A Hybrid Optimization Algorithm For Routing In Wireless Multihop Network

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Abstract: Major swarm intelligence research focused on reverse engineering and collective behavior's adaptation observed in natural systems aimed at effective algorithm design for distributed optimization. Such algorithms inspired by natural systems reveal desirable properties like adaptability, scalability and robustness which are key properties in network routing, specifically wireless network routing. This paper aims to study use of biologically inspired agents for effective packet routing in wireless networks. An issue with shortest path routing like AODV is the impossibility of efficient routing as only a lone constraint is considered because other constraints are interrelated in wireless networks making routing is a multi-constraint problem. This paper proposes a hybrid optimization, using Ant Colony Optimization (ACO) and Artificial Bee Colony (ABC), for AODV routing to ensure routing decisions are based on many constraints like Link quality and hop count and also to provide an efficient routing system for wireless networks.

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1. Introduction

Wireless multihop networks are promising technology for infrastructure less connectivity [1]. Their features like low cost and ease of deployment [2],and a large range of application scenarios from public safety communications to community-based networks and metro scale municipal networks [3] has led to wireless networks receiving more attention stimulating research activities. In fact, wireless networks have wired networks traditional challenges [4]. It is a fact that wireless multi-hop communication performance and reliability depend on routing protocol ability to select network paths in current network conditions.

For example, most routing schemes suggested for generic ad hoc networks (like DSR[5], AODV [6] and OLSR [7]) select shortest path between source and destination and forward packets through a-predetermined network device sequence, while assuming that link-layer retransmissions provide some communication reliability. But, wireless links are different from wired links. The wireless channel is an intrinsic broadcast medium having no observable boundaries outside which nodes can communicate implying that wireless links have intermediate packet loss rates [8]. Also wireless medium has time-varying and asymmetric propagation properties due to phenomena like interference from external signals, wireless propagation impairments and fading [9]. The above peculiarities of wireless communications suggest it is necessary to consider link qualities when choosing best route between a source–destination pair to improve wireless networks performance.

Some link-aware routing metrics were implemented and tested in real network deployments with experiments showing that they can achieve improved performance compared to traditional shortest-path routing algorithm. But, these traditional routing protocols pre-compute one or more minimum-cost paths [10–12] for every source–destination pair. Experiments [13, 14, 15] proved that using predetermined paths are ineffective when dealing with unreliable/varying wireless environments.

Routing algorithms are generally defined as multi-objective optimization problems in a dynamic stochastic environment. But to formalize routing, optimization problems need full knowledge of traffic between each network node; but this is prohibitively difficult to model in rapidly changing network dynamics in wireless networks. Hence, heuristic policies often create quasi-optimal routing in wireless networks. There is great research in designing efficient heuristic based routing protocols/metrics for wireless networks [16 - 19]. A new family of routing algorithms is proposed in wired networking domains, based on swarm intelligence by Dorigo et al. titled Ant Colony Optimization (ACO) framework [20, 21], a meta-heuristic approach to solve hard optimization problems.

This paper addresses packet routing problems for data forwarding in wireless multihop networks. Network traffic usually flows between regular nodes and a few Internet gateways (rarely end-to-end between regular nodes). This results in uneven link loading causing path saturation. Similarly, existence of inter-flow interference among nodes and intra-flow interference within a transmission path could affect node traffic loads in a multi-radio network. A routing protocol should effectively distribute traffic by selecting channel diverse paths with reduced inter/intra flow interference., Constraints like collisions, traffic level, buffer occupancy, battery power, should be considered in wireless network as considering a single constraint is not enough, due to a complex inter constraint relationship. Multi-constrained routing is a NP-complete issue without a polynomial solution needing varied heuristics/soft computing techniques to solve them [22].

This paper proposes hybrid optimization, using Ant Colony Optimization (ACO) and mechanisms from Artificial Bee Colony (ABC) for AODV routing to ensure that routing decisions are based on constraints like Link quality and hop count and also to provide an efficient wireless routing systems. Section 2 explains research methods. Section 3 details simulation results and section 4 concludes the paper.

