

Wireless Routing Using Automata Theory and Formal Language

Hassan KH Mohamed *

Department of Computer Science, College of Arts and Sciences, University of Benghazi,
Salouq, Libya.

*Corresponding author: hasanelfakhari@uob.edu.ly

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Abstract:

In wireless sensor networks (WSNs), routing is still a major problem that affects network longevity, energy consumption, and data transmission efficiency. The explicit modeling of cluster head (CH) and gateway assignments to successfully balance efficiency and adaptability has received relatively little attention, despite the fact that the majority of current research focuses on either network coverage optimization or adaptive routing path optimization. The current study fills this gap by presenting a novel routing architecture based on finite automata theory that is intended to dynamically manage gateway assignments and CH in clustered WSNs. The suggested system makes use of deterministic and non-deterministic finite automata (DFA and NFA) to enable energy-conscious, adaptive reactions to variations in resource availability and network structure. Comprehensive simulations and comparative analyses against existing Cellular Automata (CA) and Learning Automata (LA) methods demonstrate superior scalability, reduced complexity, and enhanced network lifetime. By integrating theoretical automata insights with practical routing requirements, this study provides a strong foundation for future large-scale WSN management.

Keywords: Wireless Sensor Networks, Routing, Automata Theory, Cellular Automata, Learning Automata, Cluster Head Selection, Gateway Selection.

التوجيه اللاسلكي باستخدام نظرية الآلات واللغة الشكلية

حسن خليفة محمد امقاوي *

قسم علوم الحاسوب، كلية الآداب والعلوم، جامعة بنغازي، سلق، ليبيا.

الملخص

في شبكات المستشعرات اللاسلكية (WSNs)، لا يزال التوجيه يُعدّ من أبرز التحديات التي تؤثر على عمر الشبكة، واستهلاك الطاقة، وكفاءة نقل البيانات. وعلى الرغم من أن معظم الدراسات الحالية تركز على تحسين تغطية الشبكة أو تحسين مسارات التوجيه التكريرية، إلا أن النمذجة الصريحة لآليات تعيين رؤوس العناقيد (CH) وبوابات الربط (Gateway) لتحقيق توازن فعال بين الكفاءة والقدرة على التكيف لم تحظَ بالاهتمام الكافي.

تسند هذه الدراسة هذه الفجوة من خلال تقديم معمارية توجيه جديدة تعتمد على نظرية الآلات المحدودة (Finite Automata) بهدف إدارة تعيينات رؤوس العناقيد والبوابات بشكل ديناميكي داخل شبكات WSN المعقدة. يستخدم النظام المقترح كلاً من الآلات المحدودة الحتمية وغير الحتمية (DFA) و (NFA)، مما يتيح استجابات تكيفية وواعية للطاقة وفقاً للتغيرات في توفر الموارد وبنية الشبكة.

كما تُظهر عمليات المحاكاة الشاملة والتحليلات المقارنة مع نماذج قائمة مثل الخلايا الذكية (Cellular Automata – CA) وآلات التعلم (Learning Automata – LA) تفوقاً واضحاً من حيث قابلية التوسع، وانخفاض التعقيد، وزيادة

عمر الشبكة. ومن خلال دمج الأسس النظرية لنماذج الآلات مع متطلبات التوجيه العملية، توفر هذه الدراسة أساسًا قويًا لإدارة شبكات WSN واسعة النطاق مستقبلاً.

الكلمات المفتاحية: شبكات المستشعرات اللاسلكية، التوجيه، نظرية الآلات، الخلايا الذكية، آلات التعلم، اختيار رئيس العنقود، اختيار بوابة الربط.

