Distributed $K$-Backup-Placement and Applications to Virtual Memory in Heterogeneous Networks

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Abstract. The Backup Placement problem in networks in the CONGEST distributed setting considers a network graph $G = (V, E)$, in which the goal of each vertex $v \in V$ is selecting a neighbor, such that the maximum number of vertices in $V$ that select the same vertex is minimized $\lceil \frac{\log n}{\log \log n} \rceil$. The problem is called 1-Backup-Placement when each vertex selects exactly one neighbor. A more general version, in which each vertex selects $K$ neighbors, for a positive parameter $K$, is called $K$-Backup-Placement. In $\lceil \frac{\log n}{\log \log n} \rceil$ Barenboim and Oren studied approximate backup placement algorithms in sparse and dense networks and proved their correctness, specifically that each vertex is selected by at most $O(1)$ neighbors (the approximation ratio), and achieving a desired load-balancing. Moreover, they proved that the algorithms can be implemented with messages of size $O(\log n)$ per link per round, and also considered two variants of networks: faultless networks and faulty networks. For the latter, they obtained a self-stabilizing algorithm and proved stabilization within 1 to 3 rounds. However, those algorithm suffer from obliviousness to some main factors of heterogeneous wireless network. Specifically, in $\lceil \frac{\log n}{\log \log n} \rceil$ there is no consideration of the nodes memory and storage capacities and the heterogeneity of capacity, and no reference to a case in which nodes have different energy capacity, and thus can leave (or join) the network at any time. Those parameters coupled in wireless networks, as the load on different parts of the network can differ greatly, thus requiring more messages, energy, memory and storage. In this work we suggest two complementary algorithms which address this problem. In the first one we divide the memory of each node to many small parts, but assign each vertex the memories of a large number of its neighbors. Thus more memory for more vertices is gained but with much fragmentation. In the second algorithm we execute more rounds, but do not produce fragmentation, and allow for a larger virtual memory per vertex. A key technical contribution of ours is an algorithm for $K$-Backup-Placement, that is used as a building block for these two procedures. Its running time is just one round.

Keywords: Wireless Sensor Networks · Distributed Backup-Placement.
1 Introduction

We consider the $K$-Backup-Placement problem in networks in the CONGEST distributed setting. In the distributed setting, the Backup Placement problem was introduced by Halldorsson, Kohler, Patt-Shamir, and Rawitz [7] in 2015. It is very well motivated by computer networks whose nodes may have memory faults, and wish to store backup copies of their data at neighboring nodes [14]. But neighboring nodes may incur faults as well, and so the number of nodes that select the same backup-node should be minimized. This way, if a backup node incurs faults, the number of nodes in the network that lose data is minimized. Moreover, a proper backup placement allows each vertex to perform a backup to a neighboring node, rather than a more distant destination, and thus improves network performance. In addition, nodes’ memories are used to the minimum extent for the purpose of backups, which makes it possible to maximize the memory available for other purposes of the vertices.

The precise definition of the distributed variant of the problem is as follows. The computer network is represented by an unweighted unoriented graph $G = (V, E)$, where $V$ is the set of nodes, and $E$ is the set of communication links. Communication proceeds in synchronous discrete rounds. In each round vertices receive and send message, and perform local computations. A message sent over an edge in a certain round arrives to the endpoint of that edge by the end of the round. In 1-Backup-Placement the goal of each vertex is selecting a neighbor, such that the maximum number of vertices that make the same selection is minimized. More generally, in $K$-Backup-Placement in graphs with minimum degree at least $K$, each vertex selects $K$ neighbors, such that the maximum number of vertices that select the same vertex is minimized. The algorithm terminates once every vertex outputs its selection of neighbors for the backup placement. The running time is the number of rounds from the beginning until all vertices make their decisions.