2. Methodology

2.1 Artificial Bee Colony (ABC)

The Honey-Bee Mating Optimization Algorithm proposed by Abbass [23, 24], is based on the Artificial Bee Colony (ABC) A honey-bee colony consists of queen(s) (best solution), drones (incumbent solutions), worker(s) (heuristic), and broods (trial solutions). The mating optimization algorithm simulates the queen bee's natural mating behaviour when she mates with the drones after leaving the hive. [23, 24]. After every successful mating, the queen's spermatheca is replenished by the drone's sperm. Before mating flight the queen is initialized with some energy and ends her mating flight when her energy level drops below threshold level (which is close to zero) [25].

The queen mates with a drone probabilistically, as follows:

$$p\left(Queen, Drone_i\right) = e^{\left[\frac{-\Delta(f_i)}{energy(t)}\right]}$$

where P(Queen, $Drone_i$) represents the probability of accepting the ith drone for mating, Δ(f) represents the absolute fitness difference between the drone and the queen, energy(t) refers to the queen's energy at mating time t. The objective function represents solution quality calculating constraint violations. The queen's energy is high when the flight starts indicating that mating possibility is high. It continues to be so when the drone's fitness is as good as the queen's. As mating flight continues, the queen's energy and speed decrease as follows:

*energy(t+1) = ∝ * energy(t) where t ∈[0,1, 2... t] and decay rate ∝within [0,1]*

speed (t+) = energy(t) - β where t∈ [0,1, 2... t] and decay rate βwithin [0,1]

where ∝ represents the decay rateand relating to the energy reduction rate after each transition in mating. To begin with, the queen's energy level is randomly generated. Then, after many mating flights, the queen moves between different states (i.e. solutions) in the allocated space, according to her energy and mates with drones. After a drone has mated with the queen, its sperm complements the queen's spermatheca. After each encounter, the queen's energy and speed are updated. The mating flight ends when the queen's energy level drops below a threshold (which is close to zero) or when the queen's maximum spermatheca size is reached.

When the mating flight ends, the queen returns to the nest and breeds by randomly selecting a drone's sperm from her spermatheca performing a crossover to produce a brood which is fed by a worker to enhance it. The workers number used for the algorithm represents the heuristics number. As the fittest brood is superior to the queen, she is replaced by it. All remaining broods if any and the former queen are destroyed leading to the initiation of another mating flight with a new queen and the same pool of drones.

2.2 Ant Colony Optimization (ACO)

An Ant Colony Optimization algorithm (ACO) is based on ant's behavioral mechanisms like cooperation and adapting [26]. Metaheuristics solve optimization problems. ACO algorithms are based on the following ideas [20]:

- A problem's solution is obtained by paths followed by ants
- Pheronome quality left on the path by ants represents a problem's solution quality
- When an ant has a c hoice of manypaths those with higher pheromone concentration are chosen.
- Ants slowly converge to a short path, representing optimum or a near-optimum solution for a target problem.

Artificial ants' characteristics aer similar to that of real ants. Artificial ants give preference for paths with a larger pheromone amounts. Shorter paths have larger pheromone growth. At each iteration, pheromone values are updated by all m ants which have built a solution in the iteration itself. The pheromone τij, associated with the edge joining nodes i and j, is updated as follows:

$$\tau_{ij} \leftarrow (1-\rho).\tau_{ij} + \sum_{k=1}^{m} \Delta\tau_{ij}^{k}$$

where, ρ is the evaporation rate, m is the number of ants and $\Delta\tau^{k}_{ij}$ is the quantity of pheromone laid on edge (i, j) by ant k:

$$\Delta\tau_{ij}^{k} = \begin{cases} Q/L_k \\ 0 \end{cases}$$

where, Q is a constant and L_k is the length of the path constructed by ant k. In a solution, ants select – through a stochastic mechanism - the following node to be visited. The partial solution is constructed by:

$$p\left(c_{ij} \mid s^P\right) = \frac{\tau_{ij}^{\alpha}\eta_{ij}^{\beta}}{\sum c_{ij} \in N\left(s^P\right)\tau_{ij}^{\alpha}\eta_{ij}^{\beta}}, \forall c_{ij} \in N\left(s^P\right)$$

where, N (s^P) is the set of feasible components.