1.Introduction

Since it has a direct impact on network energy consumption, transmission reliability, and operational lifespan, efficient routing is still one of the most important and enduring problems in wireless sensor networks (WSNs). Previous research shows that node placement strategies and the effective use of limited resources are closely related to overall performance [1]. WSN applications such as smart agriculture, healthcare, industrial automation, environmental monitoring, and security surveillance are growing quickly, which has increased demand for reliable and scalable routing protocols to satisfy a range of operational needs [1–3]. Furthermore, increasing path selection and delivery accuracy, which in turn improves routing efficiency and end-to-end performance, depends critically on precise node localization [2]. Concurrently, network-layer optimizations have been complemented by improvements in QoS-aware MAC protocols, which have increased reliability and decreased latency [3]. In order to provide context for the QoS discussion, Fig. 1 illustrates how application requirements translate into quantifiable network metrics by contrasting IntServ (flow-based guarantees) with DiffServ (packet-level differentiation) [3].

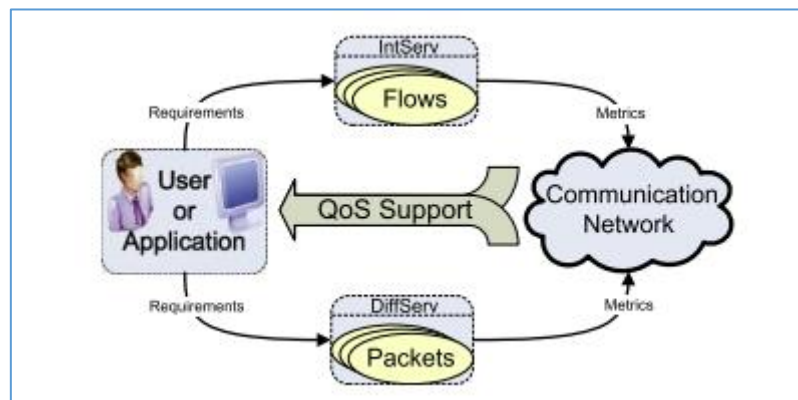


Figure 1: shows a network-specific QoS model that compares DiffServ (packet-level differentiation) and IntServ (flow-based guarantees). Based on Yiğitel et al. [3].

Energy efficiency is still a top design goal because sensor nodes are usually battery-powered and frequently placed in areas where maintenance is not feasible [4].

In WSNs, routing protocols are made to reliably and efficiently transport sensed data from sources to predetermined locations while reducing latency and protecting constrained energy budgets. Each of the delivery modes—unicast, broadcast, multicast, and geocast—is designed to meet specific communication needs [5,6]. Specifically, geocast facilitates region-centric distribution according to geographic limitations, which is advantageous for location-aware monitoring [5]. The need for energy-aware routing strategies that can strike a balance between reliability and resource conservation is highlighted by the fact that broadcast-style dissemination, including many geocast realizations, can cause redundant transmissions and hasten battery depletion [6,7].

Clustering continues to be one of the most successful architectural strategies for WSNs among the different energy-saving techniques. This method minimizes long-distance transmissions by grouping sensor nodes into clusters under the control of cluster heads (CHs), who aggregate data locally before sending it to sink nodes. The wise choice of CH and gateway roles is crucial to clustering effectiveness because it guarantees balanced load distribution, minimizes redundant forwarding, and eventually increases network lifetime [8,9]. The interaction between CHs, gateways, and sink nodes is highlighted in Fig. 2 (GARTOOL Classic WSN with CH & SEC), which shows a typical clustered network topology and demonstrates this hierarchical structure.

