Applying Balanced Incomplete Block Diagrams to ensure Reliable Deterministic Scheduling in Fully Connected Swarms

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***Abstract*—Efficient communication is critical for coordination in multi-agent robotic systems operating under bandwidth and reliability constraints. In many existing approaches, communication is either randomized or loosely structured, leading to uncertainty in convergence time and robustness under packet loss. In this work, we propose a deterministic communication scheduling framework based on Balanced Incomplete Block Designs (BIBDs) for achieving consensus in fully connected swarms. The proposed method ensures structured and balanced pairwise communication between agents, enabling predictable information propagations. We evaluate the proposed approach in simulation against randomized and cyclic communication schedules under varying levels of packet loss. Experiments are conducted on systems of up to 91 agents with constrained communication budgets. Results show that BIBD-based scheduling consistently reduces time to consensus compared to randomized scheduling, achieving on average 19.6% faster convergence than the randomized schedules and 85.8% faster convergence than the Cyclic schedule for the 91 Agent swarm. On the 7 node swarm BIBD had on average 28% faster convergence than the randomized schedule and 61% faster convergence than the Cyclic Schedule while maintaining robustness under high packet loss conditions. These results suggest that combinatorial design-based scheduling provides a promising direction for communication-aware coordination in network-constrained robotic systems.**

***Index Terms*—swarms, Balanced incomplete block diagrams, deterministic scheduling**

I. Introduction

Multi-agent robotic systems are used in applications such as search and rescue [1], [2], and warehouse automation [3] and the problem of coordination among large numbers of agents is becoming increasingly more relevant as robots get deployed at scale to solve problems. In these settings, effective communication is essential for enabling agents to share information and reach consensus on global state. However, communication is often constrained by bandwidth limitations, unreliable links, and packet loss, making efficient and robust information propagation a key challenge.

Current approaches to communication in robot swarms can broadly be categorized into stochastic, centralized, and structured interaction strategies. Stochastic methods, such as gossip-based protocols, rely on randomized pairwise communication between agents [12]. Centralized or leader-based approaches use a designated agent or controller to coordinate the swarm's behavior [1]. In contrast, structured approaches impose constraints on communication topology or scheduling, such as fixed neighbor graphs or predefined interaction patterns [5], [7].

Each of these approaches presents trade-offs. Stochastic methods often exhibit high variance in convergence time, making system behavior difficult to predict and potentially leading to uneven information dissemination across agents. Centralized approaches introduce single points of failure and limit scalability. Structured approaches improve robustness and reduce communication overhead, but typically rely on fixed topologies that do not explicitly control the sequence or coverage of pairwise interactions. As a result, some agent pairs may interact frequently while others communicate infrequently, leading to inefficiencies in information propagation, especially under packet loss.

Additionally, prior work has shown that limiting communication in robot swarms can improve adaptability and prevent the propagation of outdated information [10]. This suggests that deterministic communication strategies, rather than fully connected or random interactions, may lead to more efficient collective behavior as it allows the convergence time to be controlled and for each Agent to be equally represented in Swarm Communication

In this work, we explore deterministic communication scheduling as an alternative approach for achieving reliable and predictable consensus. Specifically, we propose the use of Balanced Incomplete Block Designs (BIBDs), a class of combinatorial designs that ensure structured and balanced interactions between agents over time. By leveraging the properties of BIBDs [6], we construct communication schedules that systematically cover agent pairs, enabling efficient dissemination of information across the network.

We evaluate the proposed approach in simulation and compare it against randomized and cyclic communication schedules under varying levels of packet loss. Experiments are conducted on systems of up to 91 agents with constrained communication budgets. These findings suggest that combinatorial design-based scheduling can provide a principled and effective framework for communication-aware coordination in network-constrained multi-agent robotic systems.

A. Assumptions and Considerations

We consider a system of N autonomous agents, where each agent can communicate with up to k other agents at each discrete timestep. Each agent initially possesses a unique data packet, and the objective is to measure the time required for all agents to obtain all data packets in the system.

Communication between agents is implemented as a bidirectional exchange of information. When two agents communicate, they share all data currently in their possession. For example, if Agent 1 has data from agents $\{1, 2, 3\}$ and Agent 4 has data from agents $\{4, 5\}$, then after communication, both agents will possess data from agents $\{1, 2, 3, 4, 5\}$.