Several solutions introduced to this problem over the last decade. Halldorsson et al. [7], who presented the problem, obtained an $O(\log n / \log \log n)$ approximation with randomized polylogarithmic time. Their algorithm remained the state-of-the-art for general graphs, as well as specific graph topologies. Barenboim and Oren [6] obtained significantly improved algorithms for various graph topologies. Specifically, they showed that $O(1)$-approximation to optimal 1-Backup-Placement can be computed deterministically in $O(1)$ rounds in wireless networks, and more generally, in any graph with neighborhood independence bounded by a constant. At the other end, they considered sparse graphs, such as trees, forests, planar graphs and graphs of constant arboricity, and obtained constant approximation to optimal 1-Backup-Placement in $O(\log n)$ deterministic rounds. They also considered two variant of networks, specifically faultless networks and faulty networks. For the latter, they obtained a self-stabilizing algorithm and proved stabilization within 1 to 3 rounds [5]. These algorithms are extremely efficient.

1 Neighborhood independence is the maximum number of independent neighbors a vertex in the graph has.
for wireless networks models. However, in practice, heterogeneous nodes and network attributes should be taken into account, and therefore those algorithms should be extended to include other important aspects [14], such as:

- **Memory and Storage**: As the amount of RAM and Storage of the node is final and non-uniform [8] - either because the nodes themselves differ in those parameters or because the nodes joined the network in non-synchronized periods - backup placement cannot be oblivious to it. Moreover, because the RAM acts as a buffer towards the flash memory [9], the pages amount is limited by the RAM capacity, which is usually about an order of magnitude smaller than the flash capacity. Therefore, the size of the packets cannot exceed the RAM capacity during the backup operation [18].

- **Communication and Energy**: The amount of available energy of a node - as well as the amount of communication rounds the node can perform - is final and non-uniform [9]. This is either because the nodes themselves can hold different battery capabilities and communication range; or because the nodes joined the network in non-synchronized periods; or performed in different roles which require different amount of energy [17] - backup placement cannot be oblivious to it.

- **Nodes that Join or Leave**: The backup placement algorithm cannot be oblivious to premature death of nodes and joining of new ones to the network [15]. This is because we cannot assume that the network able to make appropriate cluster adaptation (i.e. triggered to re-cluster in these changes of the topology) nor in the capability of the backup placement algorithm to address those changes without loosing backups or missing the new opportunity to backup to new joined nodes [10].

In order to solve the problem of backup-placement in heterogeneous wireless networks as described above, we devise a $K$-Backup-Placement algorithm. Indeed, if a vertex selects $K$ neighbors, even if some of them crash, there is still a possibility to employ the neighbors that remain. We stress that the desired procedure should compute $O(1)$-approximate backup placement in graphs with constant neighborhood independence $c$. The notion of neighborhood independence was introduced in [2] and has been intensively studied since then [3] [4] [11] [1]. The rational behind the usage of neighborhood independence bounded by a constant for backup-placement is that many wireless sensor network topologies have neighborhood independence bounded by a constant. For example, UDG, QUDG, UBG, GBG, etc. Moreover, we assume that each vertex knows only about its neighbors, and each vertex has a unique ID. The procedure receives a graph $G = (V, E)$ as input, and all the selections should be performed in parallel within a single round. Indeed, in this setting we obtain an $O(1)$-approximate $K$-Backup-Placement within just a single round.

Once we have a solution for the $K$-Backup-Placement problem, we turn to a more channeling task of allocating virtual memory for nodes in wireless networks. Here the goal is partitioning the node set into classes, and obtain a scheduling in which each class is active at a time and can make use of memories of other classes
that are inactive in that time. The challenge here is coming up with the right trade-off between the number of classes (that needs to be small) and the size of the virtual memory (that becomes larger as the number of classes increase). To obtain the desired balance we compute a certain coloring in which all vertices of the same color class have considerable amount of virtual memory, while keeping the number of classes sufficiently small.

