

Capacity of Clustered Distributed Storage

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Abstract—A new system model reflecting the clustered structure of distributed storage is suggested to investigate interplay between storage overhead and repair bandwidth as storage node failures occur. Large data centers with multiple racks/disks or local networks of storage devices (e.g. sensor network) are good applications of the suggested clustered model. In realistic scenarios involving clustered storage structures, repairing storage nodes using intact nodes residing in other clusters is more bandwidth-consuming than restoring nodes based on information from intra-cluster nodes. Therefore, it is important to differentiate between intra-cluster repair bandwidth and cross-cluster repair bandwidth in modeling distributed storage. Capacity of the suggested model is obtained as a function of fundamental resources of distributed storage systems, namely, node storage capacity, intra-cluster repair bandwidth and cross-cluster repair bandwidth. The capacity is shown to be asymptotically equivalent to a monotonic decreasing function of number of clusters, as the number of storage nodes increases without bound. Based on the capacity expression, feasible sets of required resources which enable reliable storage are obtained in a closed-form solution. Specifically, it is shown that the cross-cluster traffic can be minimized to zero (i.e., intra-cluster local repair becomes possible) by allowing extra resources on storage capacity and intra-cluster repair bandwidth, according to the law specified in the closed-form. The network coding schemes with zero cross-cluster traffic are defined as *intra-cluster repairable codes*, which are shown to be a class of the previously developed *locally repairable codes*.

Index Terms—Capacity, Distributed storage, Network coding

I. INTRODUCTION

MANY enterprises, including Google, Facebook, Amazon and Microsoft, use cloud storage systems in order to support massive amounts of data storage requests from clients. In the emerging Internet-of-Thing (IoT) era, the number of devices which generate data and connect to the network increases exponentially, so that efficient management of data center becomes a formidable challenge. However, since cloud storage systems are composed of inexpensive commodity disks, failure events occur frequently, degrading the system reliability [2].

In order to ensure reliability of cloud storage, distributed storage systems (DSSs) with erasure coding have been considered to improve tolerance against storage node failures [3]–[8]. In such systems, the original file is encoded and distributed into multiple storage nodes. When a node fails,

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a newcomer node regenerates the failed node by contacting a number of survived nodes. This causes traffic burden across the network, taking up significant repair bandwidth. Earlier distributed storage systems utilized the 3-replication code: the original file was replicated three times, and the replicas were stored in three distinct nodes. The 3-replication coded systems require the minimum repair bandwidth, but incur high storage overhead. Reed-Solomon (RS) codes are also used (e.g. HDFS-RAID in Facebook [9]), which allow minimum storage overhead; however, RS-coded systems suffer from high repair bandwidth.

The pioneering work of [10] on distributed storage systems focused on the relationship between two required resources, the storage capacity α of each node and the repair bandwidth γ , when the system aims to reliably store a file \mathcal{M} under node failure events. The optimal (α, γ) pairs are shown to have a fundamental trade-off relationship, to satisfy the maximum-distance-separable (MDS) property (i.e., any k out of n storage nodes can be accessed to recover the original file) of the system. Moreover, the authors of [10] obtained capacity C , the maximum amount of reliably storable data, as a function of α and γ . The authors related the failure-repair process of a DSS with the multi-casting problem in network information theory, and exploited the fact that a cut-set bound is achievable by network coding [11]. Since the theoretical results of [10], explicit network coding schemes [12]–[14] which achieve the optimal (α, γ) pairs have also been suggested. These results are based on the assumption of homogeneous systems, i.e., each node has the same storage capacity and repair bandwidth.

However, in real data centers, storage nodes are dispersed into multiple clusters (in the form of disks or racks) [7], [8], [15], allowing high reliability against both node and rack failure events. In this clustered system, repairing a failed node gives rise to both intra-cluster and cross-cluster repair traffic. While the current data centers have abundant intra-rack communication bandwidth, cross-rack communication is typically limited. According to [16], nearly a 180TB of cross-rack repair bandwidth is required everyday in the Facebook warehouse, limiting cross-rack communication for foreground map-reduce jobs. Moreover, surveys [17]–[19] on network traffic within data centers show that cross-rack communication is *oversubscribed*; the available cross-rack communication bandwidth is typically 5–20 times lower than the intra-rack bandwidth in practical systems. Thus, a new system model which reflects the imbalance between intra- and cross-cluster repair bandwidths is required.

A. Main Contributions

This paper suggests a new system model for *clustered* DSS to reflect the clustered nature of real distributed storage

systems wherein an imbalance exists between intra- and cross-cluster repair burdens. This model can be applied to not only large data centers, but also local networks of storage devices such as the sensor networks or home clouds which are expected to be prevalent in the IoT era. This model is also more general in the sense that when the intra- and cross-cluster repair bandwidths are set to be equal, the resulting structure reduces to the original DSS model of [10]. This paper only considers recovering a single node failure at a time, as in [10]. The main contributions of this paper can be seen as twofold: one is the derivation of a closed-form expression for capacity, and the other is the analysis on feasible sets of system resources which enable reliable storage.

1) *Closed-form Expression for Capacity:* Under the setting of functional repair, storage capacity \mathcal{C} of the clustered DSS is obtained as a function of node storage capacity α , intra-cluster repair bandwidth β_I and cross-cluster repair bandwidth β_c . The existence of the cluster structure manifested as the imbalance between intra/cross-cluster traffics makes the capacity analysis challenging; Dimakis' proof in [10] cannot be directly extended to handle the problem at hand. We show that symmetric repair (obtaining the same amount of information from each helper node) is optimal in the sense of maximizing capacity given the storage node size and total repair bandwidth, as also shown in [20] for the case of varying repair bandwidth across the nodes. However, we stress that in most practical scenarios, the need is greater for reducing cross-cluster communication burden, and we show that this is possible by trading with reduced overall storage capacity and/or increasing intra-repair bandwidth. Based on the derived capacity expression, we analyzed how the storage capacity \mathcal{C} changes as a function of L , the number of clusters. It is shown that the capacity is asymptotically equivalent to $\underline{\mathcal{C}}$, some monotonic decreasing function of L .

2) *Analysis on Feasible $(\alpha, \beta_I, \beta_c)$ Points:* Given the need for reliably storing file \mathcal{M} , the set of required resource pairs, node storage capacity α , intra-cluster repair bandwidth β_I and cross-cluster repair bandwidth β_c , which enables $\mathcal{C}(\alpha, \beta_I, \beta_c) \geq \mathcal{M}$ is obtained in a closed-form solution. In the analysis, we introduce $\epsilon = \beta_c/\beta_I$, a useful parameter which measures the ratio of the cross-cluster repair burden (per node) to the intra-cluster burden. This parameter represents how scarce the available cross-cluster bandwidth is, compared to the abundant intra-cluster bandwidth. We here stress that the special case of $\epsilon = 0$ corresponds to the scenario where repair is done only locally via intra-cluster communication, i.e., when a node fails the repair process requires intra-cluster traffic only without any cross-cluster traffic. Thus, the analysis on the $\epsilon = 0$ case provides a guidance on the network coding for data centers for the scenarios where the available cross-cluster (cross-rack) bandwidth is very scarce.

Similar to the non-clustered case of [10], the required node storage capacity and the required repair bandwidth show a trade-off relationship. In the trade-off curve, two extremal points - the minimum-bandwidth-regenerating (MBR) point and the minimum-storage-regenerating (MSR) point - have been further analyzed for various ϵ values. Moreover, from the analysis on the trade-off curve, it is shown that the

minimum storage overhead $\alpha = \mathcal{M}/k$ is achievable if and only if $\epsilon \geq \frac{1}{n-k}$. This implies that in order to reliably store file \mathcal{M} with minimum storage $\alpha = \mathcal{M}/k$, sufficiently large cross-cluster repair bandwidth satisfying $\epsilon \geq \frac{1}{n-k}$ is required. Finally, for the scenarios with the abundant intra-cluster repair bandwidth, the minimum required cross-cluster repair bandwidth β_c to reliably store file \mathcal{M} is obtained as a function of node storage capacity α .

B. Related Works

Several researchers analyzed practical distributed storage systems with a goal in mind to reflect the non-homogeneous nature of storage nodes [20]–[31]. A heterogeneous model was considered in [20], [21] where the storage capacity and the repair bandwidth for newcomer nodes are generally non-uniform. Upper/lower capacity bounds for the heterogeneous DSS are obtained in [20]. An asymmetric repair process is considered in [22], coining the terms, cheap and expensive nodes, based on the amount of data that can be transferred to any newcomer. The authors of [23] considered a flexible distributed storage system where the amount of information from helper nodes may be non-uniform, as long as the total repair bandwidth is bounded from above. The view points taken in these works are different from ours in that we adopt a notion of cluster and introduce imbalance between intra- and cross-cluster repair burdens.

Recently, some researchers considered the clustered structure of data centers [1], [24]–[31]. Some recent works [24]–[27] provided new system models for clustered DSS and shed light on fundamental aspects of the suggested system. In [24], the idea of [22] is developed to a two-rack system, by setting the communication burden within a rack much lower than the burden across different racks, similar to our analysis. However, the authors of [24] only considered systems with two racks, while the current paper considers a general setting of L racks (clusters), and provides mathematical analysis on how the number of clusters (i.e., the dispersion of nodes) affects the capacity of clustered distributed storage. Similar to the present paper, the authors of [25], [26] obtained the capacity of clustered distributed storage, and provided capacity-achieving regenerating coding schemes. However, the coding schemes considered in [25], [26] do not satisfy the MDS property, and the capacity expression is obtained for limited scenarios when intra-cluster repair bandwidth β_I is set to its maximum value. In contrast, the current paper provides the capacity expression for general values of β_I, β_c parameters, and analyzes the behavior of capacity as a function of the ratio $\epsilon = \beta_c/\beta_I$ between intra- and cross-cluster repair bandwidths. Moreover, unlike in the previous work, the capacity-achieving coding schemes (whose existence is shown) here satisfy the MDS property. In [27], the security issue in clustered distributed storage systems is considered, and the maximum amount of securely storable data in the existence of passive eavesdroppers is obtained.

There also have been some recent works [28]–[31] on network code design appropriate for clustered distributed storage. Motivated by the limited available cross-rack repair bandwidth

in real data centers, the work of [28] provides a network coding scheme which minimizes the cross-rack bandwidth in clustered distributed storage systems. However, the suggested coding scheme is applicable for some limited (n, k, L) parameters and the minimum storage overhead ($\alpha = M/k$) setting. On the other hand, the current paper provides the capacity expression for general (n, k, L, α) setting, and proves the existence of capacity-achieving coding scheme. The authors of [29] proposed coding schemes tolerant to rack failure events in multi-rack storage systems, but have not addressed the imbalance between intra- and cross-cluster repair burdens in node failure events, which is an important aspect of the current paper. The authors of [30] considers the scenario of having grouped (clustered) storage nodes where nodes in the same group are more accessible to each other, compared to the nodes in other groups. However, the focus is different to the present paper: [30] focuses on the code construction which has the minimum amount of accessed data (called the optimal access property), while the scope of the present paper is on finding the optimal trade-off between the node storage capacity and the repair bandwidth, as a function of the ratio ϵ of intra- and cross-cluster communication burdens. Finally, a locally repairable code which can repair arbitrary node within each group is suggested in [31]; this code can suppress the inter-group repair bandwidth to zero. However, the coding scheme is suggested for the $\epsilon = 0$ case only, while the present paper provides the capacity expression for general $0 \leq \epsilon \leq 1$, and proves the existence of an optimal coding scheme.

Compared to the conference version [1] of the current work, this paper provides the formal proofs for the capacity expression, and obtains the feasible (α, γ) region for $0 \leq \epsilon \leq 1$ setting¹ (only $\epsilon = 0$ is considered in [1]). The present paper also shows the behavior of capacity as a function of L , the number of clusters, and provides the sufficient and necessary conditions on $\epsilon = \beta_c/\beta_I$, to achieve the minimum storage overhead $\alpha = M/k$. Finally, the asymptotic behaviors of the MBR/MSR points are investigated in this paper, and the connection between what we call the intra-cluster repairable codes and the existing locally repairable codes [32] is revealed.

C. Organization

This paper is organized as follows. Section II reviews preliminary materials about distributed storage systems and the information flow graph, an efficient tool for analyzing DSS. Section III proposes a new system model for the clustered DSS, and derives a closed-form expression for the storage capacity of the clustered DSS. The behavior of the capacity curves is also analyzed in this section. Based on the capacity expression, Section IV provides results on the feasible resource pairs which enable reliable storage of a given file. Further research topics on clustered DSS are discussed in Section V, and Section VI draws conclusions.

¹The reason why the present paper considers this regime is provided in Section III-B.

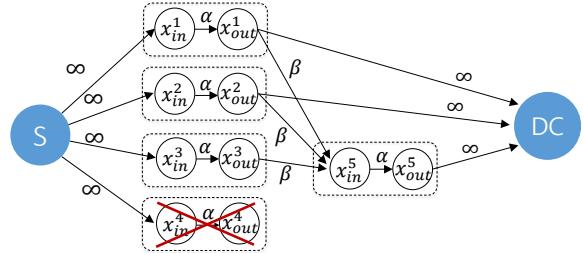


Fig. 1: Information flow graph ($n = 4, k = 3, d = 3$)

II. BACKGROUND

A. Distributed Storage System

Distributed storage systems can maintain reliability by means of erasure coding [33]. The original data file is spread into n potentially unreliable nodes, each with storage size α . When a node fails, it is regenerated by contacting $d < n$ helper nodes and obtaining a particular amount of data, β , from each helper node. The amount of communication burden imposed by one failure event is called the repair bandwidth, denoted as $\gamma = d\beta$. When the client requests a retrieval of the original file, assuming all failed nodes have been repaired, access to any $k < n$ out of n nodes must guarantee a file recovery. The ability to recover the original data using any $k < n$ out of n nodes is called the maximal-distance-separable (MDS) property. Distributed storage systems can be used in many applications such as large data centers, peer-to-peer storage systems and wireless sensor networks [10].

