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Emergent Harmonic Field Routing for Dynamic Networks

Bartłomiej Mastej

***Abstract*—Routing in dynamic networks, such as MANETs, remains a challenging problem due to the need for continuous adaptation, robustness to topology changes, and limited coordination among nodes. Traditional routing approaches, including Distance Vector and Link-State protocols often underperform, leading to instability or high overhead in dynamic environments.**

In this paper, we propose Harmonic Field Routing (HFR), in which forwarding decisions base on a self-organizing potential field maintained through purely local interactions. Each node iteratively updates a scalar state based on neighboring values, leading to the implicit solution of a discrete Laplace equation with Dirichlet boundary conditions. The resulting harmonic field continuously adapts to network changes and induces a loop-free routing structure, where packets follow the steepest descent of the potential.

We analyze the theoretical foundations of the method by relating it Jacobi iterative solver. Additionally, we propose two asynchronous HFRs: Red-Black Gauss-Seidel HFR and Chaotic HFR. Experimental evaluation shows that HFR methods provide superior reliability in dynamic scenarios. Furthermore, due to emergence of the early gradient, HFR can find the route comparably fast to the Distance Vector.

***Keywords*—Harmonic Field Routing; MANETs; Dynamic Networks; Self-organizing system**

I. Introduction

DYNAMIC networks have been a subject of research since the very beginning of the internet. Over the years compute and communication capabilities of mobile network terminals and IoT devices have increased significantly, prompting the use of their resources. Consequently, recently there can be observed an increased interest in mobile ad hoc networks (MANETs) [1] and their specializations, such as vehicle ad hoc networks (VANETs) [2] which deals with highly dynamic vehicular networks. Even MANETs operating in difficult environments, when the continuous end-to-end is unavailable, is under heavy reseach called Opportunistic Network [3].

In every network there is a need to transmit the information from the source to the given destination. Classic classes of routing algorithms such as Distance Vector Routing or Link-state Routing were made for the computer networks which assumes static and reliable environments. Nonetheless, those algorithms does not scale well [4], also dynamic systems introduce continuous topology changes, making the classical routing algorithms underperforming, inefficient, faulty, and quickly inoperative. Therefore, other the years there were created numerous algorithms which aimed to target different types of MANETs [5]. However, as indicated by [6] most of MANETs routing protocols evolved from the traditional protocols; hence, they try to mitigate the inherited problems.

Author is with Warsaw University of Technology, Warsaw, Poland (e-mail: bartlomiej.mastej.dokt@pw.edu.pl.

Furthermore, dynamic distributed networks introduce certain unpredictability [1], and require certain features such as scalability, flexibility, adaptivity, and robustness [7]. As indicated by [7] self-organizing systems provides those features. Such systems are commonly called Swarm Intelligence (SI) as the global behavior emerge from local interactions [8]. Nevertheless, designing SI systems is difficult as local interactions of independent agents creates new information which is not embedded in initial or bounadary conditions creating a complex system [9].

In this article we propose another approach towards routing - continuous field computed via harmonic potentials. A potential is a scalar value computed iteratively by each node through local averaging. It is providing a monotonic gradient between source and destination. The resulting field of potentials corresponds to the harmonic solution of the graph Laplace equation. A preliminary version of this concept was presented in [10], here we significantly extend it both theoretically and experimentally.

As the global field emerges from local interactions, the proposed routing mechanism is a Swarm Intelligence algorithm. Moreover, topology changes cause the field to relax into a new equilibrium making the field self-healing. Due to its properties, the potential field allows for multipath routing as well as implementation of load-balancing techniques. The proposed routing algorithm guarantees fast convergance towards the new solution, making it suitable even for highly mobile networks such as VANETs.

This paper makes the following contributions: there is proposed general Harmonic Field Routing (HFR) model. Subsequently, there is proposed a synchronous HFR acting as distriuted Dirichlet solver. Further there are described HFR's properties and asynchronous algorithms derived from the basic HFR. Finally, the family of HFR algorithms is compared against basic Distance Vector algorithm in static and dynamic networks.

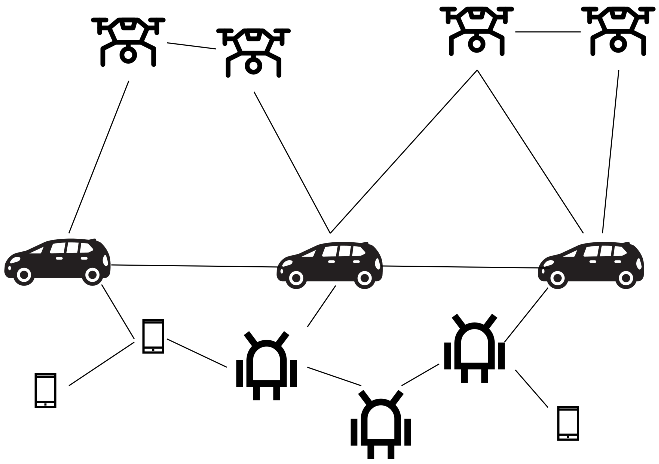


Fig. 1. Examplary overview of dynamic network topology.