2 Problem Formulation in Wireless Sensor Networks

– **The Setting**: The wireless sensor network is modeled by \( n \) nodes, each of which has the same communication range (of 1 unit) and memory size (1 unit). Within a single round all nodes can communicate with other nodes in their communication range. Each node can send a message of unrestricted size to each of the nodes in its communication range. (Henceforth, neighboring nodes.) The nodes goal is to sense and process some data, that changes periodically. Each node may be required to process more data than the amount of memory it can contain. We assume that the degree of each vertex is at most \( \Delta \).

– **The Phase**: A phase is defined as follows. Suppose that just a single node \( v \) in the network senses the data. The others, \( V \setminus v \), do not perform their own tasks, but assist \( v \) with data processing. (By exchanging messages with \( v \) and performing computations, but not sensing new data.) A phase consists of the rounds required to complete this task. A *rate of data change is given by a parameter \( R \).* It defines the number of phases during which data remains unchanged.

– **The main problem**: Given the parameter \( R \), devise an algorithm in which all nodes complete their sensing and processing task, such that the available memory per processor (its own, plus memories assigned to it by assisting nodes) is as large as possible. (Henceforth, node virtual memory.)

– **Intermediate problem**: \( K \)-Backup-Placement: Given a network graph \( G = (V, E) \), the goal of each vertex \( v \in V \) is selecting \( K \) neighbors, such that the maximum number of vertices in \( V \) that select the same vertex is minimized.

– **Solution idea for the main problem**: Color the network with \( O(\Delta) \) colors. Partition the graph using *super-classes*\(^2\), each class consists of \( O(\Delta/R) \) colors, \( R < \Delta \). Perform \( R \) phases, each with one active super-class. Each active node \( v \) is assisted by all its neighbors. Each such neighbor assigns \( v \) a fraction of \( O(R/\Delta) \) of its memory. In case when all degrees are roughly the same, we have \( O(R) \) memory units per node. This is the node’s virtual memory, that is greater by a factor of \( R \) than the node’s physical memory.

\(^2\)A subset of vertices assigned to the same color is called a *color class*, every such class forms an *independent set*. Thus, a \( k \)-coloring is the same as a partition of the vertex set into \( k \) independent sets. We define *super-class* to include a range of color classes.
3 Backup Placement by $K$-Next-Modulo

We begin with devising a procedure for $K$-Backup-Placement, with load at most $O(c \cdot K)$ in graphs with bounded neighborhood independence $c$. We assume that each vertex knows only about its neighbors, and each vertex has a unique ID. We generalize the algorithm Next-modulo [5] that is applicable only for 1-Backup-Placements. This generalization allows us to obtain efficient $K$-Backup-Placement. The notion behind this algorithm is that a usage of a version of the Next-Module function [5] in the selection process of the backup placement can effectively bound the load on all of the vertices while keeping good performances.

We define an operation $K$-next-modulo that receives a vertex $v$, a set of its neighbors $\Gamma(v)$ in the graph $G$, and the parameter $K$. The operation $K$-next-modulo($v$, $\Gamma(v)$, $K$), selects the $K$ neighbors that immediately succeed $v$, in a circular ordering according to vertex IDs. Formally, denote $d = \text{deg}(v) + 1$, and let $u_1, u_2, ..., u_t = v, u_{t+1}, ..., u_{\text{deg}(v)+1}$ be an ordering of the neighborhood of $v$, according to IDs, in ascending order. Then $v$ selects the $K$ neighbors: $u_{(i+1)} \mod d, u_{(i+2)} \mod d, ..., u_{(i+K)} \mod d$. All these selections are performed in parallel within a single round. This completes the description of the algorithm. Its pseudocode is provided in Algorithm 1. The next theorem summarizes its correctness.