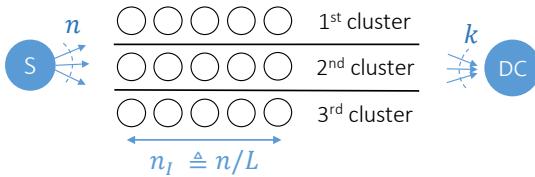
B. Information Flow Graph

Information flow graph is a useful tool to analyze the amount of information flow from source to data collector in a DSS, as utilized in [10]. It is a directed graph consisting of three types of nodes: data source S , data collector DC , and storage nodes x^i as shown in Fig. 1. Storage node x^i can be viewed as consisting of input-node x_{in}^i and output-node x_{out}^i , which are responsible for the incoming and outgoing edges, respectively. x_{in}^i and x_{out}^i are connected by a directed edge with capacity identical to the storage size α of node x^i .

Data from source S is stored into n nodes. This process is represented by n edges going from S to $\{x^i\}_{i=1}^n$, where each edge capacity is set to infinity. A failure/repair process in a DSS can be described as follows. When a node x^j fails, a new node x^{j+1} joins the graph by connecting edges from d survived nodes, where each edge has capacity β . After all repairs are done, data collector DC chooses arbitrary k nodes to retrieve data, as illustrated by the edges connected from k survived nodes with infinite edge capacity. Fig. 1 gives an example of information flow graph representing a distributed storage system with $n = 4, k = 3, d = 3$.

C. Notation used in the paper

This paper requires many notations related to graphs, because it deals with information flow graphs. Here we provide the definition of each notation used in the paper. For the given system parameters, we denote \mathcal{G} as the set of all possible

Fig. 2: Clustered distributed storage system ($n = 15, L = 3$)

information flow graphs. A graph $G \in \mathcal{G}$ is denoted as $G = (V, E)$ where V is the set of vertices and E is the set of edges in the graph. For a given graph $G \in \mathcal{G}$, we call a set $c \subset E$ of edges as *cut-set* [34] if it satisfies the following: every directed path from S to DC includes at least one edge in c . An arbitrary cut-set c is usually denoted as $c = (U, \bar{U})$ where $U \subset V$ and $\bar{U} = V \setminus U$ (the complement of U) satisfy the following: the set of edges from U to \bar{U} is the given cut-set c . The set of all cut-sets available in G is denoted as $C(G)$. For a graph $G \in \mathcal{G}$ and a cut-set $c \in C(G)$, we denote the sum of edge capacities for edges in c as $w(G, c)$, which is called the *cut-value* of c .

A vector is denoted as \mathbf{v} using the bold notation. For a vector \mathbf{v} , the transpose of the vector is denoted as \mathbf{v}^T . A set is denoted as $X = \{x_1, x_2, \dots, x_k\}$, while a sequence x_1, x_2, \dots, x_N is denoted as $(x_n)_{n=1}^N$, or simply (x_n) . For given sequences (a_n) and (b_n) , we use the term “ a_n is asymptotically equivalent to b_n ” [35] if and only if

$$\lim_{n \rightarrow \infty} \frac{a_n}{b_n} = 1. \quad (1)$$

We utilize a useful notation:

$$\mathbb{1}_{i=j} = \begin{cases} 1, & \text{if } i = j \\ 0, & \text{otherwise.} \end{cases}$$

For a positive integer n , we use $[n]$ as a simplified notation for the set $\{1, 2, \dots, n\}$. For a non-positive integer n , we define $[n] = \emptyset$. Each storage node is represented as either $x^t = (x_{in}^t, x_{out}^t)$ as defined in Section II-B, or $N(i, j)$ as defined in (A.2). Finally, important parameters used in this paper are summarized in Table I.

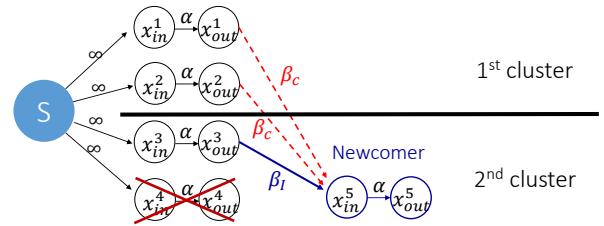
III. CAPACITY OF CLUSTERED DSS

A. Clustered Distributed Storage System

A distributed storage system with multiple clusters is shown in Fig. 2. Data from source S is stored at n nodes which are grouped into L clusters. The number of nodes in each cluster is fixed and denoted as $n_I = n/L$. The storage size of each node is denoted as α . When a node fails, a newcomer node is regenerated by contacting d_I helper nodes within the same cluster, and d_c helper nodes from other clusters. This paper considers functional repair [33] in the regeneration process; the newcomer node may store different content from that of the failed node, while maintaining the MDS property of the code. The amount of data a newcomer node receives within the same cluster is $\gamma_I = d_I \beta_I$ (each node equally contributes to β_I), and that from other clusters is $\gamma_c = d_c \beta_c$ (each node equally contributes to β_c). Fig. 3 illustrates an example of

TABLE I: Parameters used in this paper

n	number of storage nodes
k	number of DC-contacting nodes
L	number of clusters
$n_I = n/L$	number of nodes in a cluster
$d_I = n_I - 1$	number of intra-cluster helper nodes
$d_c = n - n_I$	number of cross-cluster helper nodes
\mathbb{F}_q	base field which contains each symbol
α	storage capacity of each node
β_I	intra-cluster repair bandwidth (per node)
β_c	cross-cluster repair bandwidth (per node)
$\gamma_I = d_I \beta_I$	intra-cluster repair bandwidth
$\gamma_c = d_c \beta_c$	cross-cluster repair bandwidth
$\gamma = \gamma_I + \gamma_c$	repair bandwidth
$\epsilon = \beta_c / \beta_I$	ratio of β_c to β_I ($0 \leq \epsilon \leq 1$)
$\xi = \gamma_c / \gamma$	ratio of γ_c to γ ($0 \leq \xi < 1$)
$R = k/n$	ratio of k to n ($0 < R \leq 1$)

Fig. 3: Repair process in clustered DSS ($n = 4, L = 2, d_I = 1, d_c = 2$)

information flow graph representing the repair process in a clustered DSS.

B. Assumptions for the System

We assume that d_c and d_I have the maximum possible values ($d_c = n - n_I, d_I = n_I - 1$), since this is the capacity-maximizing choice, as formally stated in the following proposition. The proof of the proposition is in Appendix G-A.

Proposition 1. Consider a clustered distributed storage system with given γ and γ_c . Then, setting both d_I and d_c to their maximum values maximizes storage capacity.

Note that the authors of [10] already showed that in the non-clustered scenario with given repair bandwidth γ , maximizing the number of helper nodes d is the capacity-maximizing choice. Here, we are saying that a similar property also holds for clustered scenario considered in the present paper. Under the setting of the maximum number of helper nodes, the overall repair bandwidth for a failure event is denoted as

$$\gamma = \gamma_I + \gamma_c = (n_I - 1)\beta_I + (n - n_I)\beta_c \quad (2)$$

Data collector DC contacts any k out of n nodes in the clustered DSS. Given that the typical intra-cluster communication bandwidth is larger than the cross-cluster bandwidth in real systems, we assume

$$\beta_I \geq \beta_c$$

throughout the present paper; this assumption limits our interest to $\epsilon \leq 1$. Moreover, motivated by the security issue, we assume that a file cannot be retrieved entirely by contacting any single cluster having n_I nodes. Thus, the number k of nodes contacted by the data collector satisfies

$$k > n_I. \quad (3)$$

We also assume

$$L \geq 2 \quad (4)$$

which holds for most real DSSs. Usually, all storage nodes cannot be squeezed in a single cluster, i.e., $L = 1$ rarely happens in practical systems, to prevent losing everything when the cluster is destroyed. Note that many storage systems [7], [8], [16] including those of Facebook uses $L = n$, i.e., every storage node reside in different racks (clusters), to tolerate the rack failure events. Finally, according to [16], nearly 98% of data recoveries in real systems deal with single node recovery. In other words, the portion of simultaneous multiple nodes failure events is small. Therefore, the present paper focuses single node failure events.

C. The closed-form solution for Capacity

Consider a clustered DSS with fixed n, k, L values. In this model, we want to find the set of *feasible* parameters $(\alpha, \beta_I, \beta_c)$ which enables storing data of size \mathcal{M} . In order to find the feasible set, min-cut analysis on the information flow graph is required, similar to [10]. Depending on the failure-repair process and k nodes contacted by DC, various information flow graphs can be obtained.

Let \mathcal{G} be the set of all possible flow graphs. Consider a graph $G^* \in \mathcal{G}$ with minimum min-cut, the construction of which is specified in Appendix A. Based on the max-flow min-cut theorem in [11], the maximum information flow from source to data collector for arbitrary $G \in \mathcal{G}$ is greater than or equal to

$$\mathcal{C}(\alpha, \beta_I, \beta_c) := \text{min-cut of } G^*,$$

which is called the *capacity* of the system. In order to send data \mathcal{M} from the source to the data collector, $\mathcal{C} \geq \mathcal{M}$ should be satisfied. Moreover, if $\mathcal{C} \geq \mathcal{M}$ is satisfied, there exists a linear network coding scheme [11] to store a file with size \mathcal{M} . Therefore, the set of $(\alpha, \beta_I, \beta_c)$ points which satisfies $\mathcal{C} \geq \mathcal{M}$ is *feasible* in the sense of reliably storing the original file of size \mathcal{M} . Now, we state our main result in the form of a theorem which offers a closed-form solution for the capacity $\mathcal{C}(\alpha, \beta_I, \beta_c)$ of the clustered DSS. Note that setting $\beta_I = \beta_c$ reduces to capacity of the non-clustered DSS obtained in [10].

Theorem 1. *The capacity of the clustered distributed storage system with parameters $(n, k, L, \alpha, \beta_I, \beta_c)$ is*

$$\mathcal{C}(\alpha, \beta_I, \beta_c) = \sum_{i=1}^{n_I} \sum_{j=1}^{g_i} \min \left\{ \alpha, \rho_i \beta_I + (n - \rho_i - j - \sum_{m=1}^{i-1} g_m) \beta_c \right\}, \quad (5)$$

where

$$\rho_i = n_I - i, \quad (6)$$

$$g_m = \begin{cases} \lfloor \frac{k}{n_I} \rfloor + 1, & m \leq (k \bmod n_I) \\ \lfloor \frac{k}{n_I} \rfloor, & \text{otherwise.} \end{cases} \quad (7)$$

The proof is in Appendix A. Note that the parameters used in the statement of Theorem 1 have the following property, the proof of which is in Appendix G-B.

Proposition 2. *For every (i, j) with $i \in [n_I], j \in [g_i]$, we have*

$$\rho_i \beta_I + (n - \rho_i - j - \sum_{m=1}^{i-1} g_m) \beta_c \leq \gamma. \quad (8)$$

Moreover,

$$\sum_{m=1}^{n_I} g_m = k \quad (9)$$

holds.

D. Relationship between \mathcal{C} and $\epsilon = \beta_c / \beta_I$

In this subsection, we analyze the capacity of a clustered DSS as a function of an important parameter

$$\epsilon := \beta_c / \beta_I, \quad (10)$$

the cross-cluster repair burden per intra-cluster repair burden. In Fig. 4, capacity is plotted as a function of ϵ . From (2), the total repair bandwidth can be expressed as

$$\begin{aligned} \gamma &= \gamma_I + \gamma_c = (n_I - 1)\beta_I + (n - n_I)\beta_c \\ &= (n_I - 1 + (n - n_I)\epsilon)\beta_I. \end{aligned} \quad (11)$$

Using this expression, the capacity is expressed as

$$\mathcal{C}(\epsilon) = \sum_{i=1}^{n_I} \sum_{j=1}^{g_i} \min \left\{ \alpha, \frac{(n - \rho_i - j - \sum_{m=1}^{i-1} g_m)\epsilon + \rho_i}{(n - n_I)\epsilon + n_I - 1} \gamma \right\}. \quad (12)$$

For fair comparison on various ϵ values, capacity is calculated for a fixed $(n, k, L, \alpha, \gamma)$ set. The capacity is an increasing function of ϵ as shown in Fig. 4. This implies that for given resources α and γ , allowing a larger β_c (until it reaches β_I) is always beneficial, in terms of storing a larger file. For example, under the setting in Fig. 4, allowing $\beta_c = \beta_I$ (i.e., $\epsilon = 1$) can store $\mathcal{M} = 48$, while setting $\beta_c = 0$ (i.e., $\epsilon = 0$) cannot achieve the same level of storage. This result is consistent with the previous work on asymmetric repair in [20], which proved that the symmetric repair maximizes capacity. Therefore, when the total communication amount γ is fixed, a loss of storage capacity is the cost we need to pay in order to reduce the communication burden β_c across different clusters.

