text{Imp}(\text{E}(\text{E}_{\text{tj}}/C_{tj}))}\right)/m \tag{19}$$

3- Calculate the Global weight (GW):

Finally, the following equation is used to get the essential global weight for each main criterion and associated sub-criterion.

$$\text{GW} = \text{LW(for main criteria)}^{*}\text{LW(for its sub criteria)} \tag{20}$$

2) STAGE 2: ZCR- FDOSM-BM

This section provides an overview of the steps of the ZCR-FDOSM-BM method to rank DM alternatives (routing algorithms), as shown in Figure 3. The ZCR-FDOSM-BM is introduced in this section. The expert selected the data transformation unit and data processing step of ZCR-FDOSM-BM is described below.

Step 1: Data transformation is the focus of this step. A choice matrix is transformed into an opinion matrix by following these procedures, according to [12].

The first step: Experts preferences are utilised in this stage to determine the optimal answer for each criterion in the DM. As a result, the perfect solution is therefore defined as:

$$\left\{\left(\left(\max_i v_{ij} \mid j \in J\right) \cdot \left(\min_i v_{ij} \mid j \in J\right) \cdot \left(Op_{ij} \in I.J\right) \mid i = 1, 2 \ldots m\right)\right\} \tag{21}$$

where max = the ideal value with benefit criteria, min = the ideal solution for cost criteria, and finally $\boldsymbol{Op_{ij}}$ = the critical value, when the ideal is a value between the max and the min. Second step: This step compares the optimal situation and other values per criterion. The subjective evaluation of these differences determines the significance of the differences between the perfect solution and the alternatives. In this research, the reference comparisons are displayed employing five scales, allowing for an extensive evaluation of the following terms: "No differences," "Slight differences," "Different," "Big differences," and "Huge differences." Researchers can use this framework to effectively assess and classify the varied degrees of dissimilarity or divergence among the analysed parameters, allowing for a more nuanced and detailed analysis.

$$Op_{Lang} = \left\{\left(\left(\underset{ij}{\tilde{v}} \otimes v_{ij} \mid j \in J\right) . \mid i = 1.2.3. \ldots .m\right)\right\} \tag{22}$$

where $\otimes$ represent the reference comparison between the ideal solution and the alternatives and $\underset{ij}{\tilde{v}}$ refer to the cell in the matrix. The output of these equations is the opinion matrix, see (23).

$$Op_{Lang} = \begin{array}{c} A_1 \\ \vdots \\ A_m \end{array} \begin{bmatrix} op_{11} & \cdots & op_{1n} \\ \vdots & \ddots & \vdots \\ op_{m1} & \cdots & op_{mn} \end{bmatrix} \tag{23}$$

$\mathrm{Op}_{\mathrm{mn}}$ indicates the decision maker's opinion in the matrix.

Step 2: Data Processing: The opinion matrix reflects the output produced by the transformation unit. Following that, the last stage is to transform the linguistic terms of the opinion matrix into the ZC values using Table 6, which produces a fuzzy opinion decision matrix. The idea behind implementing the 5-point Likert scale lies in its frequent usage as a commonly used measurement tool within decision-making environments [27]. The suggested ZCR-FDOSM method is then introduced, providing its relevance in evaluating and benchmarking routing algorithms via both individual and group decision-making strategies.

TABLE 4. Converting the linguistic terms into ZC Likert scales 5 [39].

A				B			
Linguistic terms	Cloud value			Linguistic terms	TFNs		
Not important	0.000	0.673	0.101	Very small (VS)	0.100	0.200	0.300
Slight important	3.098	0.453	0.068	Small (S)	0.300	0.400	0.500
Moderately important	5.000	0.278	0.041	Medium (M)	0.600	0.700	0.800
Important	8.262	0.579	0.086	High (H)	0.700	0.800	0.900
Very important	10	0.673	0.101	Very high (VH)	0.900	1.000	1.000

TABLE 5. Fuzzy EDM ($\widetilde{EDM}$).

