Performance of Generalized Hypercubes in Dynamic Peer-to-Peer Networks

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Abstract

Highly dynamic peer-to-peer networks are becoming very popular due to their wide range of applications. Although many structures were proposed to deploy peer-to-peer networks, hypercube structures could grasp the researchers’ attention for study because of their desirable properties. A lot of studies have considered binary hypercubes for research. In this paper, we study more generalized topology of hypercubes, namely generalized hypercubes and measure their performance in dynamic networks where nodes can enter and leave the network at any time. Python code was developed to simulate the networks and visualize the results. In addition to being highly flexible and scalable, generalized hypercubes proved to have lower average path length and lower vertex density than binary hypercubes.

1 Introduction

Peer-to-peer (P2P) networks have become very popular due to their distinguished properties that make them widely used in different applications. P2P networks are capable of functioning, self organizing, scaling with large number of network nodes [13] and is prone to network failures [16]. Not only do they outperform client/server networks in file sharing [14], but their applications extend to include other areas such as conferencing [10] and content distribution [12] as well as wireless communication networks [21]. The popularity of P2P networks encouraged the proposal of several structures to interconnect the nodes within the network such as hypercubes. Hypercubes are a type of network topology that are widely used to connect computers and processors in parallel and distributed networks. In turn, hypercubes combine a group of desirable characteristics that are ideal for modeling the connection of nodes in a network [22]. For instance, they possess low graph diameter (the maximum distance between any pair of nodes) and relatively low node degree (the number of edges per node) as well as being tolerant to nodes failures.

The functioning of P2P networks depends on what is called sessions, which is defined in [11] as a cycle of a node join, participation and leaving. The join and leave of a big number of nodes is called node churn that makes P2P networks highly dynamic [15]. Hence, it is important to study the performance of hypercubes in a dynamic P2P network in terms of maintenance and scalability. Maintenance refers to the graph’s ability to handle the events of nodes entering and leaving the network, and scalability defines if a graph could absorb the increase in the number of nodes. In general, hypercube structures can be categorized into three main categories

- Conventional hypercubes with number of nodes $N = W^D$ where $W, D \in \mathbb{N}$, $D$ is the number of dimensions and $W$ is the number of nodes in each dimension [9].
- Generalized hypercubes (GHCs) [1] with $N = \prod_{i=0}^{r-1} m_i$ where $m_i$ is the radix of the $i^{th}$ dimension.
- Binary hypercubes with $N = 2^D$ [8]. It is a special case of the conventional hypercubes where $W = 2$. It is also considered as a special case of GHC structures where $m_i = 2$ for $0 \leq i < r$.

Most research investigating hypercubes in the last few decades has focused on identifying and evaluating binary hypercubes. A. Toce et al. [3, 2], for example, proposed a protocol to build and maintain $n$-dimensional binary hypercube in a Dynamic Distributed Federated Databases and dynamic P2P networks respectively whose routing algorithm was further enhanced in [20]. In [16], hypercubes were used to to cluster nodes in P2P networks for optimum network load in broadcast and search. An interconnection topology was introduced in [15] to reduce the diameter of the hypercube to about its half. Wang, et al. [18] used conventional hypercubes for music information retrieval and they called the graph Hyper-Tenary Cube where an $n$-dimensional Tenary-Cube has $3^n$ nodes. To our knowledge, there are, however, relatively few studies on generalized hypercubes. In this paper, we review generalized hypercube structures and the performance in dynamic P2P networks where node churn is an issue and compare it against the performance of binary hypercubes.

The rest of the paper is organized as follows: Section 2 provides an overview of the related work. Section 3 describes the general properties of GHCs and explains two forms of GHCs being full and partial. Section 4 discusses entering and leaving nodes algorithms in a dynamic network. Section 5 presents the simulation of GHC along with the results and the comparison between GHCs and binary hypercubes. Section 6 summarizes the paper and provides suggestions for future work.

2 Background and Related Work

A P2P network is an architecture of a distributed environment whose participants (nodes) make a portion of their resources directly available to other nodes without the need for central coordination instances, i.e., network nodes play the role of the
server and the client at the same time; or as referred to in [5] as Servent. A P2P networks is different from a Client/Server network that has a single entity (the server) which acts as the provider of the services, and the clients that can only be recipients of those services.