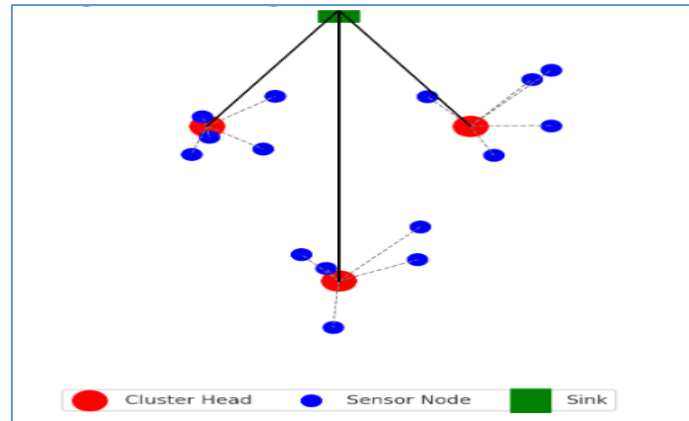


Figure. 2. *Clustering in WSN with CH and Sink*

However, the inherent dynamism and heterogeneity of WSNs—mobility, uneven density, and fluctuating residual energy—pose persistent challenges for the stability and performance of clustering-based routing [7,10]. Though several routing and clustering methods have been suggested, adaptable and flexible frameworks for dynamic CH and gateway allocation remain rather rare. Automata theoretic models—especially finite automata—offer a solid foundation for depicting state transitions in dispersed environments, with great potential for improving WSN routing [11,12]. Recent studies have looked into the use of Cellular Automata (CA) [11] and Cellular Learning Automata (CLA) [12], as well as Learning Automata (LA) for decentralized decision making and energy-aware path selection [13,14], and they have shown significant enhancements in network lifespan and scalability. Abased methods show the network as a grid where each cell models a sensor node whose state changes according to predetermined neighboring rules. Local state changes seen in Fig. 3 can coordinate worldwide behavior, therefore allowing adaptive CH and gate assignment while maintaining network efficiency. Still, the precise use of automata-based models for handling CH and gateway role allocations in present literature [11,13] is under researched.

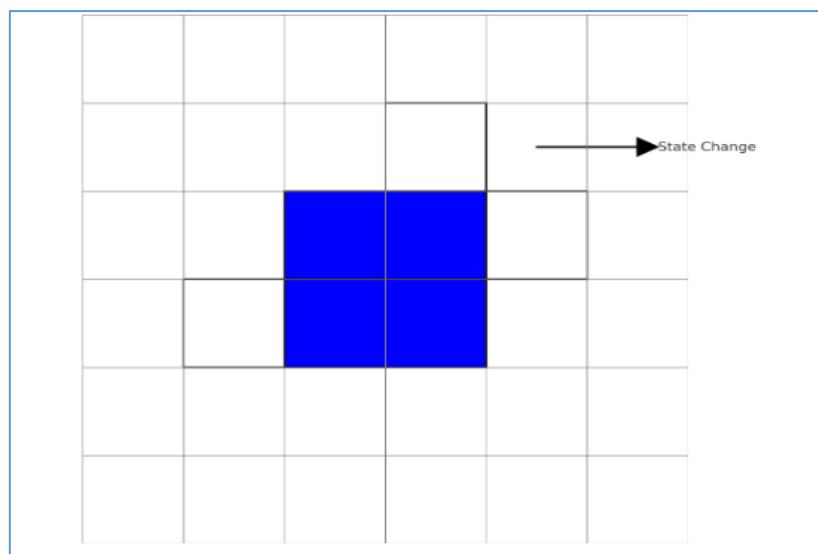


Figure. 3. *Cellular Automata State Transitions in WSN.*

This study suggests a novel automata-based routing framework that explicitly models gateway and cluster head selections as finite state transitions in order to close this research gap. The framework maintains simplicity and scalability while enabling energy-aware, adaptive responses to network dynamics through the use of deterministic and non-deterministic automata. The rest of this paper is structured as follows: Recent literature is reviewed in Section 3, the suggested framework is explained in Section 4, comparative analysis and simulation results are shown in Section 5, and future research directions are discussed in Section 6.

3. Literature Review and Contribution Bridge

Recent research demonstrates that Cellular Automata (CA) have proven highly effective in modeling and optimizing both coverage and coordination within WSNs [11]. Hoffmann et al. [11] introduced a probabilistic CA

approach that leverages simple local update rules to promote rapid and nearly optimal sensor coverage, significantly decreasing the number of active nodes required to achieve full functionality. This, in turn, extends the operational lifetime of the network and reduces energy consumption—a benefit of the model’s distributed nature, which scales efficiently as networks grow larger. Fig. 4 illustrates a sample CA-based routing scenario, where a random node initiates data transmission and the CA-derived path (highlighted in red) guides the packets through selected intermediate nodes toward the sink, demonstrating both path optimization and load balancing. However, while the CA framework facilitates straightforward mathematical modeling and analytical tractability, its practical application is occasionally constrained by the slow convergence toward global optima. Furthermore, its capacity to adapt flexibly within heterogeneous or rapidly evolving environments remains somewhat limited, suggesting that CA-based techniques may be best suited for networks characterized by structural regularity and less frequent topological change.