In the proposed routing protocol, every node maintains a pheromone table and a probability routing table. Pheromone values for neighbors for a particular destination are initialized to the same value to ensure unbiased search. Initial pheromone values change depending on the ants moving towards a particular neighbour. The path where more ants move towards a link is considered a destination's optimal path. Pheromone entry rises as more ants move and a neighboru is assigned more probability. Neighbour's probability value is affected by the link life, processing power and energy depletion rate of neighbors.

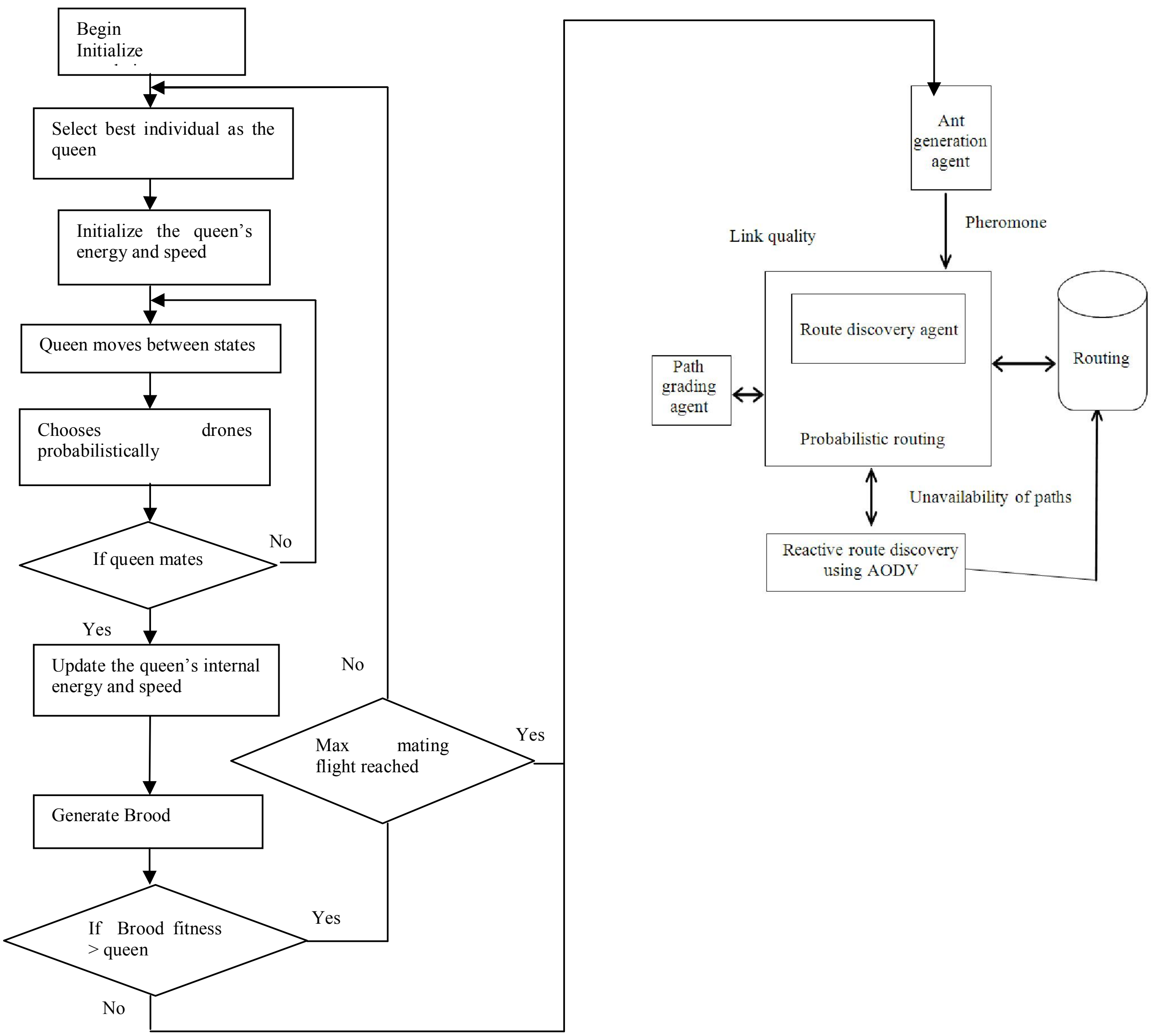

Fig. 1: The proposed ABO routing algorithm

Node quality information like battery energy and processing power is collected when request ants pass through nodes. Normalized index with value varying from 0-1 expresses the information. Overall path quality is a result of nodes normalized index value. The destination node on receipt of information from request ants checks it against a reference value maintained by it. Intermediate nodes pheromone values is updated as destination node sends out reply ants with grades. Pheromones deposits reduce bsed on evaporation rate enabling nodes to forget old paths as wireless network topology changes.

Preliminary work using ACO is given in [27] where the proposed protocol used ants foraging behavior to locate better routes depending on link quality to avoid delay. In Ant-Bee Optimization (ABO) proposed, link quality and hop count are established using a bee mating algorithm and ACO locates a reliable route based on the constraints. The proposed ABO based proactive routing process is shown in Fig. 1.

3. Results and discussion

The experimental setup consists of a lone sink with 17 nodes with 4 being the maximum hop count to reach the sink. Every node has a transmission power of 0.03 W and maximum Bandwidth of 1 MW. The experiments were conducted using:

- ACO based AODV [27]
- Proposed Ant-Bee Optimization (ABO)

The simulation results are shown in Figures 2-5. The Red line in the graphs represents the proposed ABO method and the blue line represents ACO based AODV.