	$\widetilde{C1}$	...	$\widetilde{Cn}$
E1	$\frac{Imp(\widetilde{E1}/C1)}{\sum_{j=1}^{n} Imp(\widetilde{E1}/C_{1j})}$	...	$\frac{Imp(\widetilde{E1}/C1)}{\sum_{j=1}^{n} Imp(\widetilde{E1}/C_{1j})}$
...	...	...	...
Em	$\frac{Imp(\widetilde{Em}/C1)}{\sum_{j=1}^{n} Imp(\widetilde{Em}/Cm_j)}$	...	$\frac{Imp(\widetilde{Em}/Cn)}{\sum_{j=1}^{n} Imp(\widetilde{Em}/C_{mn})}$

individual phase: This phase will go over the evaluating procedure for routing algorithms DM utilising the ZCR, which would be used in connection with FDOSM. As a result, the preceding stage's fuzzy opinion matrices would be aggregated using the formulas below.

Z-number represents an ordered pair of fuzzy numbers that appear as Z=(A, B) [40]. The computational complexity of Z The Z number is converted to ZC as well as the ZC transform to ZCR using the equations mentioned previously (equations 1 to 16) based on Table 6.

To get to the final rank, the aggregation operator must be used. In this part, the Z-cloud rough weighted average (ZCRWA) operator is described for processing extensive data using the sources [38], [39].

$$\left[\tilde{Z}_1\right] \oplus \left[\tilde{Z}_2\right] = \left[\tilde{Z}_1^L \oplus \tilde{Z}_2^L, \tilde{Z}_1^U \oplus \tilde{Z}_2^U\right] = \left[\begin{array}{c} \left(Ex_1^L + Ex_2^L, \sqrt{\left(En_1^L\right)^2 + \left(En_2^L\right)^2}, \sqrt{\left(He_1^L\right)^2 + \left(He_2^L\right)^2}\right) \\ \left(Ex_1^U + Ex_2^U, \sqrt{\left(En_1^U\right)^2 + \left(En_2^U\right)^2}, \sqrt{\left(He_1^U\right)^2 + \left(He_2^U\right)^2}\right) \end{array}\right] \tag{17}$$

Suppose $\left[\tilde{Z}_i\right] = \left[\tilde{Z}_i^L, \tilde{Z}_i^U\right] = \left[\left(\tilde{E}x_i^L, \tilde{E}n_i^L, \tilde{H}e_i^L\right), \left(\tilde{E}x_i^U, \tilde{E}n_i^U, \tilde{H}e_i^U\right)\right] (i = 1, 2, \ldots, n)$ are *nZCRNs*, and $w = (w_1, w_2, \ldots, w_n)$ is the weight vector of $\left[\tilde{Z}_i\right]$, with the condition $w_i \in [0, 1]$ and $\sum_{i=1}^{n} w_i = 1$. where the Z-cloud rough weighted average (ZCRWA) operator is defined in equation (24), as shown at the bottom of the page.

Combining the benchmarking results from several experts is required due to the difference in evaluating for routing algorithms among experts. In order to arrive at the final evaluation and benchmarking for routing algorithms, the present research used group expert to incorporate all benchmarking of the DM. Therefore, this study will adapt ZCR-FDOSM-Bonferroni aggregator (BM)-based group decision-making. BM will be employed to determine the final group decision-making score. Specifically, the best routing algorithms have the lowest score value. As a result, the expert's perspectives will be blended when the final ranking is determined. The BM is defined as follows the formula:

$$BM^{p,q}(a_1, a_2, \ldots, a_n) = \left(\frac{1}{n(n-1)} \sum_{i,j=1 i\neq j}^{n} a_i^p a_j^q\right)^{\frac{1}{p+q}} \quad (25)$$

where $BM^{p,q}$ presents averaged values obtained by applying the Bonferroni aggregator; p, q $\geq$ 0 presents sustainability parameters of the Bonferroni aggregator, N presents the number of criteria [77]. After employing group experts, each of the routing algorithms will have a unique score and will be sorted based on that score.