E. Relationship between \mathcal{C} and L

In this subsection, we analyze the capacity of a clustered DSS as a function of L , the number of clusters. For fair comparison, (n, k, α, γ) values are fixed for calculating capacity. In Fig. 5, capacity curves for two scenarios are plotted over a range of L values. First, the solid line corresponds to the scenario when the system has abundant cross-rack bandwidth

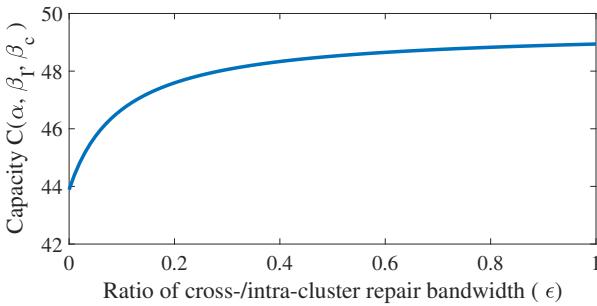


Fig. 4: Capacity as a function of ϵ , under the setting of $n = 100, k = 85, L = 10, \alpha = 1, \gamma = 1$

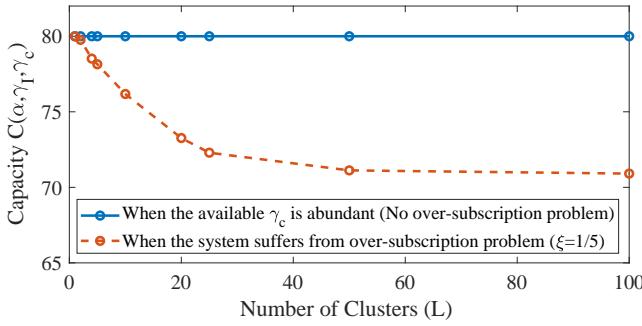


Fig. 5: Capacity as a function of L , under the setting of $n = 100, k = 80, \alpha = 1, \gamma = 10$

resources γ_c . In this ideal scenario which does not suffer from the over-subscription problem, the system can store $\mathcal{M} = 80$ irrespective of the dispersion of nodes.

However, consider a practical situation where the available cross-rack bandwidth is scarce compared to the intra-rack bandwidth; for example, $\xi = \gamma_c/\gamma = 1/5$. The dashed line in Fig. 5 corresponds to this scenario where the system has not enough cross-rack bandwidth resources. In this practical scenario, reducing L (i.e., gathering the storage nodes into a smaller number of clusters) increases capacity. However, note that sufficient dispersion of data into a fair number of clusters is typically desired, in order to guarantee the reliability of storage in rack-failure events. Finding the optimal number L^* of clusters in this trade-off relationship remains as an important topic for future research.

In Fig. 5, the capacity is a monotonic decreasing function of L when the system suffers from an over-subscription problem. However, in general (n, k, α, γ) parameter settings, capacity is not always a monotonic decreasing function of L . Theorem 2 illustrates the behavior of capacity as L varies, focusing on the special case of $\gamma = \alpha$. Before formally stating the next main result, we need to define

$$\sigma := \frac{L}{n_I} = \frac{L^2}{n}, \quad (13)$$

the *dispersion factor* of a clustered storage system, as illustrated in Fig. 6. In the two-dimensional representation of a clustered distributed storage system, L represents the number of rows (clusters), while $n_I = n/L$ represents the number of columns (nodes in each cluster). The dispersion factor σ is the

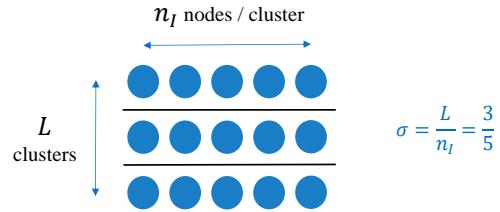


Fig. 6: An example of DSS with dispersion ratio $\sigma = 5/3$, when the parameters are set to $L = 3, n_I = 5, n = n_I L = 15$

ratio of the number of rows to the number of columns. If L increases for a fixed n_I , then σ grows and the nodes become more dispersed into multiple clusters.

Now we state our second main result, which is about the behavior of \mathcal{C} versus L .

Theorem 2. Consider the $\gamma = \alpha$ case when σ, γ, R and ξ are fixed. In the asymptotic regime of large n , capacity $\mathcal{C}(\alpha, \beta_I, \beta_c)$ is asymptotically equivalent to

$$\underline{\mathcal{C}} = \frac{k}{2} \left(\gamma + \frac{n-k}{n(1-1/L)} \gamma_c \right), \quad (14)$$

a monotonically decreasing function of L . This can also be stated as

$$\mathcal{C} \sim \underline{\mathcal{C}} \quad (15)$$

as $n \rightarrow \infty$ for a fixed σ .

Note that under the setting of Theorem 2, we have

$$n_I = \frac{n}{L} = \frac{n}{\sqrt{n}\sigma} = \Theta(\sqrt{n}),$$

$$k = nR = \Theta(n), \quad \alpha = \gamma = \text{constant},$$

$$\beta_I = \frac{\gamma_I}{n_I - 1} = \Theta\left(\frac{1}{\sqrt{n}}\right), \quad \beta_c = \frac{\gamma_c}{n - n_I} = \Theta\left(\frac{1}{n}\right)$$

in the asymptotic regime of large n . The proof of Theorem 2 is based on the following two lemmas.

Lemma 1. In the case of $\gamma = \alpha$, capacity $\mathcal{C}(\alpha, \beta_I, \beta_c)$ is upper/lower bounded as

$$\underline{\mathcal{C}} \leq \mathcal{C}(\alpha, \beta_I, \beta_c) \leq \underline{\mathcal{C}} + \delta \quad (16)$$

where

$$\delta = n_I^2(\beta_I - \beta_c)/8 \quad (17)$$

and $\underline{\mathcal{C}}$ is defined in (14).

Lemma 2. In the case of $\gamma = \alpha$, $\underline{\mathcal{C}}$ and δ defined in (14), (17) satisfy

$$\begin{aligned} \underline{\mathcal{C}} &= \Theta(n), \\ \delta &= O(n_I) \end{aligned}$$

when γ, R and ξ are fixed.

The proofs of these lemmas are in Appendix H. Here we provide the proof of Theorem 2 by using Lemmas 1 and 2.

proof (of Theorem 2). From Lemma 2,

$$\delta/\underline{\mathcal{C}} = O(1/L) = O(\sqrt{1/n\sigma}) \rightarrow 0 \quad (18)$$

as $n \rightarrow \infty$ for a fixed σ . Moreover, dividing (16) by \underline{C} results in

$$1 \leq \mathcal{C}/\underline{C} \leq 1 + \delta/\underline{C}. \quad (19)$$

Putting (18) into (19) completes the proof. \square

IV. DISCUSSION ON FEASIBLE $(\alpha, \beta_I, \beta_c)$

In the previous section, we obtained the capacity of the clustered DSS. This section analyzes the feasible $(\alpha, \beta_I, \beta_c)$ points which satisfy $\mathcal{C}(\alpha, \beta_I, \beta_c) \geq \mathcal{M}$ for a given file size \mathcal{M} . Using

$$\gamma = \gamma_I + \gamma_c = (n_I - 1)\beta_I + (n - n_I)\beta_c$$

in (2), the behavior of the feasible set of (α, γ) points can be observed. Essentially, the feasible points demonstrate a trade-off relationship. Two extreme points – minimum storage regenerating (MSR) point and minimum bandwidth regenerating (MBR) point – of the trade-off has been analyzed. Moreover, a special family of network codes which satisfy $\epsilon = 0$, which we call the *intra-cluster repairable codes*, is compared with the *locally repairable codes* considered in [32]. Finally, the set of feasible (α, β_c) points is discussed, when the system allows maximum β_I .

A. Set of Feasible (α, γ) Points

We provide a closed-form solution for the set of feasible (α, γ) points which enable reliable storage of data \mathcal{M} . Based on the range of ϵ defined in (10), the set of feasible points show different behaviors as stated in Corollary 1.

Corollary 1. Consider a clustered DSS for storing data \mathcal{M} , when $\epsilon = \beta_c/\beta_I$ satisfies $0 \leq \epsilon \leq 1$. For any $\gamma \geq \gamma^*(\alpha)$, the data \mathcal{M} can be reliably stored, i.e., $\mathcal{C} \geq \mathcal{M}$, while it is impossible to reliably store data \mathcal{M} when $\gamma < \gamma^*(\alpha)$. The threshold function $\gamma^*(\alpha)$ can be obtained as:

$$1) \text{ if } \frac{1}{n-k} \leq \epsilon \leq 1$$

$$\gamma^*(\alpha) = \begin{cases} \infty, & \alpha \in (0, \frac{M}{k}) \\ \frac{M-t\alpha}{s_t}, & \alpha \in [\frac{M}{t+1+s_{t+1}y_{t+1}}, \frac{M}{t+s_ty_t}), \\ & (t = k-1, k-2, \dots, 1) \\ \frac{M}{s_0}, & \alpha \in [\frac{M}{s_0}, \infty) \end{cases} \quad (20)$$

$$2) \text{ Otherwise (if } 0 \leq \epsilon < \frac{1}{n-k})$$

$$\gamma^*(\alpha) = \begin{cases} \infty, & \alpha \in (0, \frac{M}{\tau+\sum_{i=\tau+1}^k z_i}) \\ \frac{M-\tau\alpha}{s_\tau}, & \alpha \in [\frac{M}{\tau+\sum_{i=\tau+1}^k z_i}, \frac{M}{\tau+s_\tau y_\tau}) \\ \frac{M-t\alpha}{s_t}, & \alpha \in [\frac{M}{t+1+s_{t+1}y_{t+1}}, \frac{M}{t+s_ty_t}), \\ & (t = \tau-1, \tau-2, \dots, 1) \\ \frac{M}{s_0}, & \alpha \in [\frac{M}{s_0}, \infty) \end{cases} \quad (21)$$

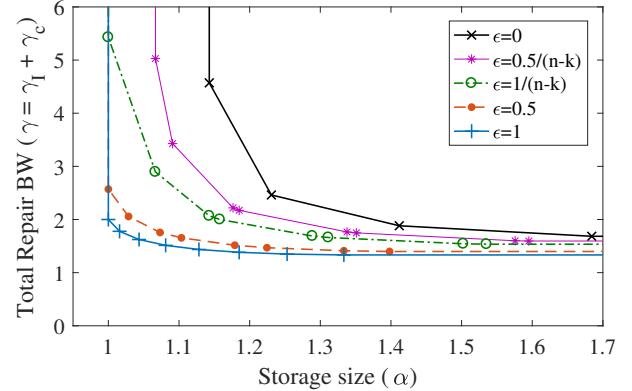


Fig. 7: Optimal tradeoff between node storage size α and total repair bandwidth γ , under the setting of $n = 15, k = 8, L = 3, \mathcal{M} = 8$

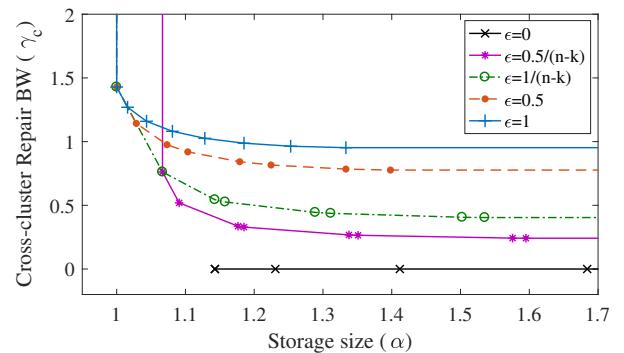


Fig. 8: Optimal tradeoff between node storage size α and cross-cluster repair bandwidth γ_c , under the setting of $n = 15, k = 8, L = 3, \mathcal{M} = 8$

where

$$\tau = \max\{t \in \{0, 1, \dots, k-1\} : z_t \geq 1\} \quad (22)$$

$$s_t = \begin{cases} \frac{\sum_{i=t+1}^k z_i}{(n_I-1)+\epsilon(n-n_I)}, & t = 0, 1, \dots, k-1 \\ 0, & t = k \end{cases} \quad (23)$$

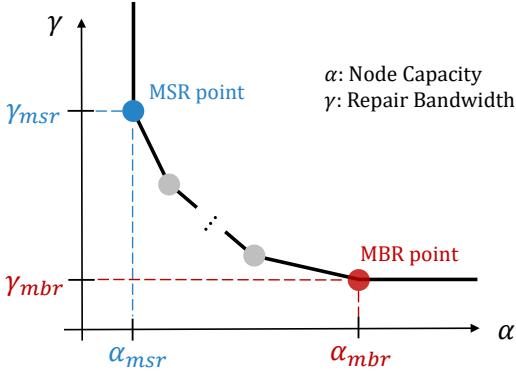
$$y_t = \frac{(n_I-1) + \epsilon(n-n_I)}{z_t}, \quad (24)$$

$$z_t = \begin{cases} (n - n_I - t + h_t)\epsilon + (n_I - h_t), & t \in [k] \\ \infty, & t = 0 \end{cases} \quad (25)$$

$$h_t = \min\{s \in [n_I] : \sum_{l=1}^s g_l \geq t\}, \quad (26)$$

and $\{g_l\}_{l=1}^{n_I}$ is defined in (7).