II. Related work

A. Background

1) Dynamic Networks: Manets and Vanets, UAV networks - and their problems Dynamic networks, such as MANETs or VANETs are facing increased interest as we can observe more and more computational devices in every day life such as smartphones, vehicles, Internet of Things devices or UAVs. Their possible applications is huge, for example, by using VANETs for intelligent transportation [11], MANETs for extending compute capabilities beyond the existing infrastructue [12], or connecting different devices for the military environment [13]. The general overview of the dynamic ad hoc networks is presented in Fig. 1.

Nonetheless, despite a significant research effort, dynamic networks still faces several challenges which reduce their potential. As indicated by [14] the foundations for VANETs functionallity are the routing protocols which would provide reliability, scalability, security, and real-time adaptation. Similar requirements for MANETs were shared by [15].

B. Routing in MANETs

Despite the routing problem being extensively studied, two fundamental paradigms still dominate network routing: Distance Vector (DV) and Link-State (LS) approaches and their successors [16].

The Link-State routing protocols such as OLSR assumes that each node knows full network topology and uses it to evaluate shortest path, typically via Dijkstra algorithm. Due to topology changes, it is frequently needed to disseminate topology updates, making LS algorithms underperforming in large dynamic networks. Moreover, as each node needs to computate shortest path, it has higher energy consumption [17] and bandwidth [18].

In contrast, DV-based protocols for MANETs, such as AODV [19], rely on distributed distance estimation derived from the Bellman-Ford algorithm. In this paradigm, nodes iteratively exchange routing information with their neighbors to update path costs. Although more lightweight in terms of state information, the distributed nature of this approach leads to well-known issues such as slow convergence and routing inconsistences under topology changes, and to routing loops.

However, on the protocol level some of those drawbacks are mitigated, e.g., by introducing sequence numbers, or triggered-based broadcasts [19], but not fully eliminated. As a result, both LS and DV paradigms may exhibit degraded performance in highly dynamic large MANET environments, motivating the exploration of alternative routing approaches that avoid these structural limitations.

C. Electrical routing and flows

Electrical networks served as a natural source of motivation for many traffic related problems. The potential differences between source and drain in electric circuit always induces current. For instance, it was a motivation for a Electric-field routing protocol [20], a multipath routing protocol which finds spatially disjoint routes by minimizing the distance to assesed ”current” line between source and destination.

The same source of inspiration was used to solve multi-comodity flow problem by electrical routing [21] In this approach, a graph $G = (V, E)$ is interpreted as an electrical network, where edges correspond to resistors with weights w_e (conductances), and vertices represent connection nodes.

Given a demand vector $\chi \in \mathbb{R}^V$ (encoding sources and sinks), node potentials $\phi \in \mathbb{R}^V$ are obtained as the solution to the Laplacian system:

$$L\phi = \chi, \quad \text{where } L = B^T W B,$$

with $B \in \mathbb{R}^{E \times V}$ being the edge-vertex incidence (discrete gradient) operator and $W \in \mathbb{R}^{E \times E}$ a diagonal matrix of edge weights.

The resulting electrical flow is then defined as:

$$f = WB\phi = WBL^{\dagger}\chi,$$

where $L^{\dagger}$ is pseudoinverse of Laplacian matrix. According to Ohm's law, the flow on each edge $e = (u, v)$ is proportional to the potential difference:

$$f_{uv} = w_{uv}(\phi_u - \phi_v).$$

Consequently, flow is distributed across all edges simultaneously, rather than being routed along a single path. The solution corresponds to a global optimum that minimizes energy dissipation in the network.

Although the proposed Harmonic Field Routing shares the same notion of node potentials and their differences, the approaches differs in both computations and their usage. Instead of solving a global linear system, HFR relies on distributed, iterative updates where each node evaluates its potential based only on information from local neighborhood. Furthermore, routing decisions are discrete and follow a steepest-descent policy, selecting the neighbor with the lowest potential, rather than splitting flow proportionally across all outgoing edges.

As a result, while both approaches are grounded in the same physical analogy and rely on potential differences, electrical routing provides a centralized, continuous-flow solution, whereas HFR compose a decentralized, self-organizing mechanism that approximates harmonic potentials and enables scalable, adaptive routing decisions.

D. Routing as optimization problem

One of the approaches that treats routing as the optimization problem is Distributed Gauss-Seidler Iteration routing (DGSI) proposed by [22]. It was made for the Wireless Sensor Networks (WSNs) and it assumes stable topology. DGSI uses a macroscopic model, which aims for energy optimization or load-balancing, that is further solved numerically in a distributed manner. As a result, instead of solving routing via graph models, the approach is spatially-oriented - there is constructed a continuous vector field pointing towards a given destination in a specific region of interest. Therefore, the boundary conditions for a optimization problem are physical boundaries of space.

Unlike DGSI, the proposed HFR emerges from a local averaging rule, which implicitly solves a discrete Laplace equation on a graph. In contrast to DGSI, which relies on structured update ordering and additional control mechanisms for convergence, HFR operates in a fully asynchronous manner and requires only the exchange of scalar potential values between neighbors. This leads to a self-organizing routing field with minimal communication overhead and inherent properties such as loop-free due to the harmonicity of the solution and self-healing through relaxation process of local perturbation. This makes HFR particularly suitable for highly dynamic networks, where iterative solvers such as DGSI may fail to converge or becomes ineffective.

