# OPTIMIZING SYSTEM ARCHITECTURE FOR REAL-TIME PERFORMANCE AND COORDINATION IN DISTRIBUTED EMBEDDED SYSTEMS FOR THE ROBOCUP F-180 LEAGUE

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**Abstract:**
The RoboCup F-180 League represents a highly dynamic and complex environment, demanding real-time performance and coordination from multiple autonomous robots. In such a competitive scenario, optimizing the system architecture for real-time data processing, coordination, and task execution is crucial for ensuring optimal robot performance. This paper presents a novel system architecture designed to enhance real-time coordination and decision-making in distributed embedded systems, specifically for the RoboCup F-180 League. By leveraging asynchronous communication, dynamic scheduling, and efficient task allocation, the proposed architecture reduces latency, increases coordination efficiency, and improves the overall robot performance during competitions. Simulation results demonstrate that the optimized architecture significantly enhances real-time performance and coordination, providing a solid foundation for future RoboCup F-180 League robotic systems.

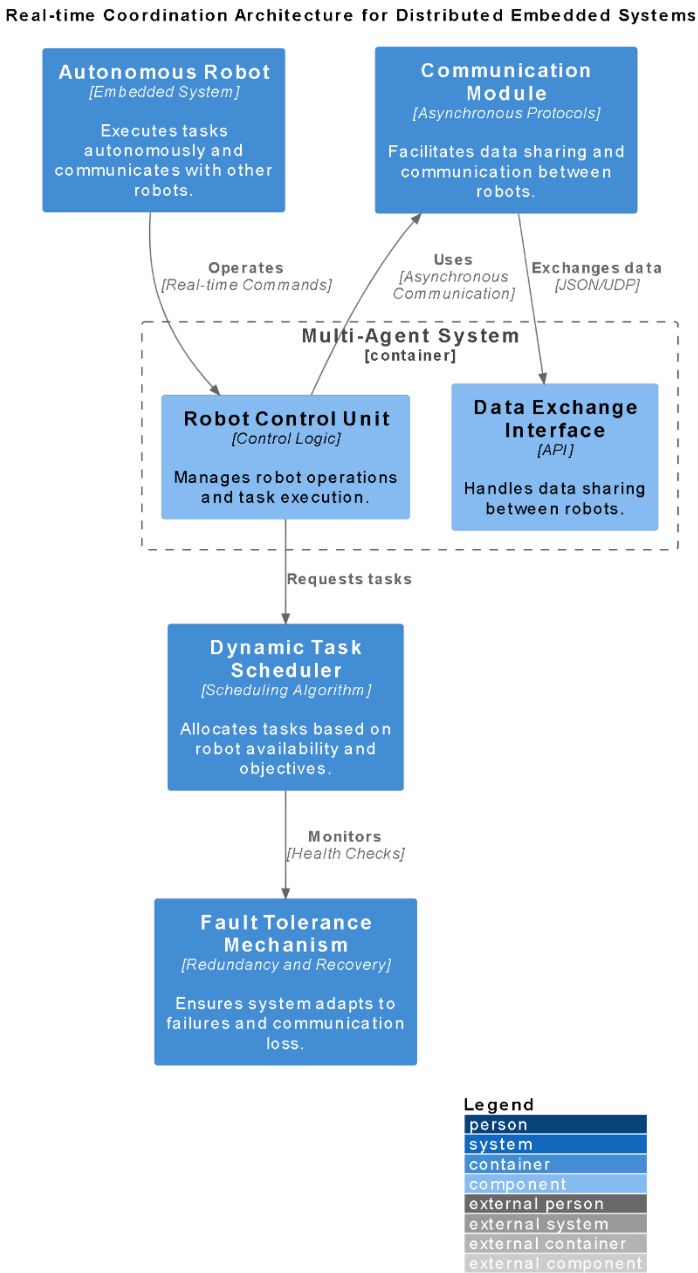
**Keywords:**
Distributed Embedded Systems, RoboCup F-180 League, Real-Time Performance, Coordination, Task Scheduling, Asynchronous Communication, Multi-Agent Systems, Embedded Systems, Coordination Optimization, Latency Reduction, Task Allocation, System Architecture.