In [7], where different topologies of P2P networks were reviewed, they were categorized into two classes: structured and unstructured. Peers in an unstructured P2P join the network randomly without prior knowledge of the topology while structured networks use Distributed Hash Tables to deterministically place location information and firmly control the network’s topology. Hypercube structures can be built over both structured and unstructured P2P networks [17].

P2P are overlay networks because they are built on top of other technologies such as the internet [23], TCP/IP networks [22] and Mobile Ad-hoc networks [19]. An overlay is a virtual network that represents the interconnection of computers in a layer that is on top of the physical layer of connections [23]. In this regard, the locality problem was introduced, that is the overlay network bears no resemblance to the underlying physical network. In other words, distance between the nodes in the overlay network might not be the same as the distance between the same peers in the real physical network. To date, several studies have investigated the locality problem including [22] where Gharib et al. proposed a locality algorithm to enhance the performance of P2P networks. The authors in [2] suggested preferential attachment mechanism that in turn could reduce the issues that rise because of the locality problem. For a comprehensive look of the locality algorithms, we refer the reader to [24].

In P2P network topologies as well as hypercube structures, each node is assigned a set of identifiers (labels). These labels play an essential role in the architecture of the hypercube as they are used to [2].

- Determine constant-time distances between each pair of nodes, thus eliminating the need to send out queries to find inter-node distance.
- Efficient bandwidth utilization and improving query optimization.
- Decide the neighbors of the nodes and hence the links (edges) between nodes.

In this paper, we follow the labeling scheme that was presented in [1].

3 Generalized Hypercubes

GHCs were first proposed in [1] to interconnect computers in large parallel and distributed networks. The properties of generalized hypercubes (GHCs) were discussed extensively in [1] and [4]. As they play an important role in the work presented in this paper, their properties are reviewed in this section in some detail. GHCs are distinguished by their small diameters and relatively small node degrees compared to the number of nodes in the network. Moreover, they possess high fault tolerance capability due to the big number of alternative routes between each pair of nodes. They have low traffic density and small average path length. In this section, two types of GHCs are explained: full and partial GHCs.

3.1 Full GHCs

A GHC that has N nodes where

\[ N = m_{r-1} \times m_{r-2} \times \ldots \times m_0 \]  

is called a full GHC [1] where \( m_i \in \mathbb{N} - \{1\} \). The node in a full GHC is represented by a (key, value) pair; the key is the node id and the value is a unique r-tuple \((x_{r-1}, \ldots, x_1, x_0)\) called a label, where \( x_i \) takes all integer values between 0 and \( m_i - 1 \). The id of the node is calculated using the following equation

\[ \text{node id} = m_0 + \sum_{i=1}^{r-1} (x_i \times \prod_{j=0}^{i-1} m_j) \]
3.2 Partial GHCs

If a GHC has a number of processors \( N \) which is less than \( m_{r-1} \times m_{r-2} \times \ldots \times m_0 \), it is called a partial GHC whose characteristics are described here as it has the focus of the work of this paper. A partial GHC is a subset of nodes of a full GHC where the labels of the missing nodes are assigned to existing nodes so that some of the nodes have more than one label. Therefore, a node in a partial GHC is represented by an \( id \) and a set of labels owned by the node. Amongst the set of labels that a node has, there exists one label that belongs to the node itself (will be referred to as a base label) and the others are spare labels. The node \( id \) follows the value of the base label which is chosen to be the minimum label as calculated in Eq. 3. In this case, two nodes \( x_1 \) and \( x_2 \) are said to be neighbors if and only if at least one of the labels in \( x_1 \) is a neighbor to at least one of the labels in \( x_2 \).

Fig. 4 shows an instance of a 9-node 2 x 3 x 2 partial GHC. As described above, nodes (4), (6) and (10) have two labels each. For example, node (4) has an \( id = 4 \) which is the \( id \) calculated from label (020); the minimum of the labels in node (4). We notice that node (4), is connected to nodes (0) and (2) which are neighbors to label (020), and is connected to nodes (3) and (1) which are neighbors to label (021) and finally connected to node (10) whose two labels are neighbors to the two labels of node (4).

It should be noted that partial GHCs originate from expanding full GHCs to accommodate new entering nodes when the GHC is full (see Section 4.1) or nodes leaving full GHC (see Section 4.3).

3.3 Preparatory

The following definitions will be utilized throughout the rest of the paper:

- A GHC = \( (V_{GHC}, E_{GHC}) \) represents an instance of a GHC with total number of nodes \( N \) = \( |V_{GHC}| \). \( V_{GHC} \) is the set of nodes constituting the graph and \( E_{GHC} \) is the set of edges connecting the nodes.