**Algorithm 1 $K$-Next-Modulo Algorithm**

1: procedure next-modulo($v$, $\Gamma(v)$, $K$)  
2: sort $\Gamma(v)$ by IDs as a Circular Linked List  
3: $v_{\text{index}} = \Gamma(v)[0]$  
4: foreach $v_{\text{neighbor}} \in \Gamma(v)$  
5: if $v_{\text{neighbor}}.\text{ID} > v.\text{ID}$  
6: $v_{\text{index}} = v_{\text{neighbor}}$  
7: break  
8: while $K > 0$ do  
9: if $\varphi(v) \neq \varphi(v_{\text{index}})$ and $v.\text{CC} \neq v_{\text{index}}.\text{CC}$ then  
10: if $v_{\text{index}} \notin v.BP$ then  
11: $v.BP.append(v_{\text{index}})$  
12: $K = K - 1$  
13: $v_{\text{index}} = v_{\text{index}}.\text{next}$  
14: return $v$

**Theorem 1.** In a graph $G = (V, E)$ with neighborhood-independence bounded by a constant $c$, and with minimum degree at least $K$, the resulting load $T$ for every vertex $v \in V$ is at most $c \cdot K$.

**Proof.** Assume for contradiction that more than $c \cdot K$ neighbors chose $v$ as a backup placement. Denote by $U$ the subset of neighbors that selected $v$. Let $w_1$ be the vertex that immediately succeeds $v$ in a circular ordering according
to IDs of $U \cup \{v\}$. It follows that $w_1$ is connected by edges to at most $k - 1$ vertices of $U \setminus \{w_1\}$. Otherwise, there are $k$ neighbors of $w_1$ that succeed $w_1$ and preceed $v$ in the circular ordering, and thus $v$ would not have been selected by $w_1$. We remove $w_1$ and its neighbors from $U$. Next, we find a remaining vertex $w_2$ in $U$ that immediately succeeds $v$ in a circular ordering according to IDs of remaining vertices in $U \cup \{v\}$. Similarly, this vertex can be connected to at most $k - 1$ vertices in $U$. We remove $w_2$ and its neighbors from $U$. We repeat this for $i = 1, 2, ..., c + 1$ iterations. (See illustration in Figure 1.) The number of neighbors in each iteration becomes smaller by at most $k$ neighbors. The initial number of neighbors is at least $c \cdot k + 1$. Therefore, it is possible to execute $c + 1$ iterations. In each iteration $i = 1, 2, ..., c + 1$ we remove a vertex $w_i$ and its neighbors from $U$. Hence the set $w_1, w_2, ..., w_{c+1}$ is an independent set of neighbors of $v$. This is a contradiction to the neighborhood independence that is bounded by $c$.

Fig. 1. Exemplifying the assumption for contradiction that more than $c \cdot K$ neighbors chose $v$ as a backup placement in $C_6$ cycle graph (some edges were removed for clarity). From top to bottom: We first assume for contradiction that all vertices select $v = 4$ as a backup placement (marked in red), while $K = 3$; then, $v.next = 5$ ($w_1$, marked in blue) forced to select $v$ and another $K - 1$ vertices for backup; then, $v.next = 2$ ($w_2$, marked in blue) finishes available selections.
The $K$-next-modulo algorithm turns out to be more useful than the next-modulo algorithm of [5], for obtaining virtual memory in wireless networks. While in the algorithm of [5] each vertex selects just one neighbor whose memory can be used, in our algorithm each vertex can use the memories of $K$ neighbors. However, we would like to prevent a situation where multiple vertices use the memory of the same neighbor in the same time. In such a case, instead of gaining an increase by a factor of $K$, we may gain as low factor as $K/(c \cdot K)$, which is not desirable. To avoid it, we prevent the possibility that two vertices use the memory of the same neighbor at the same time. To this end, we define the graph $G' = (V, E')$, where $E'$ is the set of edges selected during the $K$-next-modulo algorithm. Since each vertex selects $K$ neighbors, and is selected by $O(c \cdot K)$ neighbors, the maximum degree of $G'$ is $O(c \cdot K + K) = O(c \cdot K)$.