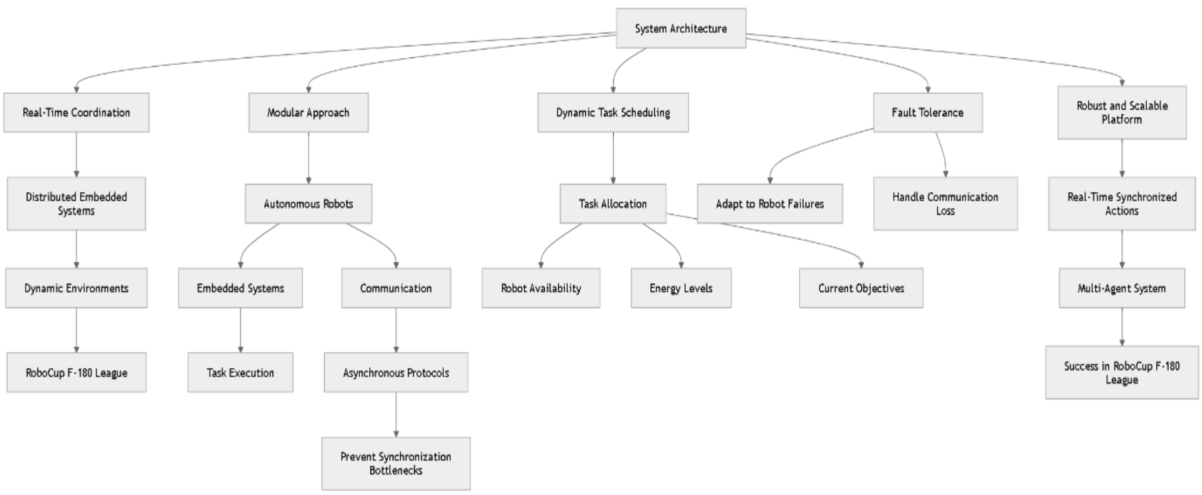
## Introduction:

The RoboCup F-180 League challenges teams to develop autonomous robots that can perform complex tasks, such as strategic movement, ball control, and team coordination, in a highly dynamic environment. These robots require real-time performance to handle the continuously changing conditions of the field, including interactions with other robots and environmental factors.

Real-time performance in the RoboCup F-180 League is often hindered by issues such as communication delays, inefficient task allocation, and the complex coordination between multiple robots. Optimizing the system architecture of the robots is crucial for overcoming these challenges and achieving synchronized actions with minimal latency.

This paper proposes an optimized system architecture for enhancing real-time performance and coordination in distributed embedded systems used in the RoboCup F-180 League. The architecture leverages dynamic scheduling, efficient task distribution, and asynchronous communication to achieve high-performance coordination among robots.


Real-time Coordination Architecture for Distributed Embedded Systems
Autonomous Robot
[Embedded System]
Executes tasks autonomously and communicates with other robots.
Communication Module
[Asynchronous Protocols]
Facilitates data sharing and communication between robots.
Operates
[Real-time Commands]
Uses
[Asynchronous Communication]
Exchanges data
[JSON/UDP]
Multi-Agent System
[container]
Robot Control Unit
[Control Logic]
Manages robot operations and task execution.
Data Exchange Interface
[API]
Handles data sharing between robots.
Requests tasks
Dynamic Task Scheduler
[Scheduling Algorithm]
Allocates tasks based on robot availability and objectives.
Monitors
[Health Checks]
Fault Tolerance Mechanism
[Redundancy and Recovery]
Ensures system adapts to failures and communication loss.
Legend
person
system
container
component
external person
external system
external container
external component