III. Harmonic Routing Model

The proposed routing approach is conceptually similar to the behavior that can be observed in physics, namely in electric circuits. Let's consider the network as the resistive circuit in which nodes correspond to electrical junctions and links correspond to resistors. The "battery" is constructed of two nodes: source and destination which are connected via the network of nodes as presented in Fig. 2. The potential difference between two points drives current to flow if a conductive path exists. Hence, we assume that the source node is maintained at potential $q_{src} = 1$ and the destination at $q_{dst} = 0$. Moreover, let's assume that each link's resistance is equal to 1Ω. In such a case, according to the Kirchhoff's Current Law, the voltage at each internal node equals the average of the voltages of its neighbors. Consequently, the obtained voltage field creates a monotonic gradient of potentials from source to destination.

Having the general intuition, let's define the system model. Let $G = (V, E)$ be the network graph and N be a set of neighbors of node i, hence $N(i) = j|(i,j) \in E$. Each node keeps its potential $q_i = [0; 1]$. As the intended communication is between the given source and destination, we define the following boundary conditions for the potential field: $q_{src} = 1$, $q_{dst} = 0$. Both source and destination potentials remain constant. For all other nodes there exist two rules:

a) Case 1: single neighbor ($|N(i)| = 1$):

$$q_i = \frac{1 + q_j}{2} \tag{1}$$

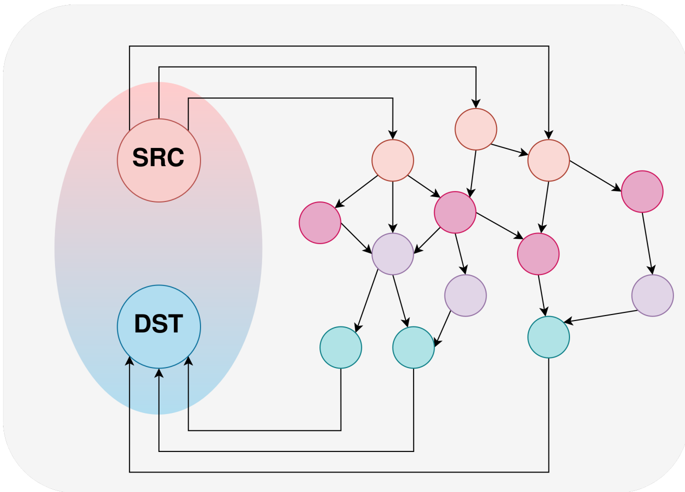


Fig. 2. Routing network represented as a harmonic potential field between source and destination.

b) Case 2: multiple neighbors ($|N(i)| > 1$):

$$q_i = \frac{1}{|N(i)|} \sum_{j=1}^{N(i)} q_j \tag{2}$$

The one can interpert those conditions as following: **if a node has multiple neighbors, then its potential equals to the average of their potentials, otherwise the given node obtains the virtual connection to the source (as $q_{src} = 1$) and similar condition is applied**. The aim of the virtual link to the source is twofold: 1) it provides wavefront initialization, 2) it increases potential of distant nodes; hence, approximating the shortest path.

The obtained harmonic potential field has two imporant properites:

1) **Maximum principle**

$$\min_{j \in N(i)} q_j < q_i < \max_{j \in N(i)} q_j \tag{3}$$

Hence, there are no internal minima and maxima.

2) **Loop-free routing** as following gradient descent always leads to the destination.

For all internal nodes the equilibrium state of the algorithm is the harmonic solution of the graph Laplacian.

Proof: Let $L = D - A$ be the graph Laplacian, where: D - degree matrix; $D_{ii} = deg(i)$, A - adjencency matrix. For a given node i:

$$(Lq)i = deg(i)q_i - \sum_{j}^{N(i)} q_j \tag{4}$$

Laplacian is harmonic iff $Lq = 0$, thus:

$$deg(i)q_i - \sum_{j}^{N(i)} q_j = 0 \tag{5}$$

Finally:

$$q_i = \frac{\sum_j^{N(i)} q_j}{deg(i)} \tag{6}$$

■

Having that we can prove the following theorem:

Theorem 1: Harmonic routing field is the unique solution of the Dirichlet problem $Lq = 0$ with boundary conditions.

Proof: Let $G = (V, E)$ be a connected undirected graph. Let two nodes $s, d \in V$ be boundary nodes with fixed potentials $q_s = 1$, $q_d = 0$. Let the Laplacian matrix L be partitioned as

$$L = \begin{bmatrix} L_{II} & L_{Ib} \\ L_{bI} & L_{bb} \end{bmatrix},$$

where:

- L_{II} corresponds to internal nodes,
- L_{Ib} couples internal nodes to boundary nodes,
- L_{bI} couples boundary nodes to internal nodes,
- L_{bb} corresponds to boundary nodes.

Let the boundary potentials be given by

$$q_b = \begin{bmatrix} q_s \\ q_d \end{bmatrix},$$

and let the full vector of node potentials be

$$q = \begin{bmatrix} q_I \\ q_b \end{bmatrix}.$$

Then,

$$Lq = \begin{bmatrix} L_{II} & L_{Ib} \\ L_{bI} & L_{bb} \end{bmatrix} \begin{bmatrix} q_I \\ q_b \end{bmatrix} = \begin{bmatrix} L_{II}q_I + L_{Ib}q_b \\ L_{bI}q_I + L_{bb}q_b \end{bmatrix}.$$

Assuming Dirichlet boundary conditions, the equation $Lq = 0$ is imposed only on internal nodes, which yields

$$L_{II}q_I + L_{Ib}q_b = 0.$$

Rearranging, we obtain

$$L_{II}q_I = -L_{Ib}q_b.$$

Since L_{II} is symmetric positive definite, it is invertible, and thus there exists a unique solution

$$q_I = -L_{II}^{-1}L_{Ib}q_b.$$

■

Consequently, the internal potentials q_I are uniquely determined by the boundary potentials q_b. This lead to the conclusion that the harmonic routing field converges to a single equilibrium.