IV. RESULTS AND DISCUSSION

This part demonstrates the weighting and ranking results of routing algorithms to enhance the performance in the context of NoC-MPSoCs. This part has been divided into two parts. Firstly, the part titled "Criteria Weighting Results" provided the ZCR-FWZIC method results of weighting and implemented criteria weights. Secondly, the part titled "Ranking Results" demonstrates the rank of routing algorithms depending on individual (ZCR-FDOSM) and group (ZCR-FDOSM-BM) decision-making are then provided.

A. CRITERIA WEIGHTING RESULTS

As mentioned earlier, the intersection of criteria with alternatives forms a decision matrix. Criteria were determined based on an analysis of previous literature on the methodology. The ZCR-FWZIC method was used to determine the weight of the criteria by employing 5 stages. As mentioned in the methodology section, the 1st stage is choosing the criteria followed by SEJ and converting the expert's opinion into a numerical scale. In the 3rd stage, EDM is built, while applying the formula 1-16 in the 4th stage to use the fuzzy function. The last stage is calculated by using the formula 17- 20 to obtain the final weight. Table 7 presents the weights of the criteria based on expert judgment and the ZCR-FWZIC method.

Table 7. presents the final weights determined based on the main and sub-criteria. Design Metrics and Performance Metrics have got the same importance (0.5). In addition, the sub-criterion that holds the greatest weight in Table 7 is Latency, with a weight of 0.1962. This suggests that the reduction of latency holds significant importance in the evaluation process. Latency pertains to the duration required for data or signals to traverse through a given system or network. In the present context, it is implied that low latency assumes

TABLE 6. Converting the linguistic terms into ZC Likert scales 5 [39].

A				B			
Linguistic terms	Cloud value			Linguistic terms	TFNs		
No difference (ND)	0.000	0.673	0.101	Very small (VS)	0.100	0.200	0.300
Slight difference (SD)	3.098	0.453	0.068	Small (S)	0.300	0.400	0.500
Difference (D)	5.000	0.278	0.041	Medium (M)	0.600	0.700	0.800
Big difference (BD)	8.262	0.579	0.086	High (H)	0.700	0.800	0.900
Huge difference (HD)	10	0.673	0.101	Very high (VH.)	0.900	1.000	1.000

$$\begin{aligned}
&\text{ZCRWA}\left(\left[\tilde{Z}_1\right], \left[\tilde{Z}_2\right], \ldots, \left[\tilde{Z}_n\right]\right) = \sum_{i=1}^{n} w_i \left[\tilde{Z}_i\right] \\
&= \left[\left(\sum_{i=1}^{n} w_i \tilde{E}x_i^L, \sqrt{\sum_{i=1}^{n} w_i \left(\tilde{E}n_i^L\right)^2}, \sqrt{\sum_{i=1}^{n} w_i \left(\tilde{H}e_i^L\right)^2}\right), \left(\sum_{i=1}^{n} w_i \tilde{E}x_i^U, \sqrt{\sum_{i=1}^{n} w_i \left(\tilde{E}n_i^U\right)^2}, \sqrt{\sum_{i=1}^{n} w_i \left(\tilde{H}e_i^U\right)^2}\right)\right] \\
&= \left[\text{ZCWA}\left(\tilde{Z}_1^L, \tilde{Z}_2^L, \ldots, \tilde{Z}_n^L\right), \text{ZCWA}\left(\tilde{Z}_1^U, \tilde{Z}_2^U, \ldots, \tilde{Z}_n^U\right)\right] \qquad (24)
\end{aligned}$$

a pivotal role and merits prioritisation when deliberating upon decisions or conducting comparisons grounded on these criteria. Systems or designs that demonstrate exceptional performance in minimising latency will be given higher priority during the comprehensive evaluation process. On the other hand, the sub-criteria that carry the least weight in Table 7 are Routing Characteristics and Packet Flit Size, with weights of 0.0569 and 0.0564, respectively. The assigned weights that these two sub-criteria are deemed to possess relatively lower significance within the evaluation process. Although they continue to make a contribution to the overall assessment, their impact is relatively less significant in comparison to other sub-criteria. In general, the table's higher values highlight the most significant factors that impact the evaluation, whereas the lower values indicate the least influential factors. This information holds significant value for decision-makers as it enables them to prioritise their attention toward crucial aspects and gain an understanding of the elements that have a comparatively lesser impact on the ultimate evaluation. These weights (final weights) were entered in ZCR-FDOSM-BM to rank routing algorithms for NoC-based MPSoC successfully.