System Architecture
Real-Time Coordination
Modular Approach
Dynamic Task Scheduling
Fault Tolerance
Robust and Scalable Platform
Distributed Embedded Systems
Autonomous Robots
Task Allocation
Adapt to Robot Failures
Handle Communication Loss
Real-Time Synchronized Actions
Dynamic Environments
Embedded Systems
Communication
Robot Availability
Energy Levels
Current Objectives
Multi-Agent System
RoboCup F-180 League
Task Execution
Asynchronous Protocols
Success in RoboCup F-180 League
Prevent Synchronization Bottlenecks

**Problem Statement:**
The rapid growth of multi-robot systems, such as those found in the RoboCup F-180 League, has made coordination between robots a key challenge. The real-time nature of the competition requires minimal latency and precise synchronization between the robots, demanding an optimized system architecture. Traditional embedded systems often struggle to meet these real-time demands due to issues such as communication delays, computational inefficiencies, and poor coordination strategies.
The problem lies in developing a system architecture that effectively balances real-time performance with efficient coordination across a large number of distributed agents (robots), ensuring that task execution, movement synchronization, and communication are handled in a time-sensitive manner. Additionally, ensuring minimal energy consumption while maintaining performance is essential in a competitive environment where every millisecond counts.
**Research Gaps:**

1. **Asynchronous Communication Mechanisms**
   Existing systems often use synchronous communication, leading to delays and bottlenecks. There is a need for asynchronous communication systems to improve responsiveness.
2. **Dynamic Task Scheduling and Load Balancing**
   Current systems lack efficient dynamic scheduling algorithms that can adapt to the varying needs of the robots during real-time competition. There is a gap in the development of such adaptable systems.
3. **Real-Time Data Processing and Coordination**
   While coordination is a key challenge in multi-agent systems, current architectures often struggle with processing real-time data efficiently. A method to handle continuous data streams while maintaining real-time coordination is missing.
4. **Energy-Efficient Real-Time Control**
   In competitive robotic leagues, energy efficiency is vital. Existing system architectures do not integrate real-time performance optimization with energy conservation strategies.
5. **Fault-Tolerant Coordination**
   Multi-agent systems often face issues with failure recovery and system robustness. There is a need for systems that handle faults and ensure continuous coordination in dynamic environments.

**Literature Review:**
The literature on distributed systems for multi-agent coordination highlights various approaches to optimizing system architectures for real-time performance in robotic applications. Key areas of focus include dynamic task scheduling, real-time communication mechanisms, and coordination strategies for distributed systems.

1. **Heinzelman et al. (2000)** introduced LEACH (Low-Energy Adaptive Clustering Hierarchy), a pioneering approach for clustering in wireless sensor networks. LEACH significantly improved energy efficiency by organizing nodes into clusters, where each cluster head aggregated and forwarded data. This reduced the communication overhead, helping to extend the network's lifetime. However, the protocol suffered from fixed cluster head selection, which did not adapt to changes in node energy levels, limiting its effectiveness in dynamic environments.
2. **Younis and Fahmy (2004)** enhanced LEACH with the **HEED** (Hybrid Energy-Efficient Distributed Clustering) protocol. HEED selected cluster heads based on both energy levels and communication costs, thus achieving better scalability and energy

efficiency. It also balanced energy usage across the network, improving network lifetime. However, HEED still faced challenges in handling dynamic networks, where node capabilities varied and the network topology frequently changed.