IV. Emergent Harmonic Routing Field

A. Distributed Dirichlet Solver

Knowing that there exists a single equilibirum of the harmonic routing field, there is a need to find it without global knowledge. Since each node evaluates its potential whenever it spots that its neighbor's potential value changed, the potential is in fact solved iteratively. That can be expressed as the Jacobi iteration:

$$q_i^{t+1} = \frac{1}{|N(i)|} \sum_{j=1}^{N(i)} q_j^t \tag{7}$$

Having that we can prove the following theorem:

Theorem 2: (Distributed Dirichlet Solver) Let $G = (V, E)$ be a connected undirected graph. Let $b \in \{s, d\}$; $\{s, d\} \in V$ be boundary nodes with fixed potentials $q_s = 1$, $q_d = 0$. Let each non-boundary node iteratively update its potential according to $q_i^{t+1} = \frac{1}{|N(i)|}\sum_{j=1}^{N(i)} q_j^t$ using values recieved from neighbors. For any initial potentials q^0, the sequence q^t converges to the unique solution q^*.

Proof: Let $T = D^{-1}A$ be the transition matrix of the graph. After reordering the vertices so that interior nodes I come first, T can be decomposed as

$$T = \begin{pmatrix} T_{II} & T_{Ib} \\ T_{bI} & T_{bb} \end{pmatrix}.$$

The update equation

$$q_i^{t+1} = \frac{1}{|N(i)|} \sum_{j=1}^{N(i)} q_j^t$$

is equivalent, when restricted to internal nodes, to

$$q_I^{(t+1)} = T_{II}q_I^{(t)} + c$$

with

$$T_{II} = D_{II}^{-1}A_{II}$$
$$c = D_{II}^{-1}A_{Ib}q_b$$

where c is constant because q_b is fixed.

For an interior node $i \in I$,

$$(T_{II})_{ij} = \frac{A_{ij}}{\deg(i)}, \qquad j \in I.$$

If the given node i is not adjacent to any boundary nodes, then:

$$\sum_{j \in N(i)} (T_{II})_{ij} = 1$$

otherwise:

$$\sum_{j \in N(i)} (T_{II})_{ij} = 1 - \frac{1}{deg(i)} \sum_{b \in \{s,d\}} A_{ib} < 1$$

Since each row is non-negative and all rows satisfy ≤ 1, hence the T_{II} is substochastic.

The full graph is connected and the boundary nodes are reachable from every interior node. Therefore the interior subgraph is connected, and hence T_{II} is irreducible. Moreover, at least one interior node is adjacent to a boundary node, so at least one row of T_{II} has sum strictly less than 1.

A standard Perron–Frobenius result for nonnegative, irreducible, substochastic matrices with at least one row sum strictly less than 1 [23] implies that

$$\rho(T_{II}) < 1$$

Thus Jacobi iteration of the internal nodes

$$q_I^{(t+1)} = T_{II}q_I^{(t)} + c$$

converges to a unique fixed solution q^*. ■

B. Wavefront initialization

The requirement for the usage of the Distributed Dirichlet Solver is that inside nodes need to have potential which can be further relaxed. Hence, there is a need to initialize the potential field. We propose the wavefront initialization - every node which obtains a message from just one neighbor evaluates its potential by creating a virtual link to the source node, according to equation 1. In practice, initially the inside nodes gets the $q_i = 1$ but when shortest path reaches the destination the relaxation begins. Further, the rule is also used when topology changes.

C. Distributed Harmonic Routing Field

To realize the harmonic field in a decentralized way, nodes must exchange messages with their neighbors and update their potentials based only on locally available data. In this way, the Dirichlet problem is solved in a fully distributed manner, where each node acts as an independent computational unit executing a local relaxation step

Each node maintains its current potential value and updates it whenever new information from neighbors is received. Let $S_i \subseteq N(i)$ denote the set of neighbors of node i for which potential values are currently available. The update rule combines two phases: (i) initialization, when information is first propagated from the boundary, and (ii) relaxation, when at least two neighbors are available. Consequently, the following algorithm is obtained Alg. 1:

Algorithm 1 Distributed Harmonic Potential Update

```
1: S_i ← {j ∈ N(i) | q_j is defined}
2: if |S_i| = 1 then
3:     q_i ← (1+q_j)/2 {wavefront initialization}
4: else if |S_i| > 1 then
5:     q_i ← 1/|S_i| ∑_{j∈S_i} q_j {Jacobi relaxation}
6: end if
7: if q_i updated then
8:     broadcast(q_i) to neighbors
9: end if
```

Once the potential field is established, routing decisions are derived directly from it (Alg. 2). As the field is monotonic, hence the routing simply follows the steepest gradient.