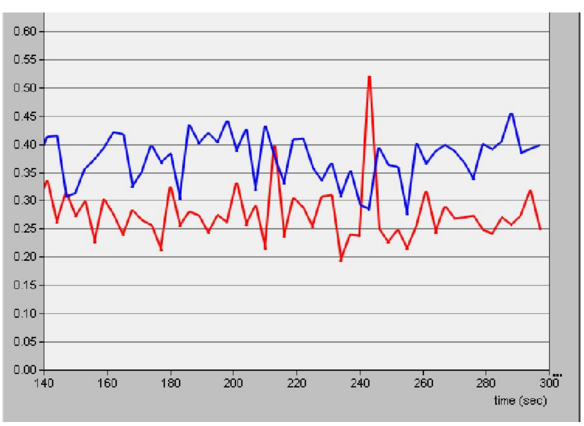

Figure 2: End to End Delay

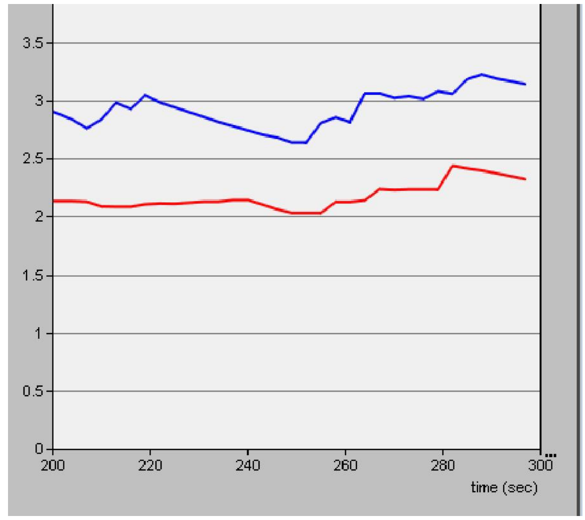

Figure 3: Route discovery time

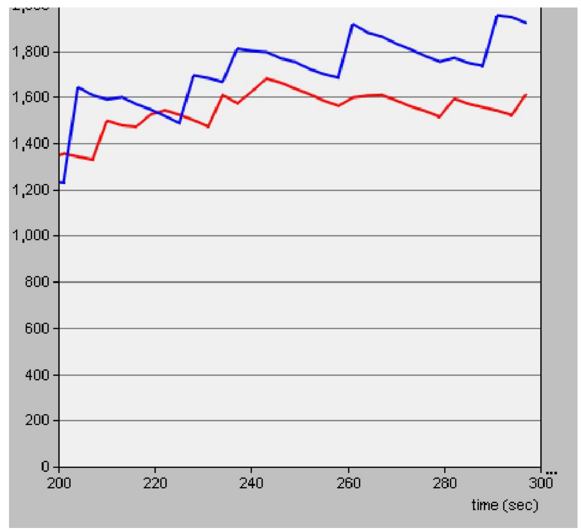

Figure 4: Packet Dropped

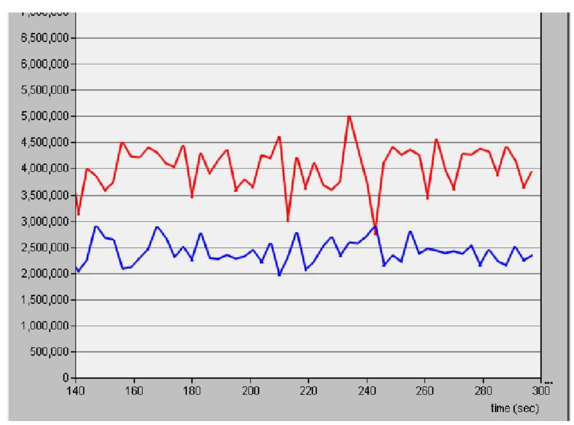

Figure 5: Throughput of the proposed system.

Figure 2 shows the end to end delay for the proposed ABO with the ACO based AODV. Figure 3 shows the route discovery time. The proposed routing protocol (red line in graph) has lower end to end delay and lower route discovery compared to ACO based AODV. Figure 4 shows the packet dropped by the nodes in the network and it can be seen that the proposed method reduces the packet dropped considerably. Similarly, the throughput as seen from Figure 5, that the proposed system has improved throughput compared to ACO based AODV.

4. Conclusion

When AODV is used in wireless networks, a major issue that crops up is the constraints to be accounted for. As traffic balancing and shortest path routing like AODV, it is not efficient routing as only a single constraint is considered when other constraints are interrelated in the wireless network. This paper proposes a hybrid optimization, using Ant Colony Optimization (ACO) and Artificial Bee Colony (ABC), for AODV routing to ensure that routing decisions are based on constraints like Link quality and hop count and are also capable of providing an efficient wireless routing system. Simulation results reveal the proposed routing achieving improved throughput.