Therefore, we devise a new scheduling algorithm which first invokes the $K$-next-modulo for computing $K$-Backup-Placement, and afterwards, the resulting subgraph $G'$ is colored by a 2-hop coloring in order to divide the vertices according to color classes, each of which is activated in a distinct round. Since the subgraph $G'$ is considered to be a general graph, and as we need to perform a 2-hop coloring, we invoke Linial algorithm for $O(\Delta^2)$-coloring [12] [13] on $G'^2$ that produces $O(\Delta')$ colors with running time of $\log^* n + O(1)$. Yet, as the subgraph $G'$ has maximal degree of $c \cdot K$, while $c$ is a small constant and $K$ is a parameter that can be sufficiently small, we keep good performances. Moreover, we stress that $K$ is de-facto represents a selective tradeoff between memory and running time, since as $K$ is larger, more memory would be dedicated for backup placement in the expense of the running time, and vice versa. The algorithm pseudocode is provided in Algorithm 2. The next lemmas summarizes its correctness.

**Algorithm 2** Backup Placement in Graphs by $K$-Next-Modulo

1: procedure GRAPH-BP(Graph $G = (V, E)$, $K$)
2: foreach active node $v \in G$ in parallel do:
3:   $v.BP = K$-next-modulo($v, \Gamma(v), K$) \triangleright Active vertices select $K$ neighbors
4: foreach active node $v \in G$ in parallel do:
5:   perform 2-hop coloring with $O(\Delta^2)$ colors \triangleright Divide active vertices to apply turns
6: foreach $cc \in$ Color-Classes do: \triangleright Each vertex knows its Color-Class
7:   foreach node $v \in G'(cc)$ in parallel do: \triangleright Round-robin for Color-Classes vertices
8:   distribute the backup-placement in parallel from each $v \in G'(cc) \rightarrow v.BP$ vertices

**Lemma 1.** The virtual memory of each active vertex in $V$ is increased by $K$.

**Proof.** In each time period only a single color class, out of $O(K^4)$, is activated. For each vertex $v$ in such a color class, all its neighbors in $G'$, and the neighbors of its neighbors in $G'$, are not activated. This is because the color classes belong to
a 2-hop coloring of $G'$, and thus vertices at distance at most 2 from $v$ in $G'$ have distinct colors than that of $v$. Now, consider the set of vertices $\{u_1, u_2, ..., u_k\}$ selected by $v$. Any vertex $w$ in $G$ that also selected at least one of these vertices is at distance at most 2 from $v$ in $G'$. Hence the color of $w$ is distinct from the color of $v$, and thus $w$ is not active in this time period. The vertices $\{u_1, u_2, ..., u_k\}$ are at distance 1 from $v$, and thus are not active as well. The only active vertex that selected at least one of them is $v$. Hence, the memories of these $K$ vertices are assigned solely to $v$ in this time period.

Lemma 2. The algorithm terminates within $O(\log^* n + K^4)$ rounds.

Proof. First, $K$-next-module is performed in parallel within a single round. Afterwards, the construction of $O(\Delta^2)$ 2-hop coloring of the subgraph $G'$ of $G$ requires running time of $\log^* n + O(1)$ [12] [13]. Finally, the round-robin fashion of the scheduling is done for $O(\Delta^4(G'))$ color-classes, where each color-class performs all of the work in parallel. Yet, as the subgraph $G'$ has maximal degree of $c \cdot K$, while $c$ is a small constant and $K$ is selective, the running time of the algorithm is $O(\log^* n + K^4)$.

4 Virtual Memory by Color Super-Classes

In this section we devise a procedure in which several color classes can be employed in parallel. The procedure is applicable to graphs with bounded growth, in which one can color a 4-hop neighborhood with $O(\Delta)$ colors. (See, e.g., [16].) In such graphs the neighborhood independence is bounded by a constant $c$. Moreover, here we assume a roughly uniform distribution of processors on the surface, so that the minimum degree is $\Omega(\Delta)$.