B. RANKING RESULTS

Every expert records their opinion using A 5-point Likert scale was used to create an opinion decision matrix based on the assessment decision matrix. By applying formula (21), the ideal solution for every criterion is done. After that, employ formula (22) to compare the ideal solution with other values in the same alternative. Below, we display the opinion matrix for the first four criteria from the perspective of the decision-maker in Table 8. Furthermore, there is a comprehensive opinion matrix in the Online Appendix, which is shown in the Tables Appendix I, and Appendix II. Next, according to Table 6, the opinion matrix is converted to ZC fuzzy number opinion matrix. Table 9 describes the ZC fuzzy number opinion matrix of the first criteria of the first expert and others in Appendix III, IV, and V.

Next, according to Table 6, the opinion matrix is converted to ZC fuzzy number opinion matrix. Table 9 describes the ZC fuzzy number opinion matrix of the first criteria of the first expert. The matrix is comprised of two distinct columns denoted "A" and "B," and it is observed to possess a total of 10 rows representing various alternatives.

By applying formula (1- 16) the ZC fuzzy will convert into ZCR number. To get the final rank, the aggregation operator must be used and defuzzification. The Z-cloud rough weighted average (ZCRWA) formula (24) and centroid defuzzification were used to get the final rank. Table 10 shows the outcomes for individuals by using ZCR-FDOSM.

The alternative (routing algorithms) ranking outcomes are shown in Table 10, which explains the significance of the DM's judgment in each criterion. There are two categories of routing algorithms: those with the highest scores and those with the lowest scores. (ADBR) was best rated by all 3 experts as (0.9350), (0.8136), and (0.8504), respectively. This means that the panel of experts unanimously agreed that "ADBR" is the best-performing algorithm among the options considered. In addition, (Free Rider) received the second-ranking from the first expert, with scores of (1.3776) as well as the second rankings according to the second and third experts was (DyAd) with scores of (1.5171), and (1.5567), respectively. Finally, the lower rank was (EDXY) from the point of the first expert with scours of (1.8350), while the (MaS Routing) was the lower rank from the opinion of the second and third experts with the score of (1.8867) and (1.9672), respectively. The findings can help organisations and individuals use the highest quality algorithm to achieve the best success in their objectives. Finally, this table reflects a compelling and comprehensive evaluation that has the potential to substantially influence decision-making and drive advancement in this NoC-based MPSoC domain.

The observed results reveal that the rankings of alternatives from the point of view of all DMs consistently and distinctly vary. This means a clear discrepancy in the order of alternatives for each expert. Hence, a comprehensive ranking that incorporates group experts becomes imperative to address the issue of variance effectively. By employing formula (25), Table 11 shows the ZCR-FDOSM-BM results in the context of group decision-making.

ZCR-FDOSM-BM's context followed the lowest score concept, which also applied to the group decision-making (GDM) environment. Table 11 represents the results of GDM using the ZCR-FDOSM-BM. The evaluation aims to rank various routing algorithms based on their performance. The top-ranking tools, such as "ADBR," "DyAd," and "MCAR," are considered the most effective and promising options, while other tools also demonstrate competitiveness and potential based on their respective ranks. These results guide decision-makers in selecting the most suitable routing algorithms for their specific requirements and contribute to the advancement of the domain. After completing GDM using ZCR-FDOSM-BM, this outcome must be assessed for stability using the systematic ranking (evaluation) given in the next section.