An example for the trade-off results of Corollary 1 is illustrated in Fig. 7, for various $0 \leq \epsilon \leq 1$ values. Here, the $\epsilon = 1$ (i.e., $\beta_I = \beta_c$) case corresponds to the symmetric repair in the non-clustered scenario [10]. The plot for $\epsilon = 0$ (or $\beta_c = \gamma_c = 0$) shows that the cross-cluster repair bandwidth can be reduced to zero with extra resources (α or γ_I), where the amount of required resources are specified in Corollary 1. Note that in the case of $\epsilon = 0$, the storage system is *completely localized*, i.e., nodes can be repaired exclusively from their

Fig. 9: Set of Feasible (α, γ) Points

cluster. From Fig. 7, we can confirm that as ϵ decreases, extra resources (γ or α) are required to reliably store the given data \mathcal{M} . Moreover, Corollary 1 suggests a mathematically interesting result, stated in the following Theorem, the proof of which is in Appendix B.

Theorem 3. *A clustered DSS can reliably store file \mathcal{M} with the minimum storage overhead $\alpha = \mathcal{M}/k$ if and only if*

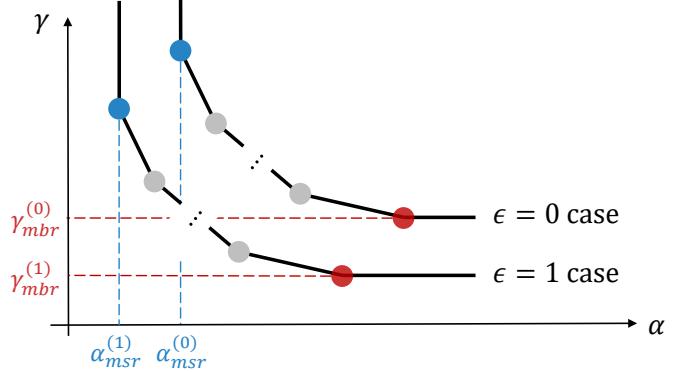
$$\epsilon \geq \frac{1}{n-k}. \quad (27)$$

Note that $\alpha = \mathcal{M}/k$ is the minimum storage overhead which can satisfy the MDS property, as stated in [10]. The implication of Theorem 3 is shown in Fig. 7. Under the $\mathcal{M} = k = 8$ setting, data \mathcal{M} can be reliably stored with minimum storage overhead $\alpha = \mathcal{M}/k = 1$ for $\frac{1}{n-k} \leq \epsilon \leq 1$, while it is impossible to achieve minimum storage overhead $\alpha = \mathcal{M}/k = 1$ for $0 \leq \epsilon < \frac{1}{n-k}$. Finally, since reducing the cross-cluster repair burden γ_c is regarded as a much harder problem compared to reducing the intra-cluster repair burden γ_I , we also plotted feasible (α, γ_c) pairs for various ϵ values in Fig. 8. The plot for $\epsilon = 0$ obviously has zero γ_c , while $\epsilon > 0$ cases show a trade-off relationship. As ϵ increases, the minimum γ_c value increases gradually.

B. Minimum-Bandwidth-Regenerating (MBR) point and Minimum-Storage-Regenerating (MSR) point

According to Corollary 1, the set of feasible (α, γ) points shows a trade-off curve as in Fig. 9, for arbitrary n, k, L, ϵ settings. Here we focus on two extremal points: the minimum-bandwidth-regenerating (MBR) point and the minimum-storage-regenerating (MSR) point. As originally defined in [10], we call the point on the trade-off with minimum bandwidth γ as MBR. Similarly, we call the point with minimum storage α as MSR². Let $(\alpha_{msr}^{(\epsilon)}, \gamma_{msr}^{(\epsilon)})$ be the (α, γ) pair of the MSR point for given ϵ . Similarly, define $(\alpha_{mbr}^{(\epsilon)}, \gamma_{mbr}^{(\epsilon)})$ as the parameter pair for MBR points. According to Corollary 1, the explicit (α, γ) expression for the MSR and MBR points are as in the following Corollary, the proof of which is given in Appendix F-B.

²Among multiple points with minimum γ , the point having the smallest α is called the MBR point. Similarly, among points with minimum α , the point with the minimum γ is called the MSR point.

Fig. 10: Optimal trade-off curves for $\epsilon = 0, 1$

Corollary 2. *For a given $0 \leq \epsilon \leq 1$, we have*

$$\begin{aligned} & (\alpha_{msr}^{(\epsilon)}, \gamma_{msr}^{(\epsilon)}) \\ &= \begin{cases} \left(\frac{\mathcal{M}}{\tau + \sum_{i=\tau+1}^k z_i}, \frac{\mathcal{M}}{\tau + \sum_{i=\tau+1}^k z_i} \frac{\sum_{i=\tau+1}^k z_i}{s_\tau} \right), & 0 \leq \epsilon < \frac{1}{n-k} \\ \left(\frac{\mathcal{M}}{k}, \frac{\mathcal{M}}{k} \frac{1}{s_{k-1}} \right), & \frac{1}{n-k} \leq \epsilon \leq 1 \end{cases} \end{aligned} \quad (28)$$

$$(\alpha_{mbr}^{(\epsilon)}, \gamma_{mbr}^{(\epsilon)}) = \left(\frac{\mathcal{M}}{s_0}, \frac{\mathcal{M}}{s_0} \right). \quad (29)$$

Now we compare the MSR and MBR points for two extreme cases of $\epsilon = 0$ and $\epsilon = 1$. Using $R := k/n$ and the dispersion ratio σ defined in (13), the asymptotic behaviors of MBR and MSR points are illustrated in the following theorem, the proof of which is in Appendix C.

Theorem 4. *Consider the MSR point $(\alpha_{msr}^{(\epsilon)}, \gamma_{msr}^{(\epsilon)})$ and the MBR point $(\alpha_{mbr}^{(\epsilon)}, \gamma_{mbr}^{(\epsilon)})$ for $\epsilon = 0, 1$. The minimum node storage for $\epsilon = 0$ is asymptotically equivalent to the minimum node storage for $\epsilon = 1$, i.e.,*

$$\alpha_{msr}^{(0)} \sim \alpha_{msr}^{(1)} = \mathcal{M}/k \quad (30)$$

as $n \rightarrow \infty$ for arbitrary fixed σ and $R = k/n$. Moreover, the MBR point for $\epsilon = 0$ approaches the MBR point for $\epsilon = 1$, i.e.,

$$(\alpha_{mbr}^{(0)}, \gamma_{mbr}^{(0)}) \rightarrow (\alpha_{mbr}^{(1)}, \gamma_{mbr}^{(1)}), \quad (31)$$

as $R = k/n \rightarrow 1$. The ratio between $\gamma_{mbr}^{(0)}$ and $\gamma_{mbr}^{(1)}$ is expressed as

$$\frac{\gamma_{mbr}^{(0)}}{\gamma_{mbr}^{(1)}} \leq 2 - \frac{k-1}{n-1} \quad (32)$$

Note that under the setting of Theorem 4, we have

$$\alpha_{msr}^{(1)} = \text{constant}, \quad k = nR = \Theta(n), \quad \mathcal{M} = \Theta(n)$$

in the asymptotic regime of large n . According to Theorem 4, the minimum storage for $\epsilon = 0$ can achieve \mathcal{M}/k as $n \rightarrow \infty$ with fixed $R = k/n$. This result coincides with the result of Theorem 3. According to Theorem 3, the sufficient and necessary condition for achieving the minimum storage of $\alpha = \mathcal{M}/k$ is

$$\epsilon \geq \frac{1}{n-k} = \frac{1}{n(1-R)}. \quad (33)$$

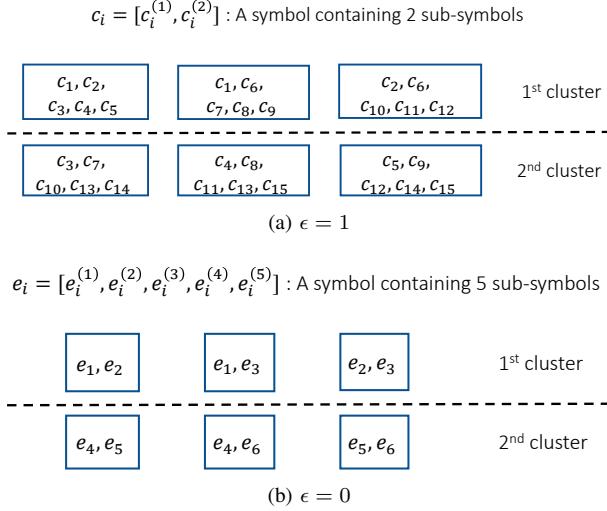


Fig. 11: MBR coding schemes for $n = 6, k = 5, L = 2, \alpha = 10$ [sub-symbol], $\gamma = 10$ [sub-symbol]

As n increases with a fixed R , the lower bound on ϵ reduces, so that in the asymptotic regime, $\epsilon = 0$ can achieve $\alpha = \mathcal{M}/k$.

Moreover, Theorem 4 states that the MBR point for $\epsilon = 0$ approaches the MBR point for $\epsilon = 1$ as $R = k/n$ goes to 1. Fig. 11 provides two MBR coding schemes with $(n, k, L) = (6, 5, 2)$, which has different ϵ values; one coding scheme in Fig. 11a satisfies $\epsilon = 1$, while the other in Fig. 11b satisfies $\epsilon = 0$. The RSKR coding scheme [12] is applied to the six nodes in Fig. 11a. Each node (illustrated as a rectangular box) contains five c_i symbols, where each symbol c_i consists of two sub-symbols, $c_i^{(1)}$ and $c_i^{(2)}$. Note that any symbol c_i is shared by exactly two nodes in Fig. 11a, which is due to the property of RSKR coding. This system can reliably store fifteen symbols $\{c_i\}_{i=1}^{15}$, or $\mathcal{M} = 30$ sub-symbols $\{c_i^{(1)}, c_i^{(2)}\}_{i=1}^{15}$, since it satisfies two properties – the exact repair property and the data recovery property – as illustrated below. First, when a node fails, five other nodes transmit five symbols (one distinct symbol by each node), which exactly regenerates the failed node. Second, we can retrieve data, $\mathcal{M} = 30$ sub-symbols $\{c_i^{(1)}, c_i^{(2)}\}_{i=1}^{15}$, by contacting any $k = 5$ nodes. In Fig. 11b, each node contains two e_i symbols, where each symbol e_i consists of five sub-symbols, $\{e_i^{(j)}\}_{j=1}^5$. Note that in Fig. 11b, any symbol e_i is shared by exactly two nodes which reside in the same cluster. This is because we applied RSKR coding at each cluster in the system of Fig. 11b. This system can reliably store six symbols $\{e_i\}_{i=1}^6$, or $\mathcal{M} = 30$ sub-symbols $\bigcup_{i \in [6], j \in [5]} \{e_i^{(j)}\}$, since it satisfies the exact repair property and the data recovery property.

Note that both DSSs in Fig. 11 reliably store $\mathcal{M} = 30$ sub-symbols, by using the node capacity of $\alpha = 10$ sub-symbols and the repair bandwidth of $\gamma = 10$ sub-symbols. However, the former system requires $\gamma_c = 6$ cross-cluster repair bandwidth for each node failure event, while the latter system requires $\gamma_c = 0$ cross-cluster repair bandwidth. For example, if the leftmost node of the 1st cluster fails in Fig. 11a, then four sub-symbols $\{c_1^{(i)}, c_2^{(i)}\}_{i=1}^2$ are transmitted within that cluster,

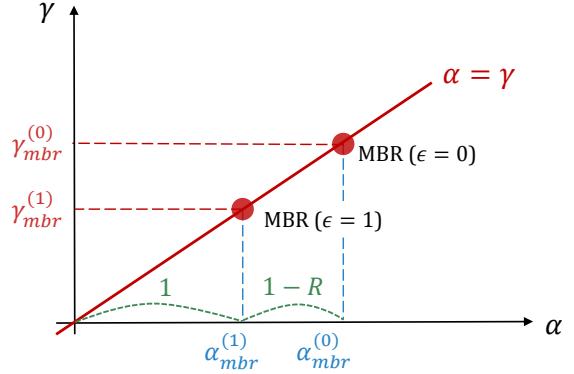


Fig. 12: Relationship between MBR point of $\epsilon = 0$ and that of $\epsilon = 1$

while six sub-symbols $\{c_3^{(i)}, c_4^{(i)}, c_5^{(i)}\}_{i=1}^2$ are transmitted from the 2nd cluster. In the case of $\epsilon = 0$ in Fig. 11b, ten sub-symbols $\{e_1^{(i)}, e_2^{(i)}\}_{i=1}^5$ are transmitted within the 1st cluster and no sub-symbols are transmitted across the clusters, when the leftmost node of the 1st cluster fails. Thus, transition from the former system (Fig. 11a) to the latter system (Fig. 11b) reduces the cross-cluster repair bandwidth to zero, while maintaining the storage capacity \mathcal{M} and the required resource pair (α, γ) . Likewise, we can reduce the cross-cluster repair bandwidth to zero while maintaining the storage capacity, in the case of $R = k/n \rightarrow 1$.

Note that $\gamma_{mbr}^{(\epsilon)} = \alpha_{mbr}^{(\epsilon)}$ for $0 \leq \epsilon \leq 1$, from (29). Thus, the result of (32) in Theorem 4 can be expressed as Fig. 12 at the asymptotic regime of large n, k . According to Fig. 12, intra-cluster only repair ($\epsilon = 0$ or $\beta_c = 0$) is possible by using additional resources (α and γ) in the $1 - R$ portion, compared to the symmetric repair ($\epsilon = 1$) case.