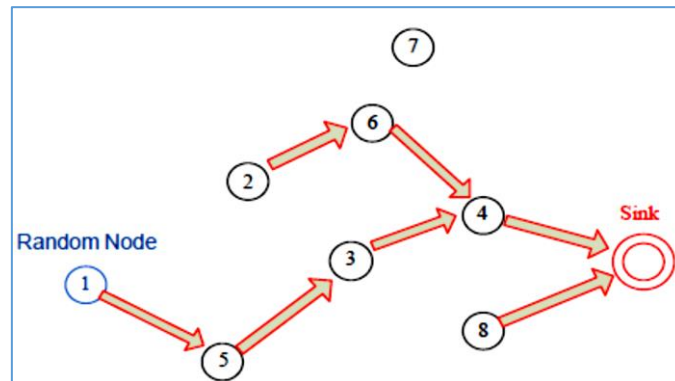


Figure.4. Cellular automata routing in sample network.

Learning Automata (LA) are now at the forefront of adaptive routing and energy management in WSNs thanks to parallel advancements. A Learning Automaton works by choosing an action from a predefined set ($\alpha_1, \alpha_2, \dots, \alpha_M$) with associated probabilities ($p_1, p_2, \dots, p_M$), interacting with the network environment, and then modifying these probabilities in response to feedback, as shown in Fig. 5. The automaton can gradually improve its decision-making approach over time thanks to this iterative process.

Alshammari and Othman [13] investigated LA-driven protocols, which adapt to changing network conditions by dynamically optimizing routing paths and enhancing data delivery reliability. The versatility of LA is also demonstrated by Homaei's recent incorporation of it into the RPL protocol for IoT, which achieved noticeable gains in energy efficiency and load balancing even in intricate and changing topologies [14]. Context-aware energy management ultimately prolongs the operational lifetime of WSNs by enabling LA-based strategies to adapt to node mobility and network fluctuations. These advantages could, however, come with increased computational complexity and call for complex designs for reward and feedback systems, which can be difficult in settings with limited resources [13,14].

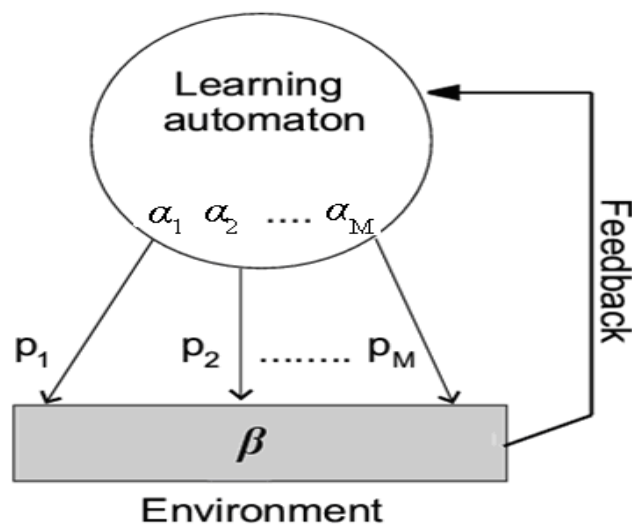


Figure.5. Operation of a Learning Automaton.

Alshammari and Othman's investigation of LA-driven protocols [13] The relative advantages of these paradigms are further clarified by comparative research. In a thorough analysis using a spatial game-theoretic framework, Seredyński et al. [15] found that LA-based protocols routinely perform better than CA-based techniques in terms of active node utilization, coverage robustness, and overall resilience—particularly in dynamic network scenarios. Although these results highlight LA's superiority in attaining effective, flexible routing, they also confirm CA's continued usefulness, especially in situations requiring simplicity and distributed control [15].