5. References

[1] A. Raniwala and T.-C. Chiueh, “Architecture and algorithms for an IEEE 802.11-based multichannel wireless mesh network,” Proc. of the IEEE INFOCOM, 2005, pp. 2223-34.

[2] R. Karrer, A. Sabharwal, E. Knightly, Enabling large-scale wireless broadband:the case for TAPs, ACM SIGCOMM Computer Communication Review 34 (1) (2004) 27–32.

[3] R. Bruno, M. Conti, E. Gregori, Mesh networks: commodity multihop ad hocnetworks, IEEE Communications Magazine 43 (3) (2005) 123–131.

[4] I. Chlamtac, M. Conti, J.-N. Liu, Mobile ad hoc networking: imperatives andchallenges, Ad Hoc Networks Journal 1 (1) (2003) 13–64.

[5] D. Johnson, Y. Hu, D. Maltz, The Dynamic Source Routing Protocol (DSR) formobile ad hoc networks for IPv4, RFC 4728, February 2007. Available from: <http://www.ietf.org/rfc/rfc4728.txt/>.

[6] C. Perkins, E. Belding-Royer, S. Das, Ad Hoc On-Demand Distance Vector(AODV) routing, RFC 3561, July 2003. Available from: <http://www.ietf.org/rfc/rfc3561.txt/>.

[7] T. Clausen, P. Jaquet, Optimized Link State Routing Protocol (OLSR), RFC 3626,October 2003. Available from: <http://www.ietf.org/rfc/rfc3626.txt/>.