- A GHC of \( r \) dimensions is full iff \( V_{GHC} = m_{r-1} \times \ldots \times m_1 \times m_0 \), and is partial if \( V_{GHC} < m_{r-1} \times \ldots \times m_1 \times m_0 \).

- A set of labels assigned to node \( v \in V_{GHC} \) is denoted by \( L(v) \) where \( \forall v \in V_{GHC}, |L(v)| = 1 \) in a full GHC, and \( \exists v \in V_{GHC}, |L(v)| > 1 \) in a partial GHC.

- Two labels are said to be neighbors if they differ in exactly one digit. Two nodes \( v, u \in V_{GHC} \) are said to be neighbors if at least one label in \( L(v) \) is a neighbor to at least one neighbor in \( L(u) \).

4 Dynamic Generalized Hypercubes

4.1 Graph Expansion Procedure

A full GHC can not accept new nodes to join the network because all the available labels are already taken by existing nodes. In this case, the GHC needs to expand (grow in size) to accommodate new entering nodes.

While only available option for expansion in a full binary hypercube is adding an extra dimension by adding a binary digit to the left of all existing labels (i.e., \( r \rightarrow r + 1 \) [3]). GHCs have the ability to expand by one of two procedures. In this section, the two procedures are explained in detail.

Expansion Procedure 1

Following on Eq. 1 to expand the GHC, we increase the \( \min \{ m_0, m_1, \ldots, m_{r-1} \} \) by 1. If there exist more than one minimum, one of them is chosen randomly and increased by 1. This means, the dimension radices will converge to an equal values after a certain number of node insertions, i.e., if \( y = \max \{ m_0, m_1, \ldots, m_{r-1} \} \) and the number of nodes in the network approaches \( y ' \), then \( m_i \) converges to \( y \) for \( 0 \leq i < r \); achieving a graph with an optimal cost in terms of the node degree [11].

When a certain dimension \( m_i \) is expanded, the number of extra labels that are created (the number of nodes that can be added to the graph) is equal to

\[
L = \prod_{i=0, i \neq x}^{r-1} m_i
\]

Example 1: suppose that we have a full GHC with \( N = 3 \times 2 \times 2 = 12 \) nodes as shown in Fig. 1a and a new node needs to be inserted. Then either \( m_0 \) or \( m_1 \) could increase by 1. If the existing labels are, \( (000), (001), (010), (011), (100), (101), (110), (111), (200), (201), (210), \) and \( (211) \), and \( m_1 \) was chosen for expansion then the added labels will be \( (020), (021), (120), (121), (220), \) and \( (221) \) as shown in Fig. 2.

In this procedure, the number of added labels is less than the original network size. For the sake of simplicity in the simulations, it is assumed that the maximum base value any radix can take is base = 10 which means that the expansions performed with this procedure can accommodate a maximum number of nodes = \( 9^r \).

Choosing to increase the minimum radix tends to achieve the balance within the graph with new nodes insertions.
4.2 Node Insertion

A node $v$ that intends to enter a GHC sends an enter request to an existing node $u$ in the graph. If $u$ has one or more extra labels, it replies back to $v$ with one of its extra labels $l \in L(u)$ (which is chosen randomly). If $u$ does not have extra labels, it sends to its neighbors requesting for extra labels. A node that has one or more extra labels replies back to $u$ with one of the extra labels randomly. As the target is finding an available label to the entering node, if a node replies with a label, it aborts the request, i.e., it does not forward the find-a-label-request to its neighbors. Hence, saving valuable resources in the network. A node that does not have an extra label and receives the request from its $l^j$ neighbor, forwards the request to its $j^h$ neighbors where $i < j < r$. If a node that has no extra labels and is an $(r-1)^i$ neighbor replies back with a null message. At the end, node $u$ replies to node $v$ with all available labels and node $v$ chooses one of them randomly. Node $v$ is then added to the graph as a node with one label assigned to it and node id which is calculated using Eq. 4. Edges are added between $v$ and the nodes which have labels that are neighbors to $l$. If label $l$ belongs originally to node $x$ before it is assigned to node $v$, the edges between $x$ and the nodes which have labels that are neighbors to $l$ are removed. If $u$ replies to $v$ with a null message, it means that the GHC is full and it needs to be expanded using either the procedures explained in Subsection 4.1. The node entering algorithm in summarized in Algorithm 1.

\[ N = m_r \cdot m_{r-1} \cdot \ldots \cdot m_0 \]  
\[ L = (m_r - 1) \prod_{i=0}^{r-1} m_i \] 

Defining these parameters in the algorithm.