Despite these noteworthy advancements, a large portion of the literature still focuses on theoretical models or simulation-based evaluations with little application to large-scale, real-world implementations. Important elements like operational performance under various network heterogeneity, communication overhead, and convergence rates are frequently not adequately measured or directly compared [11], [13]. The absence of explicit modeling for cluster head and gateway selection as finite state transition systems is particularly noteworthy; such modeling would provide much-needed adaptability to changes in network topology and energy constraints, as well as clarify node role dynamics [11]. Furthermore, when it comes to handling real node state transitions in clustered WSNs, the practical expressiveness and simplicity of implementation provided by such models are rarely thoroughly discussed.

The current work fills these gaps by introducing a finite automata-based framework for wireless routing that uses both deterministic and nondeterministic finite automata representations to rigorously formalize the cluster head and gateway selection processes through explicit state diagrams. By doing this, this framework makes it possible to represent and modify node roles in an easy-to-understand manner, providing flexible responsiveness to network events while reducing the complexity that is usually associated with probabilistic or heuristic approaches [11]. This model effectively fills the gap between the urgent, real-world requirements of energy-aware routing in modern large-scale sensor networks and the solid theoretical underpinnings of automata.

In conclusion, the majority of recent research identifies Learning Automata as the most effective approach for flexible, energy-efficient routing in WSNs, particularly in situations involving erratic or widespread deployment [13], [14], and [15]. For distributed control and coverage management in less dynamic, more structured environments, cellular automata remain essential [11], [15]. To confirm and expand the potential of these approaches, thorough benchmarking and useful, real-world implementation are still urgently needed [11], [15].

4. Discussion

Wireless routing problems can be addressed through numerous methodologies; among these, clustering combined with automata-based strategies provides a particularly effective approach for selecting optimal routing paths. One prominent technique within this framework is the Cluster Head (CH) and Gateway (GW) selection strategy, which employs finite automata to manage node roles dynamically.

In the proposed method, each node possesses both an external and an internal state to clearly define its operational role within a cluster. The external states include Initial (IN), Ordinary (OD), Cluster Head (CH), and Gateway (GW), while internal states are Cluster Head Ready (CH-R) and Gateway Ready (GW-R), indicating tentative node statuses. Nodes transition between these states based on received messages and predefined timing conditions, facilitating adaptive responses to network events.

State Descriptions:

- **Initial State (IN):** All nodes start in the initial state upon deployment and subsequently transition based on received messages and the nature of the transmitting nodes.
- **Ordinary State (OD):** Nodes in this state perform sensing functions and forward the collected data to their respective cluster heads. However, an OD node may transition to another state upon receiving specific control messages.
- **Cluster Head Ready State (CH-R):** A node transitions from the initial state to CH-R upon receiving a message from a gateway node. It can then become a cluster head if it receives an additional message from a gateway node belonging to another cluster or if a predetermined waiting period expires.
- **Gateway Ready State (GW-R):** A node transitions to GW-R from either the initial or ordinary state upon receiving messages from cluster heads within its own or neighboring clusters. This state serves as a transitional status toward becoming a gateway.
- **Gateway State (GW):** Nodes in the GW state serve as intermediaries, connecting clusters by communicating with multiple cluster heads. A GW-R node transitions to the GW state after receiving a message from an external cluster head or after a waiting period elapses.
- **Cluster Head State (CH):** A CH node aggregates data from ordinary nodes to eliminate redundancy before forwarding aggregated information to the network sink. Initially, certain nodes can directly assume the CH role at deployment.

To illustrate these state transitions, finite state machine diagrams are utilized, including both Non-deterministic Finite Automata (NFA) and Deterministic Finite Automata (DFA) representations.