C. Intra-cluster Repairable Codes versus Locally Repairable Codes [32]

Here, we define a family of network coding schemes for clustered DSS, which we call the *intra-cluster repairable codes*. In Corollary 1, we considered DSSs with $\epsilon = 0$, which can repair any failed node by using intra-cluster communication only. The optimal (α, γ) trade-off curve which satisfies $\epsilon = 0$ is illustrated as the solid line with cross markers in Fig. 7. Each point on the curve is achievable (i.e., there exists a network coding scheme), according to the result of [11]. We call the network coding schemes for the points on the curve of $\epsilon = 0$ the *intra-cluster repairable codes*, since these coding schemes can repair any failed node by using intra-cluster communication only. The relationship between the intra-cluster repairable codes and the locally repairable codes (LRC) of [32] are investigated in Theorem 5, the proof of which is given in Appendix D. Note that according to the definition in [32], an $(n, l_0, m_0, \mathcal{M}, \alpha)$ -LRC encodes a file of size \mathcal{M} into n coded symbols, where each symbol contains α bits. In addition, any coded symbol of the LRC is regenerated by accessing at most l_0 other symbols (i.e., the code has repair locality of l_0), while the minimum distance of the code is m_0 .

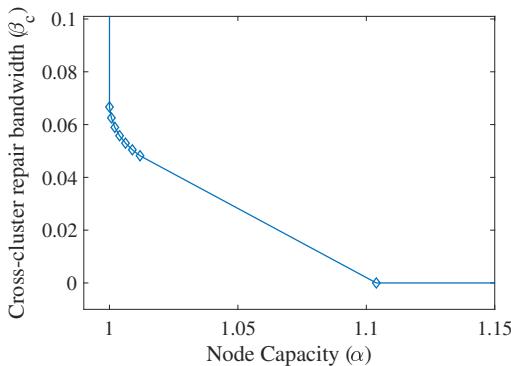


Fig. 13: Optimal tradeoff between cross-cluster repair bandwidth and node capacity, when $n = 100$, $k = 85$, $L = 10$, $\mathcal{M} = 85$ and $\beta_I = \alpha$

Theorem 5. *The intra-cluster repairable codes with storage overhead α are the $(n, l_0, m_0, \mathcal{M}, \alpha)$ -LRC codes of [32] where*

$$\begin{aligned} l_0 &= n_I - 1, \\ m_0 &= n - k + 1. \end{aligned}$$

It is confirmed that Theorem 1 of [32],

$$m_0 \leq n - \left\lceil \frac{\mathcal{M}}{\alpha} \right\rceil - \left\lceil \frac{\mathcal{M}}{l_0 \alpha} \right\rceil + 2, \quad (34)$$

holds for every intra-cluster repairable code with storage overhead α . Moreover, the equality of (34) holds if

$$\alpha = \alpha_{msr}^{(0)}, (k \bmod n_I) \neq 0.$$

D. Required β_c for a given α

Here we focus on the following question: when the available intra-cluster repair bandwidth is abundant, how much cross-cluster repair bandwidth is required to reliably store file \mathcal{M} ? We consider scenarios when the intra-cluster repair bandwidth (per node) has its maximum value, i.e., $\beta_I = \alpha$. Under this setting, Theorem 6 specifies the minimum required β_c which satisfies $\mathcal{C}(\alpha, \beta_I, \beta_c) \geq \mathcal{M}$. The proof of Theorem 6 is given in Appendix E.

Theorem 6. *Suppose the intra-cluster repair bandwidth is set at the maximum value, i.e., $\beta_I = \alpha$. For a given node capacity α , the clustered DSS can reliably store data \mathcal{M} if and only if $\beta_c \geq \beta_c^*$ where*

$$\beta_c^* = \begin{cases} \frac{\mathcal{M} - (k-1)\alpha}{n-k}, & \text{if } \alpha \in [\frac{\mathcal{M}}{k}, \frac{\mathcal{M}}{f_{k-1}}) \\ \frac{\mathcal{M} - m\alpha}{\sum_{i=m+1}^k (n-i)}, & \text{if } \alpha \in [\frac{\mathcal{M}}{f_{m+1}}, \frac{\mathcal{M}}{f_m}) \\ (m = k-2, k-3, \dots, s+1) \\ \frac{\mathcal{M} - k_0\alpha}{\sum_{i=k_0+1}^k (n-i)}, & \text{if } \alpha \in [\frac{\mathcal{M}}{f_{k_0+1}}, \frac{\mathcal{M}}{k_0}) \\ 0, & \text{if } \alpha \in [\frac{\mathcal{M}}{k_0}, \infty), \end{cases} \quad (35)$$

$$f_m = m + \frac{\sum_{i=m+1}^k (n-i)}{n-m}, \quad (36)$$

$$k_0 = k - \lfloor \frac{k}{n_I} \rfloor. \quad (37)$$

Fig. 13 provides an example of the optimal trade-off relationship between β_c and α , explained in Theorem 6. For $\alpha \geq \mathcal{M}/k_0 = 1.104$, the cross-cluster burden β_c can be reduced to zero. However, as α decreases from \mathcal{M}/k_0 , the system requires a larger β_c value. For example, if $\alpha = \beta_I = 1.05$ in Fig. 13, $\beta_c \geq 0.03$ is required to satisfy $\mathcal{C}(\alpha, \beta_I, \beta_c) \geq \mathcal{M} = 85$. Thus, for each node failure event, a cross-cluster repair bandwidth of $\gamma_c = (n - n_I)\beta_c \geq 2.7$ is required. Theorem 6 provides an explicit equation for the cross-cluster repair bandwidth we need to pay, in order to reduce node capacity α .

V. FURTHER COMMENTS & FUTURE WORKS

A. Explicit coding schemes for clustered DSS

According to the part I proof of Theorem 1, there exists an information flow graph G^* which has the min-cut value of \mathcal{C} , the capacity of clustered DSS. Thus, according to [11], there exists a linear network coding scheme which achieves capacity \mathcal{C} . Although the existence of a coding scheme is verified, explicit network coding schemes which achieve capacity need to be specified for implementing practical systems. Recently, under the setting of clustered DSS modeled in the present paper, MBR codes for all n, k, L, ϵ are constructed in [36] and MSR codes for limited parameters are designed in [37]. Explicit code construction for general parameters and/or construction of codes that requires small field size are interesting remaining issues.

B. Optimal number of clusters

According to Theorem 2, capacity \mathcal{C} is asymptotically a monotonically decreasing function of L , the number of clusters. Thus, reducing the number of clusters (i.e., gathering storage nodes into a smaller number of clusters) increases storage capacity. However, as mentioned in Section III-E, we typically want to have a sufficiently large L , to tolerate the failure of a cluster. Then, the remaining question is in finding optimal L^* which not only allows sufficiently large storage capacity, but also a tolerance to cluster failures. We regard this problem as a future research topic, the solution to which will provide a guidance on the strategy for distributing storage nodes into multiple clusters.

C. Extension to general d_I, d_c settings

The present paper assumed a maximum helper node setting, $d_I = n_I - 1$ and $d_c = n - n_I$, since it maximizes the capacity as stated in Proposition 1. However, waiting for all helper nodes gives rise to a latency issue. If we reduce the number of helper nodes d_I and d_c , low latency repair would be possible, while the achievable storage capacity decreases. Thus, we consider obtaining the capacity expression for general d_I, d_c settings, and discover the trade-off between capacity and latency for various d_I, d_c values.

D. Scenarios of aggregating the helper data within each cluster

In recent work [28], [38] on multi-rack (multi-cluster) distributed storage, the authors discuss aggregation of repair data leaving a given cluster. The idea is to allow aggregation and compression of all helper data leaving each cluster to aid reconstruction taking place in some other cluster containing a failed node. This type of repair link aggregation has been shown to reduce the cross-cluster repair burden in [28], [38]. We expect that the same method would also change the tradeoff picture for our distributed cluster model. This is certainly an interesting and important topic to investigate, but careful analysis including the effect of security breach on links will provide a more complete assessment of the merits and potential perils of repair link aggregation. We will leave this as a future endeavor.

VI. CONCLUSION

This paper considered a practical distributed storage system where storage nodes are dispersed into several clusters. Noticing that the traffic burdens of intra- and cross-cluster communications are typically different, a new system model for clustered distributed storage systems is suggested. Based on the cut-set bound analysis of information flow graph, the storage capacity $\mathcal{C}(\alpha, \beta_I, \beta_c)$ of the suggested model is obtained in a closed-form, as a function of three main resources: node storage capacity α , intra-cluster repair bandwidth β_I and cross-cluster repair bandwidth β_c . It is shown that the asymmetric repair ($\beta_I > \beta_c$) degrades capacity, which is the cost for lifting the cross-cluster repair burden. Moreover, in the asymptotic regime of a large number of storage nodes, capacity is shown to be asymptotically equivalent to a monotonic decreasing function of L , the number of clusters. Thus, reducing L (i.e., gathering nodes into less clusters) is beneficial for increasing capacity, although we would typically need to guarantee sufficiently large L to tolerate rack failure events.

Using the capacity expression, we obtained the feasible set of $(\alpha, \beta_I, \beta_c)$ triplet which satisfies $\mathcal{C}(\alpha, \beta_I, \beta_c) \geq \mathcal{M}$, i.e., it is possible to reliably store file \mathcal{M} by using the resource value set $(\alpha, \beta_I, \beta_c)$. The closed-form solution on the feasible set shows a different behavior depending on $\epsilon = \beta_c/\beta_I$, the ratio of cross- to intra-cluster repair bandwidth. It is shown that the minimum storage of $\alpha = \mathcal{M}/k$ is achievable if and only if $\epsilon \geq \frac{1}{n-k}$. Moreover, in the special case of $\epsilon = 0$, we can construct a reliable storage system without using cross-cluster repair bandwidth. A family of network codes which enable $\epsilon = 0$, called the *intra-cluster repairable codes*, has been shown to be a class of the *locally repairable codes* defined in [32].

APPENDIX A PROOF OF THEOREM 1

Here, we prove Theorem 1. First, denote the right-hand-side (RHS) of (5) as

$$T := \sum_{i=1}^{n_I} \sum_{j=1}^{g_i} \min\{\alpha, \rho_i \beta_I + (n - \rho_i - j - \sum_{m=1}^{i-1} g_m) \beta_c\}. \quad (\text{A.1})$$

For other notations used in this proof, refer to subsection II-C. The proof proceeds in two parts.

Part I. Show an information flow graph $G^* \in \mathcal{G}$ and a cut-set $c^* \in C(G^*)$ such that $w(G^*, c^*) = T$:

Consider the information flow graph G^* illustrated in Fig. 14, which is obtained by the following procedure. First, data from source node S is distributed into n nodes labeled from x^1 to x^n . As mentioned in Section II-B, the storage node $x^i = (x_{in}^i, x_{out}^i)$ consists of an input-node x_{in}^i and an output-node x_{out}^i . Second, storage node x^t fails and is regenerated at the newcomer node x^{n+t} for $t \in [k]$. The newcomer node x^{n+t} connects to $n-1$ survived nodes $\{x^m\}_{m=t+1}^{n+t-1}$ to regenerate x^t . Third, data collector node DC contacts $\{x^{n+t}\}_{t=1}^k$ to retrieve data. This whole process is illustrated in the information flow graph G^* .

To specify G^* , here we determine the 2-dimensional location of the k newcomer nodes $\{x^{n+t}\}_{t=1}^k$. First, consider the 2-dimensional structure representation of clustered distributed storage, illustrated in Fig. 15. In this figure, each row represents each cluster, and each node is represented as a 2-dimensional (i, j) point for $i \in [L]$ and $j \in [n_I]$. The symbol $N(i, j)$ denotes the node at (i, j) point. Here we define the set of n nodes,

$$\mathcal{N} := \{N(i, j) : i \in [L], j \in [n_I]\}. \quad (\text{A.2})$$

For $t \in [k]$, consider selecting the newcomer node x^{n+t} as

$$x^{n+t} = N(i_t, j_t) \quad (\text{A.3})$$

where

$$i_t = \min\{\nu \in [n_I] : \sum_{m=1}^{\nu} g_m \geq t\}, \quad (\text{A.4})$$

$$j_t = t - \sum_{m=1}^{i_t-1} g_m, \quad (\text{A.5})$$

and g_m used in the method is defined in (7). The location of k newcomer nodes selected by this method are illustrated in Fig. 16. Moreover, for the $n = 12, L = 3, k = 9$ case, the newcomer nodes $\{x^{n+t}\}_{t=1}^k$ are depicted in Fig. 17. In these figures, the node with number t inside represents the newcomer node labeled as x^{n+t} .

For the given graph G^* , now we consider a cut-set $c^* \in C(G^*)$ defined as below. The cut-set $c^* = (U, \bar{U})$ can be defined by specifying U and \bar{U} (complement of U), which partition the set of vertices in G^* . First, let $x_{in}^i, x_{out}^i \in U$ for $i \in [n]$ and $x_{out}^{n+i} \in \bar{U}$ for $i \in [k]$. For $i \in [k]$, the input node x_{in}^{n+i} is included in either U or \bar{U} , depending on the condition specified in the next paragraph. Moreover, let $S \in U$ and $DC \in \bar{U}$. See Fig. 18.