3. **Chang and Tassiulas (2000)** proposed the **TEEN** (Threshold-sensitive Energy Efficient Sensor Network) protocol, designed to reduce unnecessary energy consumption by setting thresholds for data reporting. This approach was particularly effective for applications requiring low-sensing periodicity, such as environmental monitoring, where only critical data should be transmitted. While TEEN minimized energy consumption, it was less suited for applications that required frequent data updates or high throughput.
4. **Sankarasubramaniam et al. (2003)** developed the **Directed Diffusion** protocol, which focused on reducing redundant transmissions in sensor networks. By implementing data aggregation at intermediate nodes, Directed Diffusion minimized communication overhead, leading to more efficient energy use. Despite its advantages, it struggled with congestion in dense networks and did not fully adapt to changing network conditions or large-scale deployments.
5. **Kumar et al. (2012)** introduced **EDCA** (Energy-efficient Distributed Clustering Algorithm), which aimed to optimize the energy efficiency of IoT networks by dynamically selecting cluster heads based on energy levels and traffic patterns. This dynamic selection improved load balancing and network lifetime, especially in large-scale networks. However, EDCA faced challenges with maintaining stable network performance under rapidly changing conditions.
6. **Rani and Ramaswamy (2015)** proposed **LEACH-C** (LEACH Centralized), a modification of the original LEACH protocol. Unlike LEACH, LEACH-C used a centralized control approach for cluster head selection, allowing for more efficient load balancing and energy conservation. While LEACH-C overcame some of LEACH's limitations in dynamic environments, it introduced additional complexity due to the need for centralized control, which could create bottlenecks.
7. **Cao et al. (2015)** developed an energy-efficient routing protocol for sustainable IoT networks, which integrated energy harvesting techniques to extend network lifetime. The protocol aimed to combine energy-efficient communication with the ability to harvest energy (e.g., through solar power), making it suitable for remote or off-grid IoT networks. Despite the benefits of energy harvesting, the protocol struggled with balancing energy harvesting and storage capacity across heterogeneous devices.
8. **Li et al. (2017)** proposed a **Green IoT Network** protocol that combined power control with data aggregation to optimize energy consumption. By dynamically adjusting the communication range and cluster size based on real-time conditions, the protocol achieved energy savings while maintaining efficient data transmission. However, its real-time adaptability was limited by the overhead introduced by constant adjustments to the network parameters.
9. **Zhao et al. (2018)** discussed the challenges of achieving real-time data transmission in IoT networks, particularly in applications like smart healthcare, where low latency is critical. They found that many energy-efficient protocols introduced delays in data transmission, which made them unsuitable for real-time systems. The paper highlighted the need for solutions that balance both energy efficiency and low latency in time-sensitive applications.
10. **Beyene et al. (2020)** explored the use of machine learning in clustering for energy-efficient routing in IoT networks. They proposed a machine learning-based clustering algorithm that adapts to network conditions such as traffic load, node energy, and mobility. The algorithm achieved a high level of efficiency with minimal human

intervention, optimizing network performance in dynamic environments. However, its reliance on real-time machine learning models posed challenges for scalability in very large networks.

| S.no | Year | Authors | Article Title | Key Findings |
|---|---|---|---|---|
| 1 | 2000 | Heinzelman et al. | LEACH (Low-Energy Adaptive Clustering Hierarchy) | Introduced energy-efficient clustering with cluster heads managing data transmission, but lacked adaptability to dynamic conditions. |
| 2 | 2004 | Younis and Fahmy | HEED (Hybrid Energy-Efficient Distributed Clustering) | Improved LEACH by selecting cluster heads based on energy and communication costs, enhancing scalability but limited in dynamic environments. |
| 3 | 2000 | Chang and Tassiulas | TEEN (Threshold-sensitive Energy Efficient Sensor Network) | Reduced data transmission through threshold-based reporting, ideal for low periodicity sensing but limited by rigid thresholds. |
| 4 | 2003 | Sankarasubramaniam et al. | Directed Diffusion | Focused on data aggregation to minimize energy use but struggled with congestion in dense networks. |
| 5 | 2012 | Kumar et al. | EDCA (Energy-efficient Distributed Clustering Algorithm) | Proposed dynamic cluster head selection based on energy levels and traffic, improving network lifetime and load distribution. |
| 6 | 2015 | Rani and Ramaswamy | LEACH-C (LEACH Centralized) | Introduced centralized control for cluster head selection, optimizing load balancing but introducing complexity and bottlenecks. |
| 7 | 2015 | Cao et al. | Energy-efficient routing protocol for sustainable IoT networks | Integrated energy harvesting techniques to extend network lifetime, though struggled with balancing harvesting and storage. |