1) **Full Connectivity:** The communication network is fully connected, meaning any agent can communicate with any other agent.
2) **Synchronous Communication:** Time is discretized into timesteps, and all agents may perform communication actions simultaneously at each timestep.
3) **Static Agent Set:** The number of agents is fixed; no agents join or leave the system during execution.
4) **Limited Parallel Communication:** Each agent may communicate with up to k other agents per timestep.

These assumptions simplify the communication model and allow us to isolate the effects of scheduling on information propagation in fully connected networks. These assumptions simplify the communication model and allow us to focus on scheduling behavior for environments where any agent can talk to any agent.

B. Contribution

This paper explores the use of Balanced Incomplete Block Designs (BIBDs) as a deterministic communication scheduling framework for multi-agent robotic systems. While BIBDs have been previously studied in contexts such as experimental design and communication scheduling in wireless networks, their application to swarm coordination has been limited. We evaluate BIBD-based scheduling in a simulated swarm environment and compare its performance against cyclic and randomized communication strategies under varying levels of packet loss. Our results show that BIBD scheduling improves time to consensus and maintains robustness under unreliable communication conditions.

C. Background - Balanced Incomplete Block Diagrams

A Balanced Incomplete Block Diagram (BIBD) is a combinatorial structure defined by a set of v elements and a collection of subsets (blocks), each containing k elements. A BIBD can be characterized by the parameters (v, k, λ). In the BIBD structure, each pair of elements appear together in λ blocks. BIBDs and other combinatorial structures have been extensively studied in experimental design, communication scheduling, network design, coding theory and much more. [4]–[6], [8], [9] due to their balanced coverage properties. In this work, we interpret elements as agents in a swarm and blocks as communication groups. Each block defines a set of agents that communicate during a given timestep. The key property of a BIBD is that all pairs of agents interact in a balanced and systemic manner over time, ensuring uniform information exchange across the network. For example, a $(7, 3, 1)$ BIBD defines a schedule for 7 agents where each timestep involves communication among groups of 3 agents, and every pair of agents communicates exactly once over the full schedule. This structure enables predictable and efficient propagation of information, which is desirable in communication-constrained multi-agent systems.

II. Method

A. Algorithm Formulation

In practice, BIBD-based schedules are generated using difference sets similar to in [4]. A difference set is a subset of integers modulo v that defines a base communication pattern. By applying cyclic shifts of this set, we generate a sequence of communication groups that satisfy the BIBD properties. [4], [6]

For example, the $(7, 3, 1)$ design can be generated from the difference set $(0, 1, 3)$. Taking all cyclic shifts modulo 7 produces the communication groups:

$$(0, 1, 3), (1, 2, 4), (2, 3, 5), (3, 4, 6), (4, 5, 0), (5, 6, 1), (6, 0, 2)$$

Each group corresponds to a timestep in which the selected agents communicate. These groups can be represented as a binary schedule matrix S, where rows correspond to agents and columns correspond to timestep. An entry of 1 indicates that an agent participates in communication during that timestep. When the last timestep represented in the schedule is reached, the schedule repeats.

$$S = \begin{bmatrix} 1 & 0 & 0 & 0 & 1 & 0 & 1 \\ 1 & 1 & 0 & 0 & 0 & 1 & 0 \\ 0 & 1 & 1 & 0 & 0 & 0 & 1 \\ 1 & 0 & 1 & 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 1 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 1 & 1 & 0 \\ 0 & 0 & 0 & 1 & 0 & 1 & 1 \end{bmatrix} \tag{1}$$

This schedule defines a deterministic communication pattern with balanced pairwise interactions, enabling efficient information propagation under constrained communication. This structure ensures that all agents communicate in a balanced manner over time, reducing redundancy and improving convergence efficiency.

B. Experimental Setup

To test the BIBD's effectiveness, it was compared against the Cyclic algorithm and random schedules. Here the Cyclic method represents a ring configuration which is a highly structured algorithm and the randomized schedule is a completely unstructured algorithm that selects k random Agents to communicate. This is test BIBDs against both structured and unstructured algorithms. Cyclic schedules communication where every agent communicates with a different agent in a chain. The last node in the chain communicates with the first. A 7 agent Cyclic schedule can

be represented as the following matrix schedule. Where each row is a node and when the node is 0 it is not communicating and when it is 1 it is communicating.