**Algorithm 1: NodeEnter(GHC)**

**Input:** GHC with $N$ nodes, entering node $v \notin V_{GHC}$

**Output:** GHC with $N+1$ nodes

1: Select a node $u$ from $V_{GHC} \leftarrow \emptyset$, $L \leftarrow \emptyset$
2: $[L,S] \leftarrow \text{GetPossibleLabels}(GHC, u, S, L)$
3: If $L = \emptyset$ then
4: \text{ExpandGHC}(GHC)
5: $[L,S] \leftarrow \text{GetPossibleLabels}(GHC, u, S, L)$
6: end if
7: Select a label $l$ from $L$, whose original node $s \in S$
8: Assign $l$ to $v$
9: $V_{GHC} \leftarrow V_{GHC} \cup v$, $E_{GHC} \leftarrow E_{GHC} \cup edge(v,x_i)$, $\forall (l_i \in x_i) \in \text{neighborhood}(l)$
10: If $x_i \in \text{neighborhood}(l) \& \& \forall (l_i \in x_i) \in \text{neighborhood}(l)$ then
11: $E_{GHC} \leftarrow E_{GHC} - edge(s,x_i)$
12: end if
13: return GHC

**Fig. 3** follows the GHC shown in Fig. 2 after a new node insertion (marked in light blue). It should be noted that after the first node insertion that follows the expansion of the GHC, the nodes change their ids based on the new values of the dimension radices according to Eq. 4. For instance, node (9) with id = (201) according to the old radices $3 \times 2 \times 2$, has changed its id to (111) according to the new radices of $3 \times 3 \times 2$ so that Eq. 4 holds true for all scenarios.

4.3 Node Departure

A node may depart the GHC network in one of two forms:

- It informs its neighbors before departure.
node departure procedure is summarized in Algorithm 2.

In either way, a node \( u \) which is chosen randomly from the the leaving node’s neighbors takes over the responsibilities of the departed node \( v \) as follows: \( u \) takes all the labels of node \( v \), and all the edges related to node \( v \) are transformed to node \( u \). The node departure procedure is summarized in Algorithm 2.

5 Simulation Results

In this section, we evaluate the performance of the graphs under test. We first describe our metrics and then we display and discuss the obtained results.

5.1 Evaluation metrics

Evaluation metrics are the parameters that are chosen to measure the graph’s performance. We have chosen average path length, average message traffic density and node degree distribution for performance measurements.

5.1.1 Average path length

Average path length represents a robust measure of the network performance. It is defined as the sum of the shortest paths between all pairs of nodes in the network divided by the total number of nodes. The average path length for a GHC was defined in [1] as

\[
\bar{d} = \frac{\sum_{d=1}^{r} d N_d}{N - 1}
\]  

where

- \( d \) is the shortest path between pairs of nodes; i.e., the number of locations where their labels are different.
- \( N_d \) is the number of nodes at a distance \( d \) from each other.

Eq. (7) was derived based on the assumption that a GHC is a symmetric structure, i.e. all nodes have the same node degree. That holds true in case of a full GHC, however, we have known that a partial GHC is non-symmetric due to missing nodes of the complete graph and some nodes have higher node degrees than others. This non-symmetry causes some nodes to be closer to other nodes because they already control other labels rather than their own labels. Therefore, the average path length of the whole graph in Eq. (7) should be redefined to

\[
\bar{d} = \frac{1}{N} \sum_{x \in V_{GHC}} \bar{d}_x = \frac{1}{N(N-1)} \sum_{x \in V_{GHC}} \left( \sum_{d_x=1}^{r} d_x N_{d_x} \right)
\]  

where \( \bar{d}_x \) is the average path length with respect to node \( x \), \( d_x \) is the shortest path between node \( x \in V_{GHC} \) and other nodes and \( N_{d_x} \) is the number of nodes at distance \( d_x \) from \( x \).
5.2 Simulation Results

We created a Python program to generate GHC networks and investigate all the algorithms described in Section 4. Python is a powerful programming language that has a huge number of libraries among which we have used `networkx` library for the instantiation and the visualization of the graphs and `matplotlib` library to visualize the results shown in this section.