Let $U_0 = \bigcup_{i=1}^n \{x_{out}^i\}$. For $t \in [k]$, let ω_t^* be the sum of capacities of edges from U_0 to x_{in}^{n+t} . If $\alpha \leq \omega_t^*$, then we include x_{in}^{n+t} in U . Otherwise, we include x_{in}^{n+t} in \bar{U} . Then, the cut-set c^* has the cut-value of

$$w(G^*, c^*) = \sum_{t=1}^k \min\{\alpha, \omega_t^*\}. \quad (\text{A.6})$$

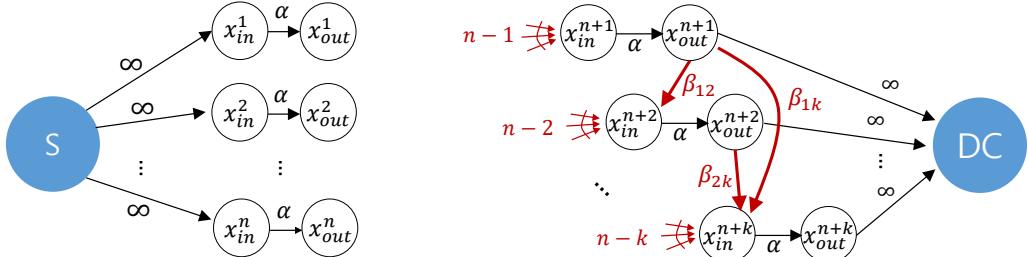
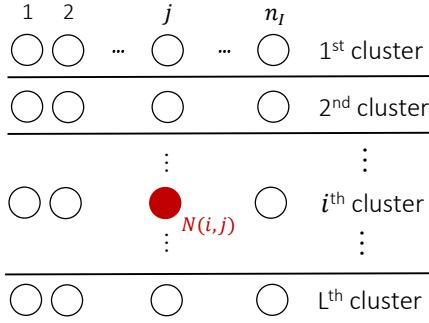
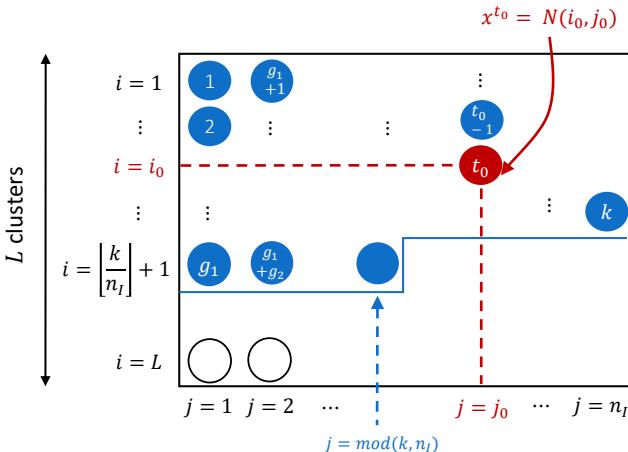
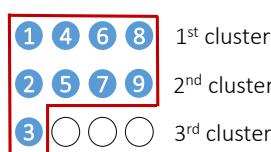
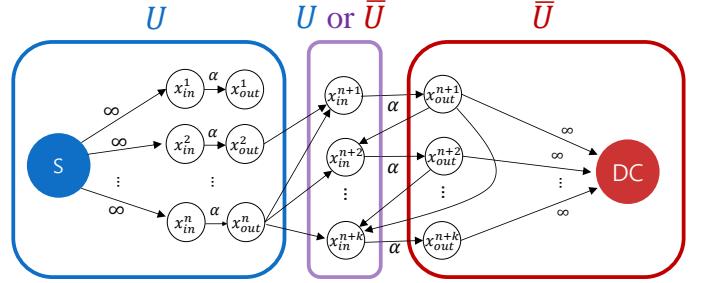
Fig. 14: The information flow graph G^* for the part I proof of Theorem 1

Fig. 15: 2-dim. structure representation

Fig. 16: The location of k newcomer nodes: x^{n+1}, \dots, x^{n+k} Fig. 17: The location of k newcomer nodes for $n = 12, L = 3, k = 9$ case

All that remains is to show that (A.6) is equal to the expression in (A.1). In other words, we will obtain the expression for ω_t^* .

Recall that in the generation process of G^* , any newcomer node x^{n+t} connects to $n - 1$ helper nodes $\{x_m^m\}_{m=t+1}^{n+t-1}$ to regenerate x^t . Among the $n - 1$ helper nodes, the $n_I - 1$ nodes reside in the same cluster with x^t , while the $n - n_I$ nodes are in other clusters. From our system setting in Section III-A, the

Fig. 18: The cut-set $c^* = (U, \bar{U})$ for the graph G^*

helper nodes in the same cluster as the failed node help by β_I , while the helper nodes in other clusters help by β_c . Therefore, the total repair bandwidth to regenerate any failed node is

$$\gamma = (n_I - 1)\beta_I + (n - n_I)\beta_c \quad (\text{A.7})$$

as in (2).

The newcomer node x^{n+1} connects to $\{x_m^m\}_{m=2}^n$, all of which are included in U_0 . Therefore, $\omega_1^* = \gamma = (n_I - 1)\beta_I + (n - n_I)\beta_c$ holds. Next, x^{n+2} connects to $n - 2$ nodes $\{x_m^m\}_{m=3}^n$ from U_0 and one node x^{n+1} from \bar{U} . Define variable β_{lm} as the repair bandwidth from x^{n+l} to x^{n+m} . Then, $\omega_2^* = \gamma - \beta_{12}$. From (A.3), we have $x^{n+1} = N(1, 1)$ and $x^{n+2} = N(1, 2)$. Therefore, x^{n+1} and x^{n+2} are in different clusters, which result in $\beta_{12} = \beta_c$. Therefore, $\omega_2^* = \gamma - \beta_{12} = \gamma - \beta_c$.

In general, x^{n+t} connects to $n - t$ nodes $\{x_m^m\}_{m=t+1}^n$ from U_0 , and $t - 1$ nodes $\{x_m^{n+m}\}_{m=1}^{t-1}$ from \bar{U} . Thus, ω_t^* for $t \in [k]$ can be expressed as $\omega_t^* = \gamma - \sum_{l=1}^{t-1} \beta_{lt}$ where

$$\beta_{lt} = \begin{cases} \beta_I, & \text{if } x^{n+l} \text{ and } x^{n+t} \text{ are in the same cluster} \\ \beta_c, & \text{otherwise.} \end{cases}$$

Recall Fig. 16. For arbitrary newcomer node $x^{n+t} = N(i_t, j_t)$, the set $\{x^{n+m}\}_{m=1}^{t-1}$ contains $i_t - 1$ nodes which reside in the same cluster with x^{n+t} , and $t - i_t$ nodes in other clusters. Therefore, ω_t^* can be expressed as

$$\omega_t^* = \gamma - (i_t - 1)\beta_I - (t - i_t)\beta_c$$

where i_t is defined in (A.4). Combined with (A.7) and (A.5), we get

$$\begin{aligned} \omega_t^* &= (n_I - i_t)\beta_I + (n - n_I - t + i_t)\beta_c \\ &= (n_I - i_t)\beta_I + (n - n_I - j_t - \sum_{m=1}^{i_t-1} g_m + i_t)\beta_c. \end{aligned}$$

Then, (A.6) can be expressed as

$$\begin{aligned} w(G^*, c^*) &= \\ \sum_{i=1}^{n_I} \sum_{t \in T_i} \min\{\alpha, (n_I - i)\beta_I + (n - n_I - j_t - \sum_{m=1}^{i-1} g_m + i)\beta_c\} \end{aligned} \quad (\text{A.8})$$

where $T_i = \{t \in [k] : i_t = i\}$. From the definition of i_t in (A.4), we have

$$T_i = \left\{ \sum_{m=1}^{i-1} g_m + 1, \sum_{m=1}^{i-1} g_m + 2, \dots, \sum_{m=1}^i g_m \right\}.$$

Thus, $j_t = 1, 2, \dots, g_i$ for $t \in T_i$. Therefore, (A.8) can be expressed as

$$\begin{aligned} w(G^*, c^*) &= \\ \sum_{i=1}^{n_I} \sum_{j=1}^{g_i} \min\{\alpha, (n_I - i)\beta_I + (n - n_I - j - \sum_{m=1}^{i-1} g_m + i)\beta_c\}, \end{aligned}$$

which is identical to T in (A.1), where ρ_i used in this equation is defined in (6). Therefore, the specified information flow graph G^* and the specified cut-set c^* satisfy $\omega(G^*, c^*) = \sum_{t=1}^k \min\{\alpha, \omega_t^*\} = T$.

Part II. Show that for every information flow graph $G \in \mathcal{G}$ and for every cut-set $c \in C(G)$, the cut-value $w(G, c)$ is greater than or equal to T in (A.1). In other words, $\forall G \in \mathcal{G}, \forall c \in C(G)$, we have $w(G, c) \geq T$.

The proof is divided into 2 sub-parts: Part II-1 and Part II-2.

Part II-1. Show that $\forall G \in \mathcal{G}, \forall c \in C(G)$, we have $w(G, c) \geq B(G, c)$ where $B(G, c)$ is in (A.14):

Consider an arbitrary information flow graph $G \in \mathcal{G}$ and an arbitrary cut-set $c \in C(G)$ of the graph G . Denote the cut-set as $c = (U, \bar{U})$. Consider an output node x_{out}^i connected to DC . If $x_{out}^i \in U$, then the cut-value $w(G, c)$ is infinity, which is a trivial case for proving $w(G, c) \geq B(G, c)$. Therefore, the k output nodes connected to DC are assumed to be in \bar{U} . In other words, at least k output nodes exist in \bar{U} . Note that every directed acyclic graph can be topologically sorted [34], where vertex u is followed by vertex v if there exists a directed edge from u to v . Consider labeling the topologically first k output nodes in \bar{U} as $v_{out}^1, \dots, v_{out}^k$. Similar to the notation for a storage node $x^i = (x_{in}^i, x_{out}^i)$ in Section II-B, we denote the storage node which contains v_{out}^i as $v^i = (v_{in}^i, v_{out}^i)$. Then, the set of ordered k -tuples $(v^i)_{i=1}^k$ can be represented as

$$\mathcal{V}_k = \{(v^1, v^2, \dots, v^k) : v^t \in \mathcal{N} \text{ for } t \in [k], v^{t_1} \neq v^{t_2} \text{ for } t_1 \neq t_2\}. \quad (\text{A.9})$$

We also define u_i , the sum of capacities of edges from U to v_{in}^i . See Fig. 19.

If $v_{in}^1 \in U$, then the cut-set $c = (U, \bar{U})$ should include the edge from v_{in}^1 to v_{out}^1 , which has the edge capacity α . Otherwise (i.e., $v_{in}^1 \in \bar{U}$), the cut-set $c = (U, \bar{U})$ should include the edges from U to v_{in}^1 . If v_{in}^1 node is directly connected to the source node S , the cut-value $w(G, c)$ is infinity (trivial case for proving $w(G, c) \geq B(G, c)$). Therefore, v_{in}^1 node is

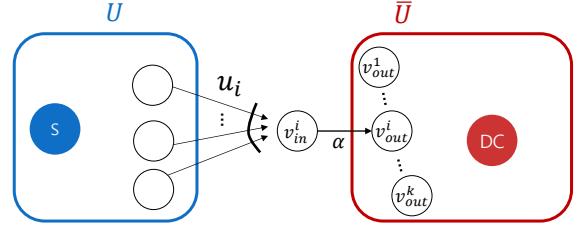


Fig. 19: Arbitrary information flow graph $G \in \mathcal{G}$ and arbitrary cut-set $c \in C(G)$

assumed to be a newcomer node helped by $n-1$ helper nodes. Note that all helper nodes of v_{in}^1 are in U , since v_{out}^1 is the topologically first output node in \bar{U} . Thus, the cut-set c should include the edges from U to v_{in}^1 , where the sum of capacities of these edges are

$$u_1 = \gamma = (n_I - 1)\beta_I + (n - n_I)\beta_c.$$

If $v_{in}^2 \in U$, then the cut-set $c = (U, \bar{U})$ should include the edge from v_{in}^2 to v_{out}^2 , which has the edge capacity α . Otherwise (i.e., $v_{in}^2 \in \bar{U}$), the cut-set $c = (U, \bar{U})$ should include the edges from U to v_{in}^2 . As we discussed in the case of v_{in}^1 , we can assume v_{in}^2 is a newcomer node helped by $n-1$ helper nodes. Since v_{in}^2 is the topologically second node in \bar{U} , it may have one helper node $v_{out}^1 \in \bar{U}$; at least $n-2$ helper nodes in U help to generate v_{in}^2 . Note that the total amount of data coming into v_{in}^2 is $\gamma = (n_I - 1)\beta_I + (n - n_I)\beta_c$, while the amount of information coming from v_{out}^1 to v_{in}^2 , denoted β_{12} , is as follows: if v^1 and v^2 are in the same cluster, $\beta_{12} = \beta_I$, otherwise $\beta_{12} = \beta_c$. Recall that the cut-set should include the edges from U to v_{in}^2 . The sum of capacities of these edges are

$$u_2 \geq \gamma - \beta_{12},$$

while the equality holds if and only if v_{out}^1 helps v_{in}^2 . In a similar way, for $i \in [k]$, u_i can be bounded as

$$u_i \geq \omega_i \quad (\text{A.10})$$

where

$$\omega_i = \gamma - \sum_{j=1}^{i-1} \beta_{ji}, \quad (\text{A.11})$$

$$\beta_{ji} = \begin{cases} \beta_I, & v^j \text{ and } v^i \text{ are in the same cluster} \\ \beta_c, & \text{otherwise.} \end{cases} \quad (\text{A.12})$$

The equality in (A.10) holds if and only if v_{out}^j helps v_{in}^i for $j \in [i-1]$.