Random Schedules is when each node communicates with k randomly selected agents. To ensure fairness the value of k is the same value of k in the (v, k, λ) BIBD

Methods are also evaluated when packet loss varies to test robustness of the algorithms to interruptions. Packet loss is measured as the probability of a communication between 2 agents failing. This method is evaluated with a smaller system of 7 agents where 3 communications can happen at a time and a bigger system of 91 agents where 10 communications can happen at a time. Each Algorithm is run 20 times and the average and standard deviation is measured.

C. Metrics

The Metric used to evaluate the algorithms is the time to consensus which is the time taken for information from all the agents to be distributed among all the agents. This is evaluated as packet loss varies from a 0.1 probability to a 0.9 probability. Simulations were run for up to 4000 time steps. If consensus was not reached within this horizon, the run was treated as non-convergent

III. Results

When run for 7 agents and 3 communications per timestep with no packet loss and as shown below the BIBD method does outperform the other methods significantly.
they scale differently with different amounts of packet loss

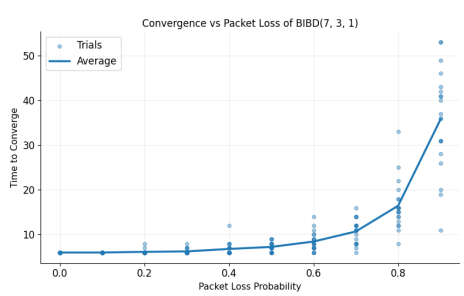

Fig. 1: Time to Convergence of Swarm using 7,3,1 BIBD when Packet Loss Probability is varied

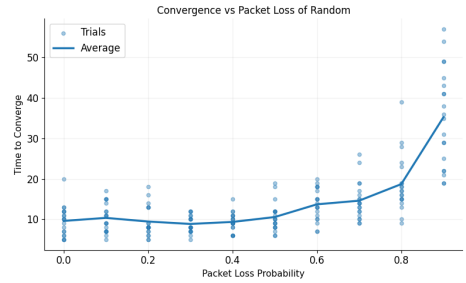

Fig. 2: Time to Convergence of Swarm using Random Schedule when Packet Loss Probability is varied

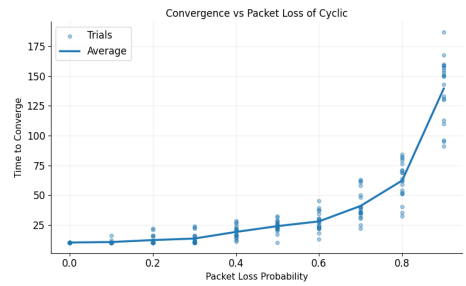

Fig. 3: Time to Convergence of Swarm using Cyclic Schedule when Packet Loss Probability is Varied

This was also run for 91 nodes

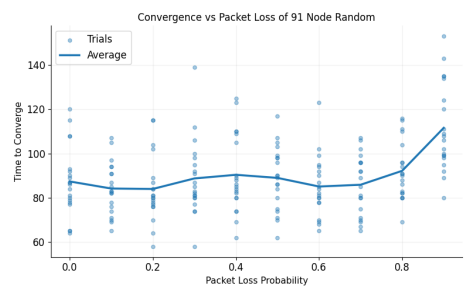

Fig. 4: Time to Convergence of Swarm using random Schedule when Packet Loss Probability is Varied

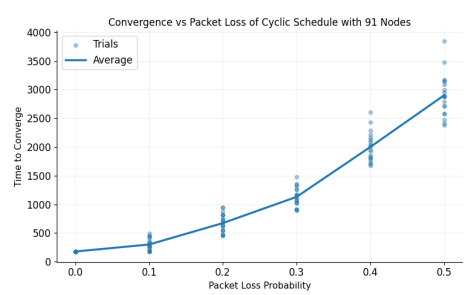

Fig. 5: Time to Convergence of Swarm using Cyclic Schedule when Packet Loss Probability is Varied. Most runs when packet loss was greater than 0.5 did not converge in 4000 time steps and were treated as non convergent.