In the following experiments, we started the simulation with each network having almost 32 nodes except for the 6−D GHC as the minimum number of nodes 6−D GHC can accommodate is equal to 64 nodes given that \( m_i > 1 \). In an attempt to assess the node degree distribution of networks of different number of dimensions, an initial deployment was established for each network with a size of about 32 nodes. Then, a sequence of node-enter and node-leave operations were simulated with probabilities 0.7 and 0.3 respectively so that the network size ultimately reaches 200 nodes. After that the number of edges at each node was obtained in order to calculate the number of nodes having the same node degrees. To increase the reliability of the measurement, each network distribution was simulated 100 times and the average values were obtained. Fig. 5 displays the results of the node degree distribution simulation. Most of the nodes preserve 15, 11, 10, 9 and 8 edges in 3−D, 4−D, 5−D, 6−D GHCs and binary hypercube respectively. Table 1 summarizes the initial size of each network with the corresponding radices. It also shows the radices after the networks reach 200 nodes. The node degree of the full graph is consistent for all nodes and is equal to \( \sum_{i=0}^{r-1} (m_i - 1) \).

### Average message traffic density

Average message traffic density is a good measure of the network performance as it indicates the speed of the network while transmitting messages between different nodes. Average message traffic density is defined in [1] as

\[
\rho = \frac{\text{Average message distance} \times \text{number of nodes}}{\text{total number of links}} \tag{9}
\]

\[
= \frac{\bar{d}N}{\sum_{i \in E_{\text{GHC}}} i}
\]

where \( \bar{d} \) is the average path length from Eq. 8, \( N \) is the number of nodes in the GHC.

### Simulation Results

Fig. 6 compares the average path length of GHC networks of different number of dimensions and a binary hypercube. Each network starts with an initial instance of about 32 nodes and then nodes are inserted sequentially into the different networks. The average path length is then calculated using Eq. 8 with each new node insertion until the number of nodes in each network reaches \( 2^{10} \) nodes. An exception occurs with the 3-D GHC because the maximum number of nodes that can be allocated is \( 9^3 = 729 \) nodes, taking the assumption that \( 2 \leq m_i \leq 9 \) (see Section 4.1).

Figure 6: Average path length for different network structures

Figure 7: Average message traffic density
The networks in Fig. 5 start with a full GHC, and hence, an expansion of the graph is needed with the first node insertion. The nodes are then inserted until the GHC is full again (this is represented by the local maxima in the different curves). With a new node insertion after the GHC is full, the average path length noticeably decreases. It is evident that in general, the lower the number of dimensions, the lower the value of the average path length for the same number of nodes. That occurs at the cost of the node degree. However, in comparison with the binary hypercube, the GHC networks prove to have lower values of average path length especially with large number of nodes. It is also worth noticing that the gap in the difference
in the average path length between GHC networks on one hand the the binary hypercube on the other hand increases with increasing number of nodes.

Fig. 4 shows the average message traffic density calculated for GHC networks of different sizes and a binary hypercube. It is evident that the density increases with the number of dimensions. It is also interesting to note that the overall traffic density decreases with increasing number of nodes within the GHC networks while the binary hypercube is retaining almost the same pattern of values which are higher than those of the GHC graphs.

6 Conclusion and Future Work

The purpose of the current study was to review GHCs and study their performance in P2P networks. The findings reported here shed new light on the capabilities of GHCs. Although there was a variation of the performance of GHC networks of different number of dimensions, GHCs in general proved to have a lower average path length and a lower average message traffic density compared to binary hypercubes. This research has also shown that in a dynamic network, most of the nodes in the partial graph maintain the same node degree as the underlying full graph. The advantages of GHChs in a dynamic P2P network can be summarized in the following points: (1) GHCs are highly flexible to fit the network’s needs. They are flexible in the number of the dimensions and value that each dimension could undertake. Therefore, the number of dimensions can be adjusted to achieve a desirable balance between the graph’s diameter and the node degree. (2) GHChs are scalable with node insertions and node deletions with high fault tolerance as there exists a number of disjoint paths between each pair of nodes and (3) they are easy to preserve in a dynamic network as they support nodes entering and leaving the network without the need of a central coordination between nodes.

Considerably more work will need to be done to (1) address locality problem with GHChs in dynamic networks for the aim of decreasing the gap between the overlay network and the underlying physical network (2) study other approaches of GHC expansion and see the effect on the performance and (3) optimize the network expansion in a way that can achieve an optimum values for the node degree and the diameter to attain an optimal-cost graph.

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