V. VALIDATION

Problems with the generalizability of findings need speedy action, which can be achieved via validation [11]. Procedures including objective validation, subject validation, sensitivity analysis, Spearman's rank correlation, and a comparison analysis are the most used method for validation [17], [78]. This research used objective validation, sensitivity analysis, and Spearman's rank correlation techniques to guarantee a rigorous categorisation scheme was applied to the DM alternatives (routing algorithms) rankings. The objective validation method includes compiling opinion matrices to produce a unified opinion matrix and ranking the routing algorithms within the unified opinion matrix. (1) The routing algorithms in the opinion matrix are sorted according to the group's decision-making outcomes in the opinion matrix. (2) After sorting, the groups are split equally. (3) Group decision-making outcomes are then derived using the mean

TABLE 7. Weights of the criteria.

Main Criteria	weigh	Sub-Criteria	weight	Main Criteria	weigh	Sub-Criteria	weight
Design Metrics	0.5	Size	0.1032	Performance Metrics	0.5	Power Dissipation (w) (pir:0.2/flit/cycle)	0.1033
		Topology	0.0774			Number of Bits	0.1099
		Routing Type	0.1026			Latency	0.1962
		Routing Characteristics	0.0569			Throughput (flit/cycle)	0.1938
		Packet Flit Size	0.0564				

(x) for each group shown below.

$$\bar{x} = \frac{1}{n}\sum\nolimits_{i=1}^{n} x_i. \tag{26}$$

where n is the number of alternatives and x is the value of alternatives.

Hence, the mean of each group is obtained. Based on the results of the comparison, the results of the arithmetic mean of the first group should be lower than or equal to the mean of the second group. Table 12 displays the assessment findings.

A scale assessment shows that each group contained five alternatives. Generally, the result of the 1st group was lower than the second group. This finding shows that groups extended based on the ZCR-FDOSM-BM results are valid.

The next stage in our research was to do a sensitivity analysis. To know the effect of changing the weights of the criterion on the final rank, a sensitivity analysis was used. The robustness of the proposed outcome is examined by varying the relative importance of the criteria used for assessment. For this reason, the sensitivity analysis estimates how shifting the criteria' relative importance would affect the electrical providers' final rankings [79]. The first step in assessing sensitivity is to choose the most relevant criteria. Based on the data shown in Table 7 (weighting of criteria), "the Latency" is the most crucial factor to consider. With the 0.1 increase as previous studies and the 9 criteria employed, Figure 4 presents a total of ten possible outcomes. The following formula was used to arrive at the weights for the other criteria.

$$w_n : (1 - w_{z1}) = w_n^* : \left(1 - w_{z1}^*\right) \tag{27}$$

where, w_n is the higher significant contribution, and w_n^* represents the original weight values computed using ZCR-FWZIC.

Figure 4 is shown that the ADBR was in 1st place, MaS Routing was in 10th place, EDXY was in the 9th rank, DyAd was in the 2nd position, and MCAR was in 3rd rank in all scenarios. In addition, CATRA was in the 5th position in the original scenario and the ninth scenario, while the rest was in the 4th position. Also, Free Rider had taken 7th place in all scenarios except for the seventh scenario in the 8th place.

TABLE 8. The opinion matrix.

Alternative	Size		TABOLOGY		Routing Type		Routing Characteristics	
	A	B	A	B	A	B	A	B
OE	BD	M	ND	VH	SD	M	ND	VH
CATR	ND	H	D	H	SD	M	D	M
ADBR	ND	VH	ND	VH	ND	VH	D	M
Free Rider	BD	H	ND	VH	SD	M	D	M
MaS Routing	BD	H	ND	VH	HD	H	HD	M
EDXY	SD	VH	ND	VH	D	H	D	M
DyAd	SD	VH	ND	VH	SD	S	D	M
Traffic Allocation	SD	H	ND	VH	SD	H	D	M
MCAR	ND	VH	ND	VH	SD	H	D	M
ZigZag	BD	M	ND	VH	D	H	D	M

A (ND=No difference, D=difference, SD =Slight difference, BD =Big difference, HB= Huge difference);
B (VS= Very small, S= small, M= Medium, H= High, VH= Very high).