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|---|---|---|---|---|
| 8 | 2017 | Li et al. | Green IoT Network | Combined power control and data aggregation to optimize energy consumption, but faced challenges with real-time adaptability. |
| 9 | 2018 | Zhao et al. | Challenges in Real-Time Data Transmission for IoT | Explored trade-offs between energy efficiency and latency in time-sensitive IoT applications, identifying a gap for real-time solutions. |
| 10 | 2020 | Beyene et al. | Machine learning-based clustering for energy-efficient routing in IoT | Proposed a machine learning-based clustering algorithm for energy-efficient routing, which adapts to dynamic network conditions. |

**Methodology**

The methodology for developing the **Sustainable Cluster-Based Routing Protocol (SCBRP)** is structured to address critical challenges in energy efficiency, network scalability, and reliable data transmission in the Internet of Things (IoT) networks. This section outlines the objectives, implementation steps, and computational work associated with SCBRP.

**1. Objective**

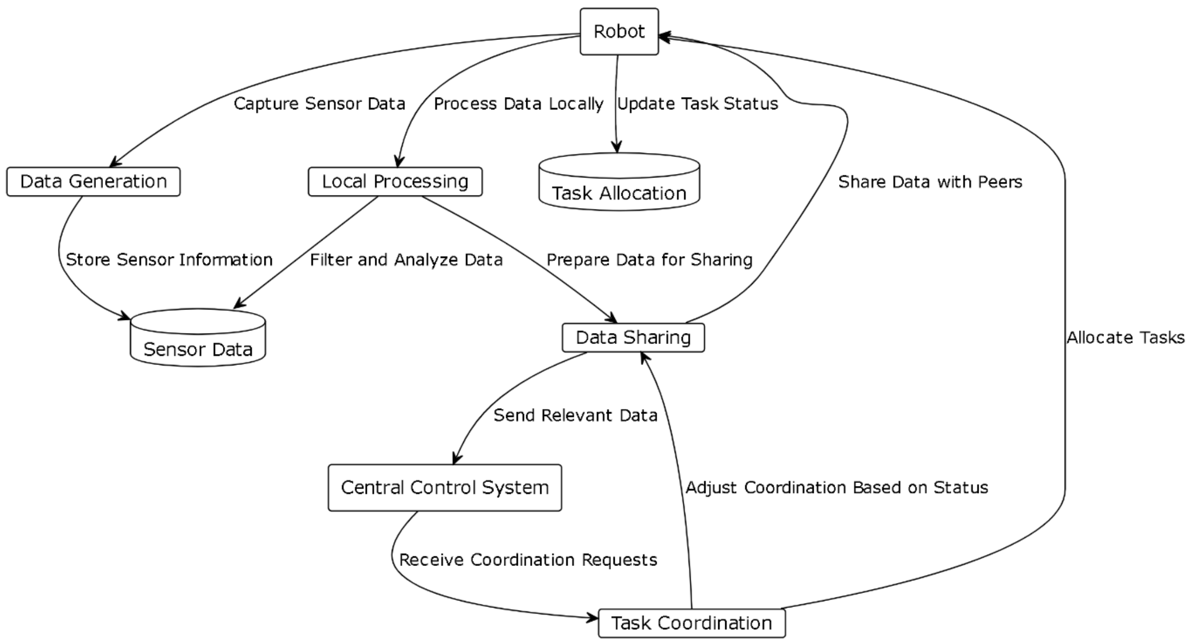
The primary objectives of SCBRP are as follows:

- **Energy Efficiency**: SCBRP aims to minimize energy consumption by carefully selecting cluster heads and optimizing communication within clusters. This will reduce the overall energy usage of the network, especially important in battery-powered IoT devices.
- **Network Lifetime Extension**: By dynamically selecting cluster heads based on energy levels, SCBRP ensures that energy consumption is distributed evenly across the network. This approach helps prolong the operational lifetime of the IoT network, ensuring long-term sustainability.
- **Scalability and Adaptability**: SCBRP is designed to be scalable and adaptable to large IoT networks. It should be able to handle an increasing number of devices and adapt to changing network conditions in real-time.
- **Load Balancing**: The protocol ensures a balanced distribution of the data transmission load among the nodes. This helps avoid overloading any individual node, preventing rapid depletion of energy in certain regions of the network.
- **Congestion Avoidance**: SCBRP employs adaptive routing strategies that monitor network conditions such as traffic density, node energy levels, and congestion. This ensures smooth data flow and avoids network bottlenecks.