Thus, v_{out}^i contributes at least $\min\{\alpha, \omega_i\}$ to the cut value, for $i \in [k]$. In summary, for arbitrary graph $G \in \mathcal{G}$, an arbitrary cut-set c has cut-value $w(G, c)$ of at least $\sum_{i=1}^k \min\{\alpha, \omega_i\}$:

$$w(G, c) \geq \sum_{i=1}^k \min\{\alpha, \omega_i\}, \quad \forall G \in \mathcal{G}, \forall c \in C(G). \quad (\text{A.13})$$

Note that $\{\omega_i\}$ depends on the relative position of $\{v_{out}^i\}_{i=1}^k$, which is determined when an arbitrary information flow graph $G \in \mathcal{G}$ and arbitrary cut-set $c \in C(G)$ are specified. This

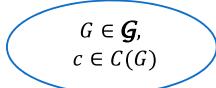


Fig. 20: Dependency graph for variables in the proof of Part II.

relationship is illustrated in Fig. 20. Therefore, we define

$$B(G, c) = \sum_{i=1}^k \min\{\alpha, \omega_i\} \quad (\text{A.14})$$

for arbitrary $G \in \mathcal{G}$ and arbitrary $c \in C(G)$. Combining (A.13) and (A.14) completes the proof *part II-1*.

Part II-2. $\min_{G \in \mathcal{G}} \min_{c \in C(G)} B(G, c) = R$:

Assume that α and k are fixed. See Fig. 20. Note that for a given graph $G \in \mathcal{G}$ and a cut-set $c = (U, \bar{U})$ with $c \in C(G)$, the sequence of topologically first k output nodes $(v_{out}^i)_{i=1}^k$ in \bar{U} is determined. Moreover, for a given sequence $(v_{out}^i)_{i=1}^k$, we have a fixed $(\omega_i)_{i=1}^k$, which determines $B(G, c)$ in (A.14). Thus, $\min_{G \in \mathcal{G}} \min_{c \in C(G)} B(G, c)$ can be obtained by finding the optimal $(v_{out}^i)_{i=1}^k$ sequence which minimizes $B(G, c)$. It is identical to finding the optimal $(v^i)_{i=1}^k$, the sequence of k different nodes out of n existing nodes in the system. Therefore, based on (A.14) and (A.11), we have

$$\min_{G \in \mathcal{G}} \min_{c \in C(G)} B(G, c) = \min_{(v^i)_{i=1}^k \in \mathcal{V}_k} \left(\sum_{i=1}^k \min\{\alpha, \gamma - \sum_{j=1}^{i-1} \beta_{ji}\} \right) \quad (\text{A.15})$$

where

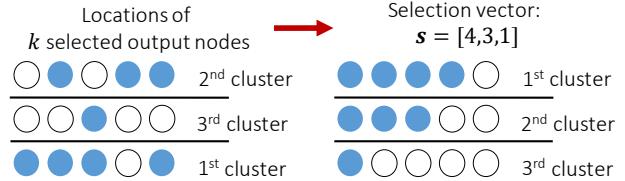
$$\beta_{ji} = \begin{cases} \beta_I, & v^j \text{ and } v^i \text{ are in the same cluster} \\ \beta_c, & \text{otherwise.} \end{cases} \quad (\text{A.16})$$

holds as defined in (A.12), and \mathcal{V}_k is defined in (A.9). In order to obtain the solution for RHS of (A.15), all we need to do is to find the optimal sequence $(v^i)_{i=1}^k$ of k different nodes, which can be divided into two sub-problems: *i*) finding the optimal way of selecting k nodes $\{v^i\}_{i=1}^k$ out of n nodes, and *ii*) finding the optimal order of selected k nodes. Note that there are $\binom{n}{k}$ selection methods and $k!$ ordering methods. Each selection method can be assigned to a *selection vector* s defined in Definition 1, and each ordering method can be assigned to an *ordering vector* π defined in Definition 2.

First, we define a selection vector s for a given $\{v^i\}_{i=1}^k$.

Definition 1. Assume arbitrary k nodes are selected as $\{v^i\}_{i=1}^k$. Label each cluster by the number of selected nodes in a descending order. In other words, the 1st cluster contains a maximum number of selected nodes, and the L th cluster contains a minimum number of selected nodes. Under this setting, define the selection vector $s = [s_1, s_2, \dots, s_L]$ where s_i is the number of selected nodes in the i th cluster.

Fig. 21 shows an example of selection vector s corresponding to the selected k nodes $\{v^i\}_{i=1}^k$. From the definition of the selection vector, the set of possible selection vectors can

Fig. 21: Obtaining the selection vector for given k output nodes $\{v_{out}^i\}_{i=1}^k$ ($n = 15, k = 8, L = 3$)

An arbitrary ordering of k nodes, for given selection vector $s = [4, 3, 1]$



Corresponding ordering vector:
 $\pi = [2, 1, 2, 3, 1, 2, 1, 1]$

Fig. 22: Obtaining the ordering vector for given an arbitrary order of k output nodes ($n = 15, k = 8, L = 3$)

be specified as follows.

$$\mathcal{S} = \{s = [s_1, \dots, s_L] : 0 \leq s_i \leq n_I, s_{i+1} \leq s_i, \sum_{i=1}^L s_i = k\}.$$

Note that even though $\binom{n}{k}$ different selections exist, the $\{\omega_i\}$ values in (A.11) are only determined by the corresponding selection vector s . This is because $\{\omega_i\}$ depends only on the relative positions of $\{v^i\}_{i=1}^k$, whether they are in the same cluster or in different clusters. Therefore, comparing the $\{\omega_i\}$ values of all $|\mathcal{S}|$ possible selection vectors s is enough; it is not necessary to compare the $\{\omega_i\}$ values of $\binom{n}{k}$ selection methods. Now, we define the ordering vector π for a given selection vector s .

Definition 2. Let the locations of k nodes $\{v^i\}_{i=1}^k$ be fixed with a corresponding selection vector $s = [s_1, \dots, s_L]$. Then, for arbitrary ordering of the selected k nodes, define the ordering vector $\pi = [\pi_1, \dots, \pi_k]$ where π_i is the index of the cluster which contains v^i .

For a given s , the ordering vector π corresponding to an arbitrary ordering of k nodes is illustrated in Fig. 22. In this figure (and the following figures in this paper), the number i written inside each node means that the node is v^i . From the definition, an ordering vector π has s_l components with value l , for all $l \in [L]$. The set of possible ordering vectors can be specified as

$$\Pi(s) = \{\pi = [\pi_1, \dots, \pi_k] : \sum_{i=1}^k \mathbb{1}_{\pi_i=l} = s_l, \forall l \in [L]\} \quad (\text{A.17})$$

Note that for given k selected nodes, there exists $k!$ different ordering methods. However, the $\{\omega_i\}$ values in (A.11) are only determined by the corresponding ordering vector $\pi \in \Pi(s)$, by similar reasoning for compressing $\binom{n}{k}$ selection methods to $|\mathcal{S}|$ selection vectors. Therefore, comparing the $\{\omega_i\}$ values of all possible ordering vectors π is enough; it is not necessary to compare the $\{\omega_i\}$ values of all $k!$ ordering methods.

Thus, finding the optimal sequence $(v^i)_{i=1}^k$ is identical to specifying the optimal (s, π) pair, which is obtained as fol-

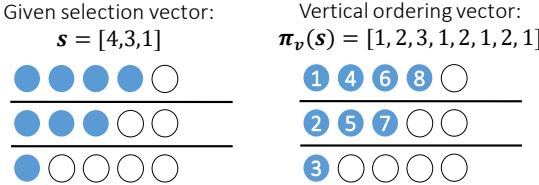


Fig. 23: The vertical ordering vector π_v for the given selection vector $s = [4, 3, 1]$ (for $n = 15, k = 8, L = 3$ case)

vertical ordering vector π_v minimizes $L(s, \pi)$. In other words, $L(s, \pi_v) \leq L(s, \pi)$ holds for arbitrary $\pi \in \Pi(s)$.

Proof. In the case of $\beta_c = 0$, we show that $L(s, \pi)$ is constant for every $\pi \in \Pi(s)$. From (A.20),

$$L(s, \pi) = \sum_{i=1}^k \min\{\alpha, a_i(\pi)\beta_I\} \quad (\text{A.28})$$

holds for $\beta_c = 0$. Using $I_l(\pi)$ in (A.26), note that $[k]$ can be partitioned into L disjoint subsets as $[k] = \bigcup_{l=1}^L I_l(\pi)$. Therefore, (A.28) can be written as

$$L(s, \pi) = \sum_{l=1}^L \sum_{i \in I_l(\pi)} \min\{\alpha, a_i(\pi)\beta_I\}.$$

Recall that $\pi \in \Pi(s)$ contains s_l components with value l for $l \in [L]$. Thus, from (A.22),

$$\bigcup_{i \in I_l(\pi)} \{a_i(\pi)\} = \{n_I - 1, n_I - 2, \dots, n_I - s_l\}$$

for $l \in [L]$. Therefore, $\sum_{i \in I_l(\pi)} \min\{\alpha, a_i(\pi)\beta_I\}$ is constant $\forall \pi \in \Pi(s)$ for arbitrary $l \in [L]$. In conclusion, $L(s, \pi)$ in (A.28) is constant irrespective of $\pi \in \Pi(s)$ for $\beta_c = 0$.

The rest of the proof deals with the $\beta_c \neq 0$ case. For a given arbitrary $s \in \mathcal{S}$, define two subsets of $\Pi(s)$ as

$$\Pi_r = \{\pi^* \in \Pi(s) : S_t(\pi) \leq S_t(\pi^*), \forall t \in [k], \forall \pi \in \Pi(s)\} \quad (\text{A.29})$$

$$\Pi_m = \{\pi^* \in \Pi(s) : L(s, \pi) \geq L(s, \pi^*), \forall \pi \in \Pi(s)\} \quad (\text{A.30})$$

where $S_t(\pi) = \sum_{i=1}^t w_i(\pi)$ is the running sum of $w_i(\pi)$. Here, we call Π_r the *running sum maximizer* and Π_m the *min-cut minimizer*. Now the proof proceeds in two steps. The first step proves that the *running sum maximizer* minimizes min-cut, i.e., $\Pi_r \subseteq \Pi_m$. The second step proves that the vertical ordering vector is a running sum maximizer, i.e., $\pi_v \in \Pi_r$.

Step 1. Prove $\Pi_r \subseteq \Pi_m$:

Define two index sets for a given ordering vector π :

$$\begin{aligned} \Omega_L(\pi) &= \{i \in [k] : w_i(\pi) \geq \alpha\} \\ \Omega_s(\pi) &= \{i \in [k] : w_i(\pi) < \alpha\} \end{aligned} \quad (\text{A.31})$$

Now define a set of ordering vectors as

$$\Pi_p = \{\pi \in \Pi(s) : i \leq j \forall i \in \Omega_L(\pi), \forall j \in \Omega_s(\pi)\}. \quad (\text{A.32})$$

The rest of the proof is divided into 2 sub-steps.

Step 1-1. Prove $\Pi_m \subseteq \Pi_p$ and $\Pi_r \subseteq \Pi_p$ by transposition:

Consider arbitrary $\pi = [\pi_1, \dots, \pi_k] \in \Pi_p^c$. Use a short-

hand notation ω_i to represent $\omega_i(\pi)$ for $i \in [k]$. From (A.32), there exists $i > j$ such that $i \in \Omega_L(\pi)$ and $j \in \Omega_s(\pi)$. Therefore, there exists $t \in [k-1]$ such that $t+1 \in \Omega_L(\pi)$ and $t \in \Omega_s(\pi)$ hold. By (A.31),

$$\omega_{t+1} \geq \alpha > \omega_t \quad (\text{A.33})$$

for some $t \in [k-1]$. Note that from (A.21), $\pi_t = \pi_{t+1}$ implies $\omega_{t+1} = \omega_t - \beta_I < \omega_t$. Therefore,

$$\pi_t \neq \pi_{t+1} \quad (\text{A.34})$$

should hold to satisfy (A.33). Define an ordering vector $\pi' = [\pi'_1, \dots, \pi'_k]$ as

$$\begin{cases} \pi'_i = \pi_i & i \neq t, t+1 \\ \pi'_t = \pi_{t+1} \\ \pi'_{t+1} = \pi_t. \end{cases} \quad (\text{A.35})$$

Use a short-hand notation ω'_i to represent $\omega_i(\pi')$ for $i \in [k]$. Note that $\{\omega'_i\}$ satisfies

$$\begin{cases} \omega'_i = \omega_i & i \neq t, t+1 \\ \omega'_t = \omega_{t+1} + \beta_c \\ \omega'_{t+1} = \omega_t - \beta_c \end{cases} \quad (\text{A.36})$$

for the following reason. First, use simplified notations a_i and a'_i to mean $a_i(\pi)$ and $a_i(\pi')$, respectively. Then, using (A.22), (A.34) and (A.35), we have

$$\begin{aligned} a'_t &= n_I - 1 - \sum_{j=1}^{t-1} \mathbb{1}_{\pi'_j = \pi'_t} = n_I - 1 - \sum_{j=1}^{t-1} \mathbb{1}_{\pi_j = \pi_{t+1}} \\ &= n_I - 1 - \sum_{j=1}^t \mathbb{1}_{\pi_j = \pi_{t+1}} = a_{t+1}. \end{aligned} \quad (\text{A.37})$$