Next, the OE took 8th place in the original and last three scenarios, from the first until the third scenario in 5th, and in the rest of the scenarios, it took 6th place. Furthermore, the Traffic Allocation was in 4th place in the original and the last two scenarios; after that, it got 6th in scenarios (1, 2, and

TABLE 9. Fuzzy opinion matrix.

C1- for the first expert					
A			B		
8.262	0.579	0.086	0.6	0.7	0.8
0	0.673	0.101	0.7	0.8	0.9
0	0.673	0.101	0.9	1	1
8.262	0.579	0.086	0.7	0.8	0.9
8.262	0.579	0.086	0.7	0.8	0.9
3.098	0.453	0.068	0.9	1	1
3.098	0.453	0.068	0.9	1	1
3.098	0.453	0.068	0.7	0.8	0.9
0	0.673	0.101	0.9	1	1
8.262	0.579	0.086	0.6	0.7	0.8

TABLE 10. The outcomes of the three decision-makers.

Alternative	First Expert		Second Expert		Third Expert	
	Score	Rank	Score	Rank	Score	Rank
OE	1.5749	6	1.7917	7	1.8307	8
CATR	1.5690	5	1.7436	6	1.7541	6
ADBR	0.9350	1	0.8136	1	0.8504	1
Free Rider	1.3776	2	1.8594	9	1.9218	9
MaS Routing	1.8152	9	1.8867	10	1.9672	10
EDXY	1.8350	10	1.8462	8	1.8271	7
DyAd	1.5326	4	1.5171	2	1.5567	2
Traffic Allocation	1.6562	8	1.6940	4	1.6753	4
MCAR	1.3999	3	1.6135	3	1.6691	3
ZigZag	1.6329	7	1.7192	5	1.7351	5

3), respectively and in the rest of the scenarios, it took 5th place. Moreover, ZigZag had achieved 6th place in scenarios (original, 8, and 9) and 8th scenarios (1, 2, 3, 4, 5, and 6) while 7th and 5th in the seventh and tenth scenarios. There were no significant general changes; approximately all five to six scenarios were identical to one alternative. Also, the constant was observed for all scenarios for 5 alternatives.

Spearman's rank is the third way to validate our result, and it is one of the most powerful techniques for determining the correlation between a set of variables. It measures the strength of the correlation between two variables. Spearman's rho (Spears' rho) is the Pearson correlation coefficient between two ranking random variables. According to importance, pro

TABLE 11. The outcome of decision-makers.

Routing algorithms	Final Rank	Rank
OE	1.7306	8
CATR	1.6878	5
ADBR	0.8656	1
Free Rider	1.7110	7
MaS Routing	1.8892	10
EDXY	1.8361	9
DyAd	1.5354	2
Traffic Allocation	1.6751	4
MCAR	1.5587	3
ZigZag	1.6954	6

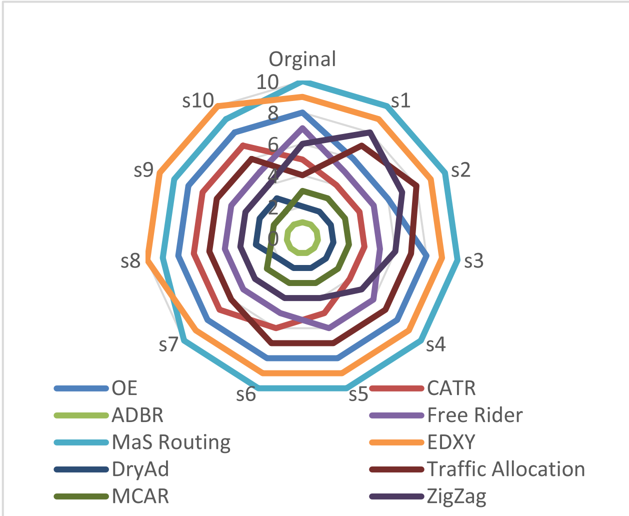

FIGURE 4. Sensitivity analysis.