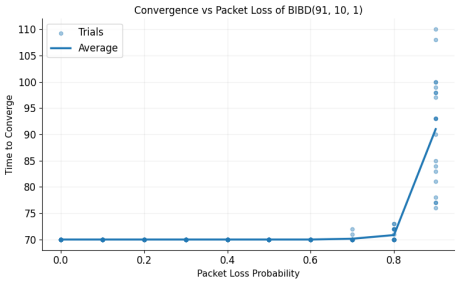

Fig. 6: Time to Convergence of Swarm using 91,10,1 BIBD when Packet Loss Probability is varied

Algorithm	Mean Convergence Time	Std. Dev.
	7 Agents	
(7,3,1) BIBD	6.25	0.54
Random	8.85	2.06
Cyclic	13.35	4.50
	91 Agents	
(91,10,1) BIBD	70.00	0.48
Random	88.75	16.60
Cyclic	1130.15	163.06

TABLE I: Mean time to consensus and standard deviation under packet loss probability $p = 0.3$.

Algorithm	Mean Convergence Time	Std. Dev.
	7 Agents	
(7,3,1) BIBD	6.00	0.00
Random	9.60	1.11
Cyclic	11.00	0.00
	91 Agents	
(91,10,1) BIBD	70.00	0.00
Random	87.40	15.26
Cyclic	178.00	0.00

TABLE II: Mean time to consensus and standard deviation with no packet loss ($p = 0$).

Overall from the packet loss trials on the 91 node swarm BIBD was on average 19.6% faster convergence than the randomized schedule and 85.8% faster convergence than the Cyclic Schedule. On the 7 node swarm BIBD had on average 28% faster convergence than the randomized schedule and 61% faster convergence than the Cyclic Schedule.

A. Analysis

The results demonstrate that BIBD-based scheduling consistently achieves faster convergence than both randomized and cyclic communication strategies, with lower mean convergence time and significantly lower variance. This behavior is observed in both the 7-agent and 91-agent systems.

As shown in Table II, under zero packet loss, all methods converge relatively quickly for the 7-agent system. The $(7, 3, 1)$ BIBD achieves the fastest convergence at 6 timesteps. While the randomized schedule occasionally produces faster outcomes in individual trials, its average performance is worse and exhibits higher variance due to its stochastic nature. The cyclic schedule performs the worst among the three. This trend remains consistent in the 91-agent system.

When packet loss is introduced (Table I), all methods experience an increase in variability. Randomized schedules show a relatively stable mean convergence time at lower packet loss rates, but their variance increases significantly due to the inherent randomness of communication. At higher packet loss probabilities, performance degrades further.

Cyclic schedules, while deterministic, are highly sensitive to packet loss. Their convergence time increases rapidly with increasing packet loss in both the 7-agent (Fig. 3) and 91-agent (Fig. 5) systems. In the larger system, cyclic scheduling fails to converge within the simulation horizon at high packet loss rates, highlighting its lack of scalability under unreliable communication.

BIBD-based scheduling shows a modest increase in convergence time as packet loss increases; however, it remains consistently more efficient than randomized scheduling across most tested conditions. For the 7-agent system(1), BIBD maintains lower convergence time than random schedules up to approximately $p = 0.8$. Additionally, its variance remains significantly lower, indicating more predictable performance.

This advantage is even more pronounced in the 91-agent system. Due to the larger communication group size, BIBD scheduling remains robust to packet loss, maintaining convergence times close to 70 time steps across a wide range of packet loss probabilities(6). In contrast, randomized schedules, despite using the same group size, exhibit higher convergence times and substantially greater variance.(I)

IV. Conclusion

This work investigates the use of Balanced Incomplete Block Designs (BIBDs) as a framework for communication scheduling in multi-agent robotic systems. We demonstrate that BIBD-based scheduling provides a deterministic and structured approach to information exchange, enabling efficient and predictable consensus.

Through simulation, we show that BIBD scheduling outperforms randomized and cyclic baselines in terms of both convergence speed and robustness to packet loss. In particular, BIBD achieves faster convergence and significantly lower variance, indicating improved reliability in communication-constrained settings.

These results suggest that combinatorial design-based scheduling is a promising direction for communication-aware coordination in swarm robotics.

A. Future Work

One of the disadvantages of using BIBDs is that there isn't a BIBD for every value of v so future work would be to implement a hybrid approach that would allow the same improvements for values of v that do not correspond to a known BIBD. In addition to this, we plan to deploy this algorithm on real hardware.

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