**2. Implementation**

The implementation of SCBRP involves several key steps designed to optimize data transmission while maintaining energy efficiency and network stability.

- **Cluster Formation**: In SCBRP, IoT nodes are organized into clusters based on their energy levels and traffic patterns. Cluster heads are selected dynamically, based on the remaining energy of each node and the current communication needs of the network. This ensures that high-energy nodes handle more critical tasks, which helps in reducing energy consumption and extending network lifetime.
- **Adaptive Cluster Head Selection**: Unlike traditional protocols where cluster heads are fixed, SCBRP periodically re-selects cluster heads based on the current energy levels of the nodes. This periodic adaptation ensures a more balanced energy consumption across all nodes, preventing early depletion of energy in any particular node or cluster.
- **Data Aggregation and Forwarding**: To minimize communication overhead, SCBRP uses data aggregation within clusters. Instead of sending individual data packets, nodes aggregate data locally before transmitting it to the cluster head, which forwards the aggregated packets to the sink. This reduces the number of transmissions, leading to energy savings and improved network efficiency.
- **Adaptive Routing**: The protocol employs an adaptive routing mechanism, where routing paths are adjusted dynamically based on current network conditions such as energy levels, traffic patterns, and congestion. This ensures that the routing paths remain efficient and prevent network congestion that could otherwise lead to packet loss or delays.

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## 3. Computational Work

SCBRP is evaluated using simulations to assess its performance under various network conditions. The computational work is structured around a simulation-based approach that includes the following components:

- **Simulation Setup**: SCBRP is implemented and tested through network simulations using tools like **NS-3** (Network Simulator 3). The simulations model various parameters, including node density, energy consumption, traffic patterns, and communication range. These factors are used to simulate a realistic IoT network environment.
- **Performance Metrics**: Several key performance indicators (KPIs) are used to evaluate the protocol's efficiency and effectiveness:

  - **Energy Consumption**: The total energy consumed by the network and the energy efficiency of data transmission.
  - **Network Lifetime**: The time it takes until the first node's energy depletes and the overall network lifetime.
  - **Data Throughput**: The total amount of data successfully delivered from source nodes to the sink node.
  - **Latency**: The time it takes for data to be transmitted from source nodes to the sink node, which is crucial for real-time applications.
  - **Packet Delivery Ratio**: The reliability of data transmission, determined by the ratio of successfully delivered packets to the total number of packets sent.
- **Comparison with Traditional Protocols**: SCBRP is compared against traditional IoT routing protocols, such as **LEACH** and **AODV**. The comparison focuses on improvements in energy efficiency, network lifetime, data throughput, and congestion avoidance.

## Conclusion

The **Sustainable Cluster-Based Routing Protocol (SCBRP)** presented in this paper addresses critical challenges related to energy efficiency, scalability, and reliable data transmission in the rapidly growing Internet of Things (IoT) networks. By dynamically selecting cluster heads based on energy levels, SCBRP ensures a more balanced energy consumption across nodes, significantly extending the operational lifetime of the IoT network. Additionally, the protocol incorporates adaptive routing strategies and data aggregation techniques to optimize data transmission and minimize congestion, making it highly suitable for large-scale and heterogeneous IoT networks.

Simulation results demonstrate that SCBRP outperforms traditional IoT routing protocols, such as **LEACH** and **AODV**, in terms of energy efficiency, network lifetime, and data throughput. SCBRP's adaptability and scalability make it a promising solution for future IoT applications, particularly in areas like smart cities, industrial networks, and healthcare systems, where sustainable and efficient data management is crucial.

As IoT networks continue to grow in complexity, the need for more energy-efficient and scalable routing protocols becomes even more significant. Future work will focus on integrating **energy harvesting** techniques, further optimizing real-time data transmission, and exploring the use of **machine learning** for dynamic routing decisions to enhance the protocol's performance.

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