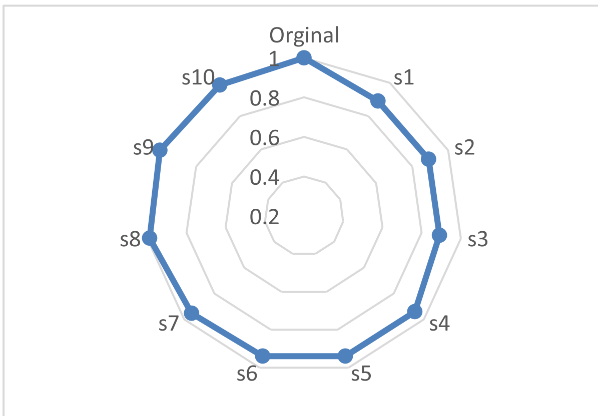

FIGURE 5. Spearman correlation coefficient.

TABLE 12. Assessment of group benchmarking results.

Groups number	Routing algorithms	Mean
First group	ADBR	1.4801
	Free Rider	
	DyAD	
	MCAR	
	ZigZag	
Second group	OE	1.7863
	CATR	
	MaS Routing	
	EDXY	
	Traffic Allocation	

TABLE 13. Comparison with ZCR-MABAC.

No	Comparison issue	ZCR-FDOSM	ZCR-MABAC
1	Missing information	√	×
2	Incomparable value	√	×
3	Offer opportunities for the decision-makers to explain their preferences.	√	×
4	Best possible solution and measurement of distance	√	×
5	uncertainty	√	√
6	A large number of alternatives	×	√
Total score		83%	33%

and con factors are ranked according to their relative size using the equation.

$$r_s = 1 - \frac{6\sum_i d_i^2}{n^3 - n} \tag{28}$$

where d is the difference between the two ranks of each observation and n is the number of observations.

For the ranking of routing algorithms, correlation analysis results are shown in Figure 5, with high values, where the lowest value was 89%, and the highest value was 100%.

VI. COMPARISON ANALYSIS

Based on previous research conducted in the field of decision-making, an analytical comparison is made using 13 indicators [29], [19], [79], [80], and the comparison is made with the best MCDM methods. In line with previous research, this section will provide a comparative analysis of various widely recognised MCDM methods operating on ZCR numbers. Firstly, it is important to note that MABAC is a widely recognised MCDM methodology that has been extensively utilised across various domains and industries. The base form

TABLE 14. Comparison between ZCR-FWZIC and ZCR-BWM.

No	Comparison issue	ZCR-FWZIC	ZCR-BWM
1	Is the nature and number of comparisons solved?	√	×
2	Is the Inconsistency problem solved?	√	×
3	Is the collection of professional opinions proving to be easy?	√	×
4	Is the weighting technique unambiguous in assigning weights to the criterion?	√	×
5	Is the dependence between the criteria handled?	√	×
6	The weighting procedure does not require a lot of time to complete.	√	×
7	Are the uncertainty issues solved?	√	√
Total score		100%	14%

of MABAC is plagued by uncertainty, prompting researchers to explore extensions that address this limitation. One such extension involves incorporating the ZCR fuzzy number, which is also utilised in the ZCR-FDOSM-BM method. This integration results in a modified version of MABAC known as fuzzy Z number MABAC (ZCR-MABAC) [39]. The ZCR-MABAC method, which integrates ZCR fuzzy numbers into the MABAC technique, effectively tackles both uncertainty and the inherent limitation of the original MABAC approach. ZCR-FDOSM was compared with ZCR-MABAC in the following contexts: 1) Handling missing information, 2) Handling incomparable criteria, 3) Offering opportunities for the decision-makers to explain their preferences, 4) Furthermore, ZCR-FDOSM displayed efficiency in dealing with best possible solution and measurement of distance for evaluating routing algorithms, 5) Moreover, it demonstrated the ability in handling ambiguity or uncertainty, and 6) Dealing with a large number of alternatives. In the routing algorithm evaluation, ZCR-FDOSM-BM demonstrated stronger robustness than ZCR-MABAC, as shown in Table 13.

While both methods were shown the ability to deal with ambiguous and vague information, ZCR-FDOSM outperforms ZCR-MABIC with (n = 5/6) and (n = 2/6), respectively.