Algorithm 2 Steepest Gradient Routing

```
1: j* ← arg min_{j∈N(i)} q_j
2: return j*
```

V. HFR Properties

Having the Harmonic Field emerging from the network, its worth to investigate some of its properties:

- Reliability
- Early routable path
- Self-healing
- Node anonymity
- Multiple destinations handling

a) Reliability: The greatest advantege of HFR is the high reliability resulting from the local evaluation of the field. Consequently, in case of significant topology changes it simply relaxes locally to the new solution. Furthermore, assuming that at least some nodes remain unchanged, they improve relaxation time towards a new solution.

b) Early routable path: As soon as any gradient between source and destination is obtained, there already exist a first routing path. Further gradients enable multipath routing or emergency path switching.

c) Self-healing: The relaxation is always based on local averaging of potentials, therefore there is no need for source or destination to restart the field creation - once created it becomes artificial unless intentionally destroyed.

d) Node anonymity: The difference in comparison with common protocols such as DV or OLSR is that the navigation is not oriented towards a specifc node but rather towards a service. It allows to move the service from a given node to another, without notifing the source - the routing field will relax towards a new destination.

e) Multiple destinations handling: Interesting property is that HFR allows for multiple destinations, however, the message is likely to be sent to one of them.It might be useful, for instance, when there is a need to notify any of the nodes in a specific area about a given event.

A. Asynchronized HFR

The HFR acting as a Jacobi solver to the Dirichlet problem presented in Eq. 7 requires the synchronization of nodes. In other words, all nodes should wait for other nodes to compute to perform the same iteration t. Even though it is possible, it is ineffective for the dynamic systems.

That being a case, one may seek asynchronous solutions. However, first it is required to investigate whether asynchronous HFR is possible. The simplest case of asynchronous solver would be to let arbitraty half of nodes to perform computations and broadcast them at even t. The other half compute new values and send them at time $t+1$. Hence, the following equation is obtained:

$$q_i^{t+1} = \frac{1}{|N(i)|}(\sum_{j=1}^{M(i)} q_j^t + \sum_{j=1}^{K(i)} q_j^{t-1}) \tag{8}$$

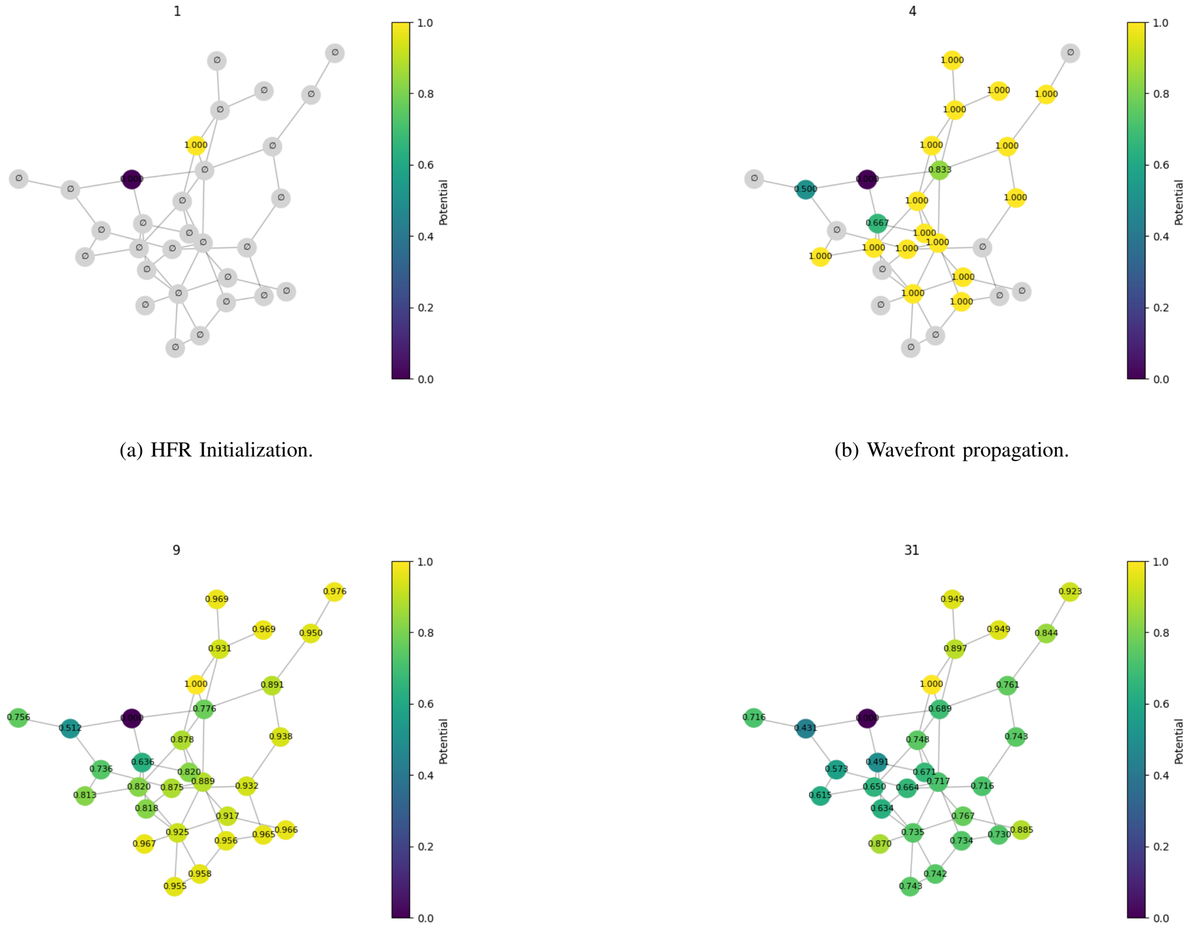
where $M(i) \cup K(i) = N(i)$; M - set of even nodes, K - set of odd nodes.