We assume that each vertex knows only about its neighbors, and each vertex has a unique ID. The procedure receives a graph $G = (V, E)$ as input and the parameter $R$, and proceeds as follows. We first color the network with $O(\Delta)$ colors. Then, we partition the graph using super-classes, each class consists of $O(\Delta/R)$ colors, $R < \Delta$. At last, we perform $R$ phases, each with one active super-class (which is allowed to perform backup placement), in which we perform backup operation in parallel to the vertices of all the non-active super-classes (which are not allowed to perform backup placement). This completes the description of the algorithm. Its pseudocode is provided in Algorithm 3. The next lemmas summarizes its correctness. This action is illustrated in Figure 2.

Lemma 3. Each vertex in $V$ is selected by at most $O(\Delta c/R)$ vertices.

Proof. As in each color-class there are $O(\Delta/R)$ colors, and the neighborhood independence of $G$ is $c$, for each vertex there are $O(\Delta c/R)$ vertices which can select it for backup.

Lemma 4. Each vertex in $v \in V$ can select at least $\deg(v) - O(\Delta c/R)$ vertices which are not active.
Algorithm 3 Backup Placement by Color Classes

1: procedure Graph-BP(Graph $G = (V, E), \Delta, c, R$)
2: do $(\Delta + 1)$-coloring of $G$
3: divide $G$ using the $(\Delta + 1)$-coloring to $[\Delta + 1]/R \rightarrow$ Super-Classes
4: foreach $sc \in$ Super-Classes do:
5: foreach node $v \in G(sc)$ in parallel do:
6: foreach vertex $v_{neighbor} \in \Gamma(v)$ in parallel do:
7: if $\phi(v) \neq \phi(v_{neighbor})$ and $v.superclass \neq v_{neighbor}.superclass$
8: $v.BP.append(v_{neighbor})$
9: divide the backup-placement by $|v.BP|$
10: distribute the divided backup-placement in parallel from each $v \in G(sc) \rightarrow v.BP$ vertices

Fig. 2. A backup placement (blue) in a graph with bounded neighborhood independence $c = 4$, 4-coloring (red, yellow, green, blue) and 2 color-classes (1, 2), which divides the coloring into 1={red, yellow} and 2={green, blue}, at the 1-color-class turn to perform backup placement.

Proof. First we analyse the number of active neighbors of $v$. Those are neighbors which belong to the same super-class. The number of colors in the super-class is $O(\Delta/R)$. As the neighborhood independence is $c$, each color class is taken by at most $c$ neighbors, therefore the super-class contains at most $O(\Delta c/R)$ neighbors. Therefore, the amount of non-active neighbors is the overall number of neighbors minus the active neighbors, which is $\text{deg}(v) - O(\Delta c/R)$.

Lemma 5. The virtual memory of each vertex in $V$ is increased by $\Theta(R)$.

Proof. Denote by $M$ the memory size that each vertex has. A vertex can be selected by at most $O(\Delta c/R)$ vertices, thus each vertex is allocating $O(M R/\Delta c)$ virtual memory for each backuping vertex. As each backuping vertex has $\text{deg}(v) - O(\Delta c/R) = O(\Delta)$ vertices to backup to, the virtual memory of each vertex in $V$ is increased by $\Theta(R)$.

Lemma 6. The algorithm terminates within $O(\log^* n + R)$ rounds.
Proof. First, the construction of \((\Delta + 1)\)-coloring of \(G\) requires \(O(\log^* n)\) rounds \[16\]. Then, the division of the coloring to color-classes is done in \(O(1)\) rounds using division of colors into super-classes. Finally, the round-robin fashion of the backup-placement is done for \(O(R)\) rounds, where each color-class performs all of the work in parallel. Therefore, the running time of the algorithm is \(O(\log^* n + R)\). \(\square\)