Secondly, the conventional BWM is recognised as a powerful MCDM technique in the literature [81]. However, the primary version of BWM has limitations, including concerns with ambiguity and uncertainty. To address these issues, the

ZCR was established to improve the BWM technique and eliminate the aforementioned difficulties [39]. Despite its efforts to deal with uncertainty, ZCR-BWM still has certain shortcomings when compared to ZCR-FWZIC. These weaknesses include issues such as the number of comparisons, which requires deciding the number of comparisons to be undertaken, as well as the type of comparisons, where challenges emerge when comparing elements of varying natures, such as sound and color. Furthermore, weight assignment and consistency difficulties result from an uneven comparison supplied by decision-makers during the process. Table 14 provides a full review of these difficulties.

The comparison between ZCR-FWZIC and ZCR-BWM in weighting illustrates that ZCR-FWZIC highlights a higher level of reliability. Therefore, the ZCR-FWZIC is more flexible and has the capacity to handle many obstacles and Uncertainty faced during the weighting procedures; thus, it was used in our research.

VII. CONCLUSION AND FUTURE DIRECTIONS

The study aims to examine and assess various routing algorithms to determine the most appropriate algorithm that would assist designers and system engineers in enhancing decision-making processes. This study employed FWZIC and FDOSM methods. The utilisation of the ZCRNs environment addresses the challenge of two types of uncertainty, providing a framework for managing ambiguity in the data and achieving higher data freedom. The methodology consists of two main phases. Firstly, the decision matrix is constructed based on the nine sub-criteria under two main criteria and routing algorithms as alternatives. Secondly, we utilised the ZCR-FWZIC method to derive the weights for each criterion and subsequently utilised the ZCR-FDOSM-BM approach to rank the routing algorithms. The purpose of using ZCR number with FWZIC and FDOSM techniques is to enable the interpretation of uncertainty and capture useful information under ambiguity in the assessment of alternatives against various criteria and converting the opinion matrix to a fuzzy opinion matrix, while the concept of zero-inconsistency helps to ensure that the weights assigned to the various criteria. The Latency obtained the highest weight, whereas the Routing Characteristics and Packet Flit Size got the lowest weight, where the scores of weightings 0.1962, 0.0569, and 0.0564, respectively. The ranking of alternatives is shown "ADBR" was the best routing algorithm with a score of 0.8797, followed by "MCAR" 1.5826 and "DyAd" 1.6161 in the second and third position, respectively. The final results were validated using an objective statistical method, sensitivity analysis, and Spearman correlation, and the results were valid. In addition, to evaluate the proposed methods, the authors compared them with the well-known MCDM method named MABAC and BWM that used the same fuzzy set; the comparison introduced the resilience of ZCR-FDOSM-BM and ZCR-FWZIC as shown in Tables 13 and 14. Ranking routing algorithms provided several implications for designers and system engineers. They can extend the current work by conducting an intensive investigation into the routing algorithms to enhance the performance of NoC- based MPSoC. The current study opens doors to future research using various MCDM methods in this field to improve the strength and performance of NoC-based MPSoC. In addition, integrate the FWZIC and FDOSM with a new fuzzy set, such as Single-valued Neutrosophic or Generalized Interval Neutrosophic Rough Set to enhance the final decision.

This study aligns with previous literature by having limitations that open doors and prospects for future research. First, this study used the FDOSM method to rank routing algorithms from best to worst. However, this method suffers from the problem of increasing the number of alternatives. Using an advanced method such as MULTIMOORA to address this limitation. Finally, this study used FWZIC to extract the weights of the criteria. One notable shortcoming of the FWZIC technique is its inability to derive weights exclusively from the inputs of a single expert.

Compliance with Ethical Standards

Conflict of Interest: All the authors of this article declare the existence of no mutual conflict of interests.

Ethical Approval: All the procedures adopted by the study, involving human participants, were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinkideclaration and its latter amendments or comparable ethical standards.

Informed Consent: Informed consent was obtained from all individual participants of the study.

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