In fact the Eq. 8 is **Gauss-Seidel solver, namely Red-Black Gauss-Seidel (RBGS)**. Importantly, Red-Black Gauss-Seidel is known converging significantly faster than Jacobi methods, often twice as fast [24].

Nevertheless, even RGBS still is not fully asynchronous. In case of fully asynchronous system, a given node has equally random probability of performing computations or just receie messages aa given time. It can be expressed as:

$$q_i^{t+1} = \frac{1}{|N(i)|}(\sum_{j=1}^{N(i)} \hat{q}_j) \tag{9}$$

where $\hat{q}_j$ is the most recently received value from neighbor j.



(a) HFR Initialization. (b) Wavefront propagation.

(c) Early gradient creation. (d) Full convergence.

Fig. 3. Convergence process for HFR on static network.

Therefore, the asynchronous relaxation is obtained that belongs to the class of chaotic relaxations. The convergence of the solver is in fact between the synchronized Jacobi (worst case) and synchronized Gauss-Seidel (best-case) with the performance comparable to RBGS on average.

VI. Experiments

The three crucial aspects were investigated during the experiments: 1) investigate HFR properties, 2) compare HFR methods, i.e., synchronous, asynchronous Red-Black Gauss-Seidel, and Chaotic relaxation against basic DV in static networks, 3) compare HFR methods with DV in dynamic networks.

All experiments were run in the simulation under the following conditions: random Erdős–Rényi graphs are generated with a probability of edge creation $p = 0.1$, unless another p is explicitly stated. Source and destination are chosen randomly. For all experiments, there were made 1000 graphs on which all algorithms were performed. The N in this section always denotes the number of nodes.

There was assumed the following stop condition for the relaxation process on each node for all HFR versions: $q_i^{t+1} - q_i^t < \epsilon$, where $\epsilon = 10^{-3}$.