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References

1. Sepehr Assadi and Shay Solomon. When algorithms for maximal independent set and maximal matching run in sublinear time. In 46th International Colloquium on Automata, Languages, and Programming (ICALP 2019). Schloss Dagstuhl-Leibniz-Zentrum fuer Informatik, 2019.
2. Leonid Barenboim and Michael Elkin. Deterministic distributed vertex coloring in polylogarithmic time. Journal of the ACM (JACM), 58(5):23, 2011.
3. Leonid Barenboim, Michael Elkin, and Tzalik Maimon. Deterministic distributed \((\Delta + o(\Delta))\)-edge-coloring, and vertex-coloring of graphs with bounded diversity. In Proceedings of the ACM Symposium on Principles of Distributed Computing, pages 175–184. ACM, 2017.
4. Leonid Barenboim and Tzalik Maimon. Distributed symmetry breaking in graphs with bounded diversity. In 2018 IEEE International Parallel and Distributed Processing Symposium (IPDPS), pages 723–732. IEEE, 2018.
5. Leonid Barenboim and Gal Oren. Distributed backup placement in one round and its applications to maximum matching approximation and self-stabilization. In Symposium on Simplicity in Algorithms, the Symposium on Discrete Algorithms, pages 99–105. ACM-SIAM, 2020.
6. Leonid Barenboim and Gal Oren. Fast distributed backup placement in sparse and dense networks. In Symposium on Algorithmic Principles of Computer Systems, the Symposium on Discrete Algorithms, pages 90–104. ACM-SIAM, 2020.
7. Magnús M Halldórsson, Sven Köhler, Boaz Patt-Shamir, and Dror Rawitz. Distributed backup placement in networks. In Proceedings of the 27th ACM symposium on Parallelism in Algorithms and Architectures, pages 274–283. ACM, 2015.
8. Gholamreza Kakamanshadi, Savita Gupta, and Sukhwinder Singh. A survey on fault tolerance techniques in wireless sensor networks. In Green Computing and Internet of Things (ICGCIoT), 2015 International Conference on, pages 168–173. IEEE, 2015.
9. Fatma Karray, Mohamed W Jmal, Alberto Garcia-Ortiz, Mohamed Abid, and Abdulfattah M Obeid. A comprehensive survey on wireless sensor node hardware platforms. Computer Networks, 144:89–110, 2018.
10. Linghe Kong, Mingyuan Xia, Xiao-Yang Liu, Min-You Wu, and Xue Liu. Data loss and reconstruction in sensor networks. In INFOCOM, 2013 Proceedings IEEE, pages 1654–1662. IEEE, 2013.
11. Fabian Kuhn, Yannic Maus, and Simon Weidner. Deterministic distributed ruling sets of line graphs. In *International Colloquium on Structural Information and Communication Complexity*, pages 193–208. Springer, 2018.

12. Nathan Linial. Distributive graph algorithms global solutions from local data. In *28th Annual Symposium on Foundations of Computer Science (sfcs 1987)*, pages 331–335. IEEE, 1987.

13. Nathan Linial. Locality in distributed graph algorithms. *SIAM Journal on Computing*, 21(1):193–201, 1992.

14. Gal Oren, Leonid Barenboim, and Harel Levin. Distributed fault-tolerant backup-placement in overloaded wireless sensor networks. In *International Conference on Broadband Communications, Networks and Systems*, pages 212–224. Springer, 2018.

15. Ali Shokouhi Rostami, Marzieh Badkoobe, Farahnaz Mohanna, Ali Asghar Rahmani Hosseinabadi, Arun Kumar Sangaiah, et al. Survey on clustering in heterogeneous and homogeneous wireless sensor networks. *The Journal of Supercomputing*, 74(1):277–323, 2018.

16. Johannes Schneider and Roger Wattenhofer. A log-star distributed maximal independent set algorithm for growth-bounded graphs. In *Proceedings of the twenty-seventh ACM symposium on Principles of distributed computing*, pages 35–44. ACM, 2008.

17. Gurkan Tuna, Vehbi Cagri Gungor, Kayhan Gulez, G Hancke, and V Gungor. Energy harvesting techniques for industrial wireless sensor networks. *Industrial wireless sensor networks: Applications, protocols, standards, and products*, pages 119–136, 2013.

18. Dorothea Wagner and Roger Wattenhofer. *Algorithms for sensor and ad hoc networks: advanced lectures*. Springer-Verlag, 2007.