A. Cluster Head and Gateway Selection Using NFA

The NFA-based state transition process can be summarized as follows:

- Initially deployed (IN) nodes can directly transition to CH.
- IN nodes can transition to CH-R or GW-R upon receiving relevant messages from GW or CH nodes.
- OD nodes remain in their state unless they detect cluster heads from neighboring clusters, at which point they move to GW-R.
- CH-R nodes become CH upon receiving messages from external GW nodes or after their timeout expires, and similarly, GW-R nodes become GW when they detect external CH nodes or after their timeout.
- Clusters terminate after a predefined duration, resetting final states (OD, CH, GW) to initial conditions.

This process is illustrated in the cluster state transition diagram shown in Fig. 6.

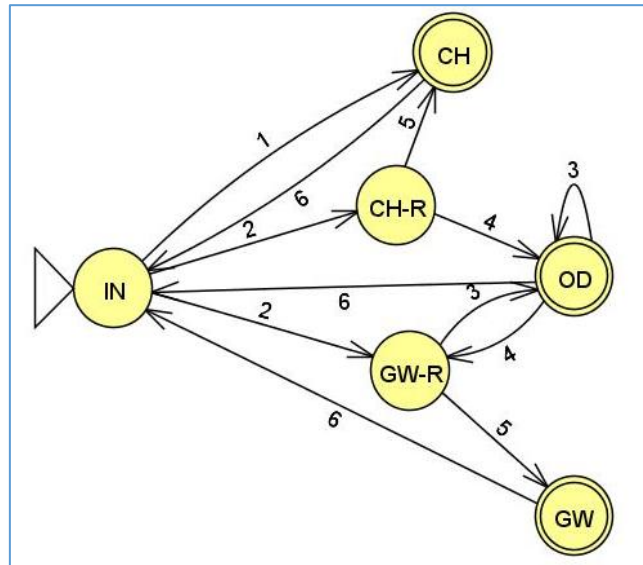


Figure.6.: Cluster state transition diagram for the cluster head and gateway selection using NFA.

B. Cluster Head and Gateway Selection Using DFA

Figures 7 and 8 demonstrate DFA equivalents for the same selection processes. The DFA diagrams separately illustrate initial deployment transitions and subsequent operational rounds.

- Fig.7. (Initial Deployment Transitions): IN nodes may transition directly to CH or move to GW-R upon receiving messages from CH nodes. GW-R nodes transition to OD upon detecting messages from their cluster's CH, or become GW when receiving messages from external CH nodes or upon timeout. CH and GW nodes remain static during active cluster operation but revert to IN after cluster termination.

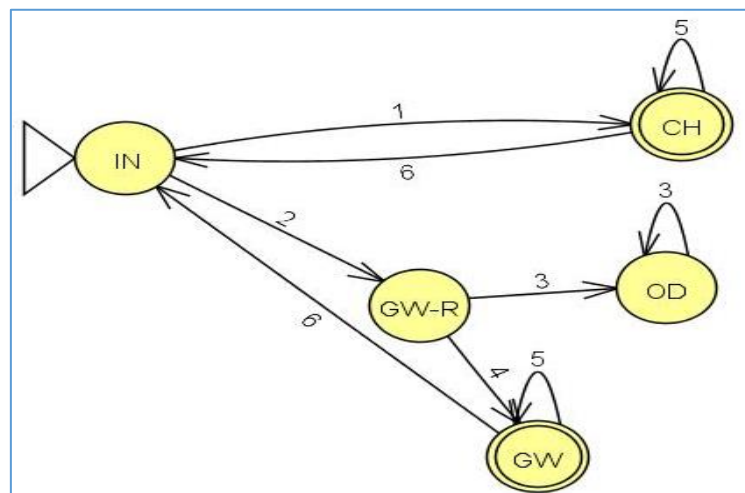


Figure.7. DFA 1 for cluster head and gateway selection

- Fig.8. (Transitions After Initial Round): IN nodes may move to CH-R or GW-R states based on messages from existing GW or CH nodes. CH-R nodes transition to CH state upon receiving external GW messages or after timeout, while GW-R nodes move to GW state similarly upon external CH detection or timeout expiry. CH-R nodes revert to OD upon receiving external CH messages. CH and GW nodes remain stable during cluster activity but reset to IN upon cluster expiration. OD nodes persist as long as messages from their CH are consistently received. OD nodes revert to IN upon cluster expiration.