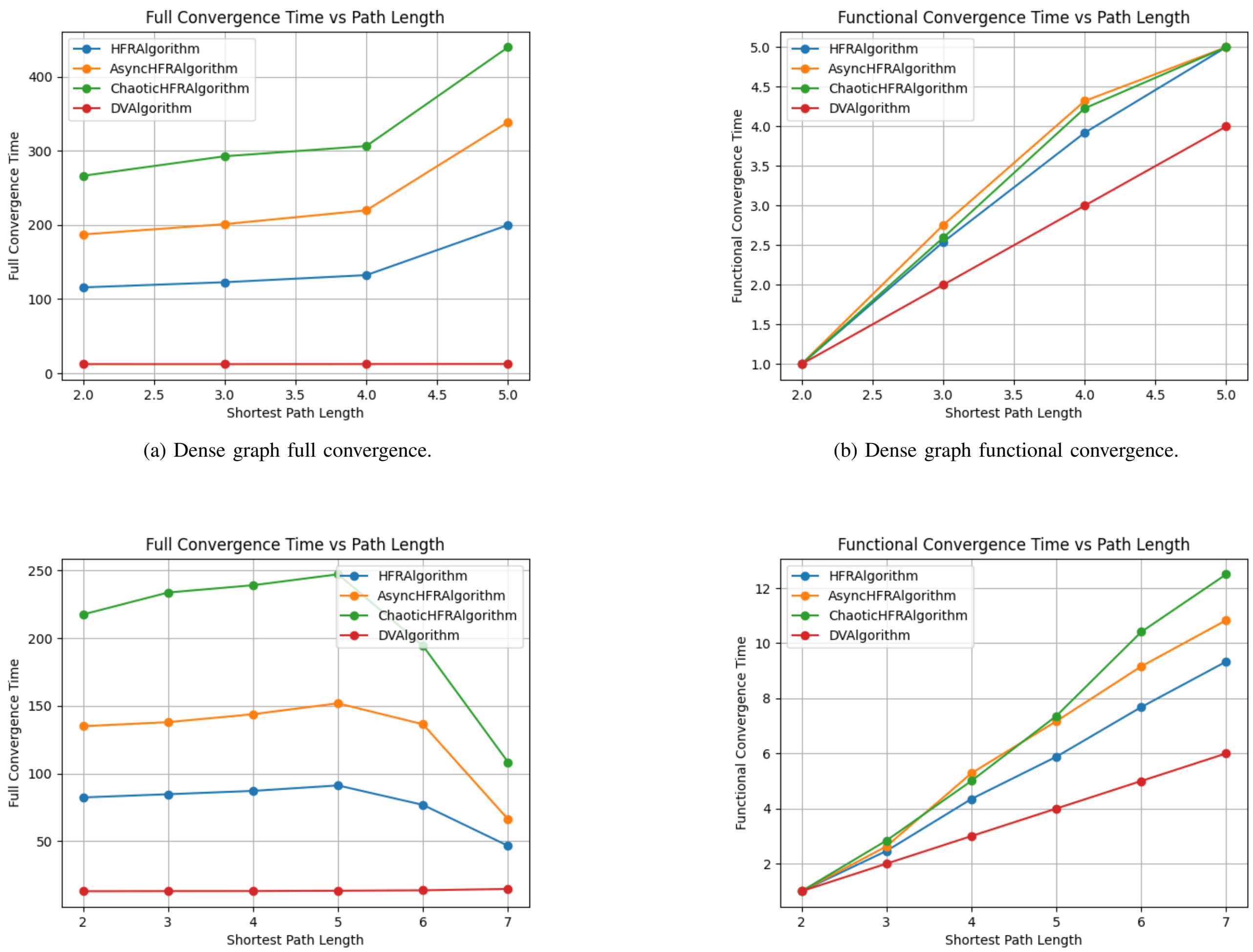
A. HFR Initialization

First of all, in Fig. there is presented the synchronized HFR relaxation process. The field is initialized by the source 3a, subsequently, when the destination is found the relaxation begins 3b. As one can observe, the early gradient is obtained significantly faster then system converges Fig. 3c. Despite the values change, the mutual ratio between nodes remains the same as when the HFR converges Fig. 3d.

B. Static graph performance

The aim of this part of experiments is to evaluate a performance on a static graph, in comparison with the basic DV. The convergence speed in this section relates to the number of iterations t required to reach the stop condition.

Although HFR main aim is reliability, the shortest path approximation was evaluated. As on can observe in Tab: I, the approximation of the shortest path for the HFR is almost



(a) Dense graph full convergence.

(b) Dense graph functional convergence.

(c) Sparse graph full convergence.

(d) Sparse graph functional convergence.

Fig. 4. Full and functional convergence speed for $N = 100$ of dense graph ($p = 0.1$) and sparse graph ($p = 0.05$).

always accurate. As expected, the DV which aims to find the shortest path always succeeded.

TABLE I
SHORTEST PATHS FOUND [%] (OVERALL)

Algorithm	$N = 30$	$N = 60$	$N = 100$
HFR	96.70	94.51	97.40
AsyncHFR	96.40	94.01	97.00
ChaoticHFR	96.60	95.20	98.00
DV	100.00	100.00	100.00

As one can observe, in the static network the DV highly outperforms all HFR algorithms in terms of message count and convergence speed. The average message count per path length, presented in Tab. II, results from the relaxation processes and for the static graph its over 10 higher than for DV. Furthermore, it is increasing with the path length.

Despite the full convergence of the HFRs algorithms is relatively slow in comparison with DV, the functional convergence speed, i.e., the number of iterations after which the path is already established (early gradient) is just slightly slower, as one can see in Fig. 4. Moreover, the graph topology makes a significant impact on the convergence speed. As one can observe in Fig. 4c, in a sparse graph HFRs converges almost as fast as DV. However, in a dense graph the functional convergence is reached significantly faster (Fig. 4b).

TABLE II
AVERAGE MESSAGE COUNT PER PATH LENGTH FOR $N = 30$

Path Length	HFR	AsyncHFR	ChaoticHFR	DV
2	1946.85	1736.86	1665.72	130.91
3	2332.41	2059.61	2199.39	127.18
4	2550.07	2291.55	2383.04	124.95
5	2860.35	2566.84	2604.77	120.50
6	3090.08	2770.37	2729.47	114.05
7	3248.29	2993.57	2833.57	104.21

In Fig. 4 one may observe that synchronous HFR is the fastest in the family; however, it might be deceiving, as asynchronous methods require a delay to transmit information. When compared in terms of messages sent, the asynchronous methods outperform synchronized HFR.