[8] [11] J. Camp, J. Robinson, C. Steger, E. Knightly, Measurement driven deployment ofa two-tier urban mesh access network, in: Proc. ACM MobiSys’06, Uppsala,Sweden, 2006, pp. 96–109.

[9] T. Rappaport, Wireless Communications: Principles and Practice, Prentice Hall,2002

[10] Y. Ganjali, A. Keshavarzian, Load balancing in ad hoc networks: single-pathrouting vs. multi-path routing, in: Proc. IEEE INFOCOM’04, vol. 2, 2004, pp.1120–1125.

[11] N. Nandiraju, D. Nandiraju, D. Agrawal, Multipath routing in wireless meshnetworks, in: Proc. IEEE MASS’06, 2006, pp. 741–746.

[12] M. Mosko, Garcia-Luna-Aceves, Multipath routing in wireless mesh networks,in: Proc. IEEE WiMesh’05, 2005.

[13] S. Biswas, R. Morris, ExOR: opportunistic multi-hop routing for wirelessnetworks, SIGCOMM Computer Communication Review 35 (4) (2005) 133–144.

[14] S. Katti, H. Rahul, W. Hu, D. Katabi, M. Médard, J. Crowcroft, XORs in the air:practical wireless network coding, IEEE/ACM Transactions on Networking 16(3) (2008) 497–510.

[15] S. Chachulski, M. Jennings, S. Katti, D. Katabi, Trading structure for randomnessin wireless opportunistic routing, in: Proc. ACM SIGCOMM’07, 2007, pp. 169–180.

[16] D.S.J. Couto, D. Aguayo, J. Bicket, and R. Morris, “A high-throughput path metric for multi-hop wireless routing,” Proc. of the ACM MOBICOM, 2003, vol. 1, pp. 134-146, Sep. 2003.

[17] R. Draves, J. Padhye, and B. Zill, “Routing in Multi-Radio, Multi-Hop Wireless Mesh Networks,” Proc. of the ACM MOBICOM, 2004, pp. 114-128.

[18] Y. Yang, J. Wang, and R. Kravets, “Interference-aware load balancing for multihop wireless networks,” Tech. Rep. UIUC DCS-R-2005-2665, Dept. of Computer Science, UIUC, 2005.

[19] A. P. Subramanian, M. M. Buddhikot, and S. C. Miller, “Interference aware routing in multi-radio wireless mesh networks,” IEEE Workshop on Wireless Mesh Networks (WiMesh), Sept. 2006, pp. 55–63.

[20] M. Dorigo and G. Di Caro, “The ant colony optimization meta-heuristic,” in D. Corne, M. Dorigo, and F. Glover, editors, New Ideas in Optimiziation, pages 11-32. MacGraw Hill, 1999.

[21] M. Dorigo, G. Di Caro, and L.M. Gambardella, "Ant algorithms for discrete optimization," Arfitcial Life, 5(2): 137-172, 1999.

[22] T. Korkmaz and M. Kmnz, "Bandwidth delay constrained path selection under inaccurate slate information," *IEEWACM TON,* June 2003, Vol. II , Issue 3, pp. 384 398.

[23] Abbass, H.A., A monogenous MBO approach to satisfiability. In: Proceeding of the International Conference on Computational Intelligence for Modeling, Control and Automation, CIMCA'2001, 2001a. Las Vegas, NV, USA.

[24] Abbass, H.A., Marriage in honey-bee optimization (MBO): A haplometrosispolygynous swarming approach. CEC2001, 2001b, pp. 207-214. Seoul, Korea.

[25] Afshar, A., Haddad, Bozog, O. Marino, M. A., Adams, B. J., Honey-bee mating optimization (HBMO) algorithm for optimal reservoir operation. Journal of the Franklin Institute, 2007, 344, 452-462.

[26] Ali, M. A. Belal and M. B. Al-Zoubi, 2010. Load Balancing of Distributed Systems Based on Multiple Ant Colonies Optimization. , 7: 428-433

[27] Selvan, V. P., & Kumar, S. S. An Optimized Ad Hoc on Demand Distance Vector Routing Protocol for Wireless Networks. Journal of Computer Science, 8.

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