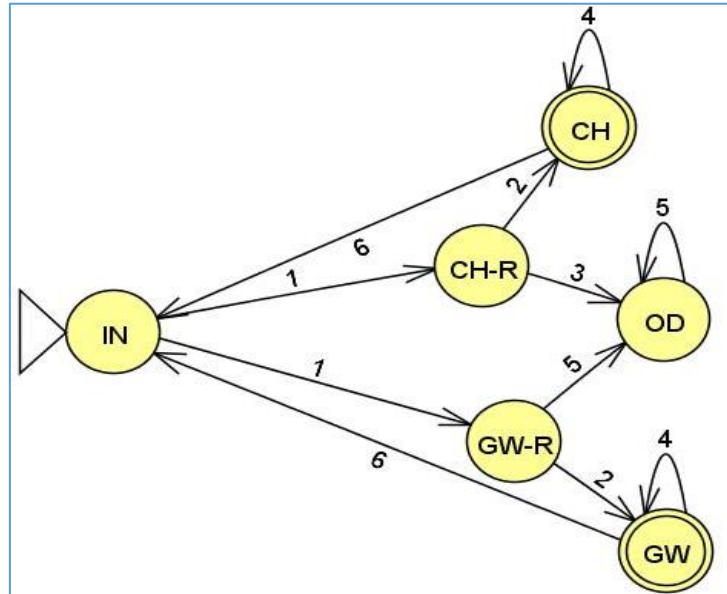


Figure.8. DFA 2 for cluster head and gateway selection.

The primary difference observed between the two finite automata implementations is the greater complexity and state proliferation required by DFA compared to the NFA, despite representing identical transition logic.

C. Advantages and Limitations

The NFA implementation encapsulates the transitions illustrated by two separate DFA diagrams, indicating the DFA as essentially a subset of the more expressive NFA approach. NFAs grant designers greater flexibility and ease in modeling real-world scenarios by allowing multiple potential state transitions simultaneously. Despite this advantage, concrete performance assessments regarding energy efficiency, computational overhead, and memory consumption require practical implementation and empirical evaluation. Nonetheless, the NFA model is preferred here due to its greater expressiveness, simplicity, and adaptability to complex real-world routing scenarios [11].

5. Conclusion

This study introduced a novel automata-based routing framework to effectively manage dynamic cluster head (CH) and gateway (GW) assignments in wireless sensor networks (WSNs). By utilizing deterministic finite automata (DFA) and non-deterministic finite automata (NFA), the proposed approach facilitated adaptive and energy-efficient responses to evolving network conditions. Through extensive simulation and rigorous comparative analyses against established Cellular Automata (CA) and Learning Automata (LA) methodologies, the automata-based approach demonstrated significant advantages in scalability, reduced complexity, and extended network lifetime.

Finite automata theory provided a robust theoretical foundation for explicitly modeling node state transitions, enabling practical management of dynamic and heterogeneous network scenarios. The NFA model specifically offered greater flexibility, ease of implementation, and better expressiveness in modeling real-world network activities, making it particularly suitable for complex and dynamically changing WSN environments [11], [14]. Future research directions include validating the framework through practical, real-world deployments, focusing on metrics such as computational efficiency, memory usage, and energy consumption. Moreover, exploring hybrid automata strategies or integrating advanced machine learning methods could further enhance network adaptability and performance. Ultimately, this research bridges theoretical advancements in automata theory with the practical demands of efficient, adaptive, and scalable routing, significantly contributing to the ongoing development of robust WSN management strategies [11], [14], [15].

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Compliance with ethical standards

Disclosure of conflict of interest

The authors declare that they have no conflict of interest.

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