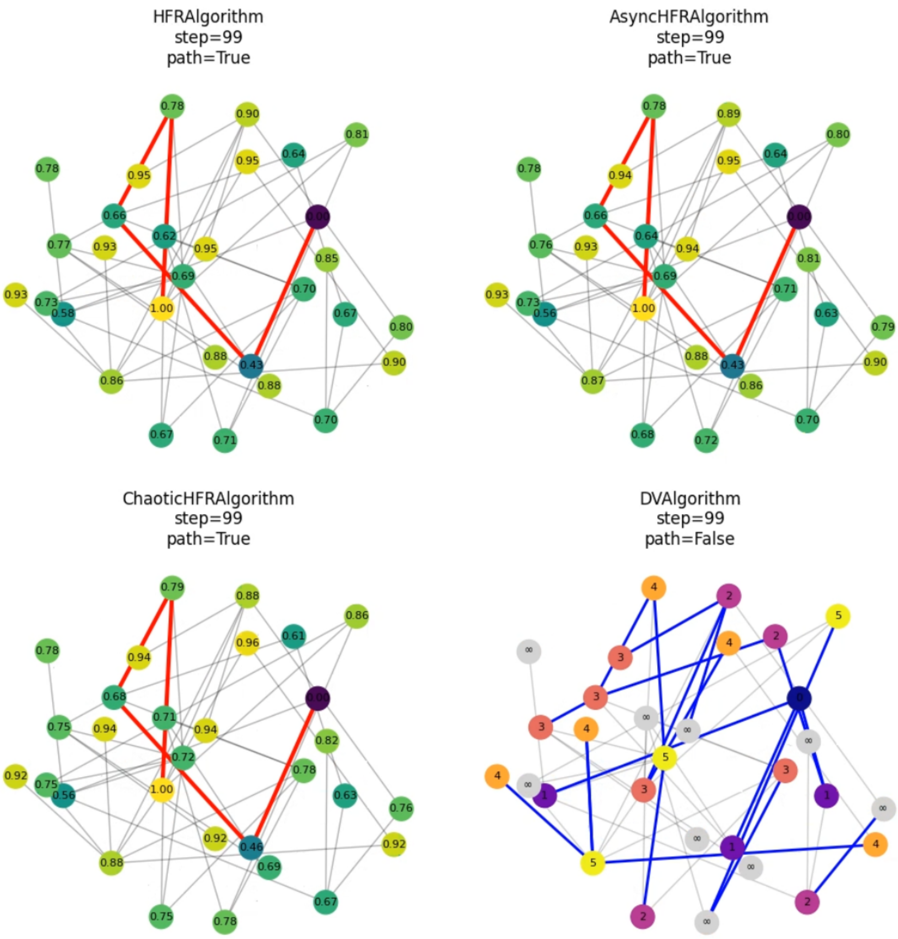


Fig. 5. Comparision of HFR routing family against DV in dynamic network, screenshot from a video [25].

C. Dynamic graph performance

For a dynamic graph experiment, there were used graphs that were first allowed to converge, and then mutated with a random probability m. During mutations $d = 30$ random edges were removed (ensuring the graph remained connected), and also the same number of edges were randomly added.

A video showing the convergence process in a dynamic network for all compared routing algorithms is available at Zenodo [25]. A screenshot from this video is presented in Fig. 5. The source and destination are the same for all algorithms (a dark node with value 0 is the destination, and a node with value 1.00 of HFR is the source). The red edge is the existing path (not necessarily the shortest path) found with the given algorithm. Nodes' values of the DV algorithm are their distance from the destination.

As one can observe, the DV has a loop; hence, no packets are sent between source and destination. The loops result from the dynamic topology changes to which DV poorly adapts by design. During the execution it is a very common behavior, as one can find out in the video. In contrast, the HFR family adapts rapidly, and as one can see, usually the path is not further changed; thus, it is almost immediately close to optimal.

The crucial property of the HFR family is reliability and self-healing. Although it can be seen in the video [25], it was crucial to verify it. As reliability and self-healing are related, both were verified by checking if the routing algorithm finds the path between source and destination without loops. It was called route availability and is presented in Tab. III. The results are meeting the expectations - the availibility even in the dynamic environment is high. What is more, HFRs family performs much better than DV.

TABLE III
AVERAGE SOURCE-DESTINATION PATH AVAILABILITY [%] IN DYNAMIC NETWORK.

Algorithm	$N = 30$	$N = 60$	$N = 100$
HFR	96.87	99.99	99.99
AsyncHFR	92.31	99.67	99.67
ChaoticHFR	87.48	99.50	99.50
DV	47.78	65.48	65.48

The differences between chaotic, asynchronous, and synchronous HFRs are twofold: on the one hand, they require more iterations, while on the other hand, they converge faster. Consequently, they sometimes mitigate the negative effect of asynchronous iterations.

TABLE IV
AVERAGE SOURCE-DESTINATION PATH AVAILABILITY [%] FOR $N = 60$ WITH DIFFERENT EDGE DENSITIES.

Algorithm	$p = 0.1$	$p = 0.07$	$p = 0.05$
HFR	99.99	79.51	75.71
AsyncHFR	92.31	78.26	71.12
ChaoticHFR	99.50	75.07	63.04
DV	65.48	49.18	32.55

Similarly as previously, the graph density has significant influence on availability, as visible in Tab. IV. The more sparse the graph, the smaller the availability. In the worst case, the graph may have at most two edges, thereby increasing the influence of perturbations.

Although in static routing tasks the basic DV performs better in terms of convergence speed, message overhead, and shortest path finding, the HFR dominates in terms of reliability and overall performance in dynamic networks. The rapid self-healing that can be observed in the video [25] as well as the measured route availability proved that. Furthermore, in static networks the early gradient allows HFR methods to compete with DV. What is more, HFR, despite being the reliability-oriented algorithm, still approximates the optimal route comparably to DV.

VII. CONCLUSIONS

In this paper, we introduced the emergent Harmonic Field Routing (HFR) as a highly reliable routing approach for dynamic networks. HFR creates a smooth harmonic field over a network through local interactions between nodes, implicitly solving a discrete Laplace equation. Routing decisions are then obtained by greedily following the steepest descent of this harmonic potential. Due to harmonic field properties, there are no loops, and due to proposed virtual link to a source rule, the shortest path is approximated with a high accuracy.

The proposed method exhibits strong robustness to topology changes. When perturbations occur, the potential field continuously adapts, allowing the routing structure to recover without requiring explicit recomputation or global coordination. Simulation results demonstrate that HFR outperforms classical Distance Vector routing in terms of reliability, primarily due to its inherent self-healing properties. Although full convergence of the field may be slower than in Distance Vector approaches, usable routing paths emerge early in the process, resulting in comparable convergence times in practice. Moreover, in practice, once the HFR converges, the adaptation to the topology changes is almost immediate making it suitable for MANETs.

Future work will focus on the design of a complete communication protocol based on HFR, as well as further investigating HFR properties such as multiple destinations and node anonymity.

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