Similarly,

$$\begin{aligned} a'_{t+1} &= n_I - 1 - \sum_{j=1}^t \mathbb{1}_{\pi'_j = \pi'_{t+1}} = n_I - 1 - \sum_{j=1}^{t-1} \mathbb{1}_{\pi'_j = \pi'_{t+1}} \\ &= n_I - 1 - \sum_{j=1}^{t-1} \mathbb{1}_{\pi_j = \pi_t} = a_t. \end{aligned} \quad (\text{A.38})$$

Therefore, from (A.11), (A.37) and (A.38), we have

$$\begin{aligned} \omega'_t &= a'_t \beta_I + (n - t - a'_t) \beta_c \\ &= a_{t+1} \beta_I + (n - t - a_{t+1}) \beta_c = \omega_{t+1} + \beta_c. \end{aligned}$$

Similarly, $\omega'_{t+1} = \omega_t - \beta_c$ holds. This proves (A.36). Thus, from (A.33) and (A.36),

$$L(s, \pi) = \sum_{i=1}^k \min\{\alpha, \omega_i\} = \sum_{i \notin \{t, t+1\}} \min\{\alpha, \omega_i\} + \omega_t + \alpha,$$

$$\begin{aligned}
L(\mathbf{s}, \boldsymbol{\pi}') &= \sum_{i=1}^k \min\{\alpha, \omega'_i\} \\
&= \sum_{i \notin \{t, t+1\}} \min\{\alpha, \omega'_i\} + \alpha + (\omega_t - \beta_c) \\
&= \sum_{i \notin \{t, t+1\}} \min\{\alpha, \omega_i\} + \alpha + (\omega_t - \beta_c).
\end{aligned}$$

Therefore, $L(\mathbf{s}, \boldsymbol{\pi}) > L(\mathbf{s}, \boldsymbol{\pi}')$ holds for $\beta_c > 0$. In other words, if $\boldsymbol{\pi} \in \Pi_p^c$, then $\boldsymbol{\pi} \in \Pi_m^c$. This proves that $\Pi_p^c \subseteq \Pi_m^c$ holds for $\beta_c \neq 0$.

Similarly, $\Pi_p^c \subseteq \Pi_r^c$ can be proved as follows. For the pre-defined ordering vectors $\boldsymbol{\pi}$ and $\boldsymbol{\pi}'$, we have $S_t(\boldsymbol{\pi}) = \sum_{i=1}^{t-1} \omega_i + \omega_t$ and $S_t(\boldsymbol{\pi}') = \sum_{i=1}^{t-1} \omega_i + \omega_{t+1} + \beta_c$. Using (A.33), we have $S_t(\boldsymbol{\pi}) < S_t(\boldsymbol{\pi}')$, so that $\boldsymbol{\pi}$ cannot be a running-sum maximizer. Therefore, $\Pi_p^c \subseteq \Pi_r^c$ holds.

Step 1-2. Prove that $L(\mathbf{s}, \boldsymbol{\pi}^*) \leq L(\mathbf{s}, \boldsymbol{\pi})$, $\forall \boldsymbol{\pi}^* \in \Pi_r$, $\forall \boldsymbol{\pi} \in \Pi_p \cap \Pi_r^c$:

Consider arbitrary $\boldsymbol{\pi}^* \in \Pi_r$ and $\boldsymbol{\pi} \in \Pi_p \cap \Pi_r^c$. For $i \in [k]$, let ω_i^* and ω_i be short-hand notations for $\omega_i(\boldsymbol{\pi}^*)$ and $\omega_i(\boldsymbol{\pi})$, respectively. Note that from Proposition 3,

$$\sum_{i=1}^k \omega_i = \sum_{i=1}^k \omega_i^*. \quad (\text{A.39})$$

Let

$$\begin{aligned}
t &= \max\{i \in [k] : \omega_i \geq \alpha\}, \\
t^* &= \max\{i \in [k] : \omega_i^* \geq \alpha\}
\end{aligned} \quad (\text{A.40})$$

Then, from (A.29),

$$\sum_{i=1}^t \omega_i \leq \sum_{i=1}^t \omega_i^*. \quad (\text{A.41})$$

Combining with (A.39), we obtain

$$\sum_{i=t+1}^k (\omega_i - \omega_i^*) \geq 0. \quad (\text{A.42})$$

Note that from the result of Step 1-1, both $\boldsymbol{\pi}$ and $\boldsymbol{\pi}^*$ are in Π_p . Therefore, $\omega_i \geq \alpha$ for $i \in [t]$. Similarly, $\omega_i^* \geq \alpha$ for $i \in [t^*]$. Therefore, (A.20) can be expressed as

$$L(\mathbf{s}, \boldsymbol{\pi}) = \sum_{i=1}^k \min\{\alpha, \omega_i\} = \sum_{i=1}^t \alpha + \sum_{i=t+1}^k \omega_i, \quad (\text{A.43})$$

$$L(\mathbf{s}, \boldsymbol{\pi}^*) = \sum_{i=1}^k \min\{\alpha, \omega_i^*\} = \sum_{i=1}^{t^*} \alpha + \sum_{i=t^*+1}^k \omega_i^*. \quad (\text{A.44})$$

If $t = t^*$, then we have

$$L(\mathbf{s}, \boldsymbol{\pi}) - L(\mathbf{s}, \boldsymbol{\pi}^*) = \sum_{i=t+1}^k (\omega_i - \omega_i^*) \geq 0$$

from (A.42). If $t > t^*$, we get

$$L(\mathbf{s}, \boldsymbol{\pi}) - L(\mathbf{s}, \boldsymbol{\pi}^*) = \sum_{i=t^*+1}^t (\alpha - \omega_i^*) + \sum_{i=t+1}^k (\omega_i - \omega_i^*).$$

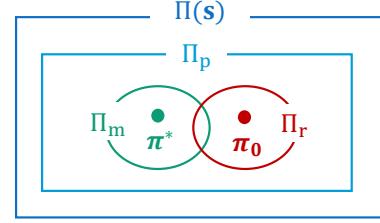


Fig. 24: Relationship between sets

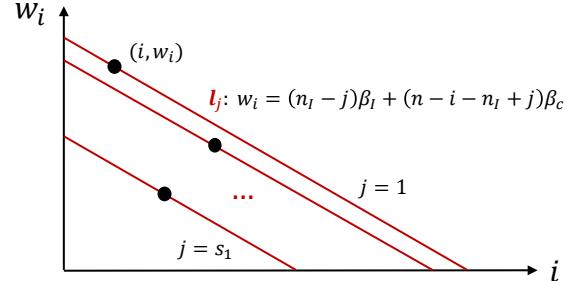


Fig. 25: Set of s_1 lines where (i, ω_i) points can position

From (A.40), $\omega_i^* < \alpha$ holds for $i > t^*$. Therefore,

$$L(\mathbf{s}, \boldsymbol{\pi}) - L(\mathbf{s}, \boldsymbol{\pi}^*) > \sum_{i=t+1}^k (\omega_i - \omega_i^*) \geq 0$$

from (A.42). In the case of $t < t^*$, define $\Delta = \sum_{i=1}^t (\omega_i - \alpha)$ and $\Delta^* = \sum_{i=1}^t (\omega_i^* - \alpha)$. From (A.43),

$$L(\mathbf{s}, \boldsymbol{\pi}) = \sum_{i=1}^t \alpha + \sum_{i=t+1}^k \omega_i = (\sum_{i=1}^k \omega_i) - \Delta.$$

Similarly, from (A.44),

$$\begin{aligned}
L(\mathbf{s}, \boldsymbol{\pi}^*) &= \sum_{i=1}^k \omega_i^* - \sum_{i=1}^{t^*} (\omega_i^* - \alpha) \\
&= \sum_{i=1}^k \omega_i^* - \Delta^* - \sum_{i=t+1}^{t^*} (\omega_i^* - \alpha) \leq \sum_{i=1}^k \omega_i^* - \Delta^*
\end{aligned}$$

where the last inequality is from (A.40). Combined with (A.39) and (A.41), we obtain

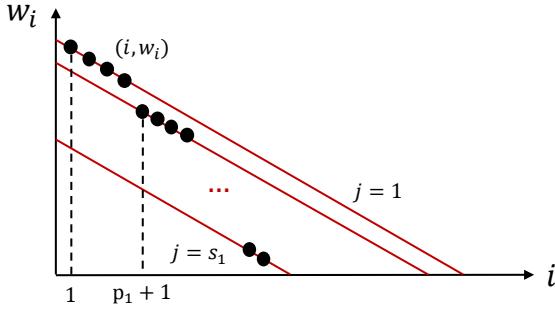
$$L(\mathbf{s}, \boldsymbol{\pi}) - L(\mathbf{s}, \boldsymbol{\pi}^*) \geq \Delta^* - \Delta \geq 0.$$

In summary, $L(\mathbf{s}, \boldsymbol{\pi}^*) \leq L(\mathbf{s}, \boldsymbol{\pi})$ irrespective of the t, t^* values, which completes the proof for Step 1-2. From the results of Step 1-1 and Step 1-2, the relationship between the sets can be depicted as in Fig. 24.

Consider $\boldsymbol{\pi}_0 \in \Pi_r$ and $\boldsymbol{\pi}^* \in \Pi_m \cap \Pi_r^c$. Then, $L(\mathbf{s}, \boldsymbol{\pi}_0) \leq L(\mathbf{s}, \boldsymbol{\pi}^*)$ from the result of Step 1-2. Based on the definition of Π_m in (A.30), we can write $L(\mathbf{s}, \boldsymbol{\pi}_0) \leq L(\mathbf{s}, \boldsymbol{\pi})$ for every $\boldsymbol{\pi} \in \Pi(\mathbf{s})$. In other words, $\boldsymbol{\pi}_0 \in \Pi_m$ holds for arbitrary $\boldsymbol{\pi}_0 \in \Pi_r$. Therefore, $\Pi_r \subseteq \Pi_m$ holds.

Step 2. Prove $\boldsymbol{\pi}_v \in \Pi_r$:

For a given selection vector $\mathbf{s} = [s_1, \dots, s_L]$, consider an arbitrary ordering vector $\boldsymbol{\pi} = [\pi_1, \dots, \pi_k] \in \Pi(\mathbf{s})$. The

Fig. 26: Optimal packing of k points

corresponding $\omega_i(\pi)$ defined in (A.21) is written as

$$w_i = (n_I - j)\beta_I + (n - i - n_I + j)\beta_c \quad (\text{A.45})$$

where $j = \sum_{t=1}^i \mathbb{1}_{\pi_t=\pi_i}$.

Consider a set of lines $\{l_j\}_{j=1}^{n_I}$, where line l_j represents an equation: $w_i = (n_I - j)\beta_I + (n - i - n_I + j)\beta_c$. Since we assume $\beta_I \geq \beta_c$, these lines can be illustrated as in Fig. 25. For a given π , consider marking a (i, ω_i) point for $i \in [k]$. Note that the (i, ω_i) point is on line l_j if and only if

$$j = \sum_{t=1}^i \mathbb{1}_{\pi_t=\pi_i} \quad (\text{A.46})$$

where the summation term in (A.46) represents the number of occurrence of π_i value in $\{\pi_t\}_{t=1}^i$. For the example in Fig. 23, when $s = [4, 3, 1]$ and $\pi = [1, 2, 3, 1, 2, 1, 2, 1] \in \Pi(s)$, line l_3 contains the point $(i, \omega_i) = (6, \omega_6)$ since $3 = \sum_{t=1}^6 \mathbb{1}_{\pi_t=\pi_6}$.

Recall that $I_l(\pi) = \{i \in [k] : \pi_i = l\}$, as defined in (A.26), where $|I_l(\pi)| = s_l$ holds $\forall l \in [L]$. For $j \in [n_I]$, consider $l \in [L]$ with $s_l \geq j$. Let i_0 be the j^{th} smallest element in $I_l(\pi)$. Then, $j = \sum_{t=1}^{i_0} \mathbb{1}_{\pi_t=l}$ and $\pi_{i_0} = l$ hold. Thus, the (i_0, ω_{i_0}) point is on line l_j . Similarly, we can find

$$p_j = \sum_{l=1}^L \mathbb{1}_{s_l \geq j} \quad (\text{A.47})$$

points on line l_j , irrespective of the ordering vector $\pi \in \Pi(s)$. Note that

$$\sum_{j=1}^{n_I} p_j = \sum_{l=1}^L \sum_{j=1}^{n_I} \mathbb{1}_{s_l \geq j} = \sum_{l=1}^L s_l = k, \quad (\text{A.48})$$

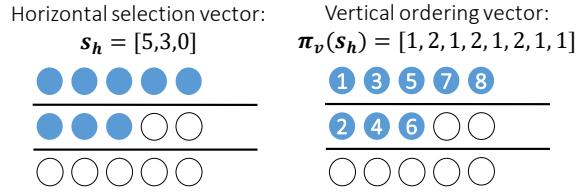
which confirms that Fig. 25 contains k points. Moreover,

$$\forall j \in [n_I - 1], p_j \geq p_{j+1} \quad (\text{A.49})$$

holds from the definition in (A.47).

In order to maximize the running sum $S_t(\pi) = \sum_{i=1}^t w_i(\pi)$ for every t , the optimal ordering vector packs p_1 points in the leftmost area ($i = 1, \dots, p_1$), pack p_2 points in the leftmost remaining area ($i = p_1 + 1, \dots, p_1 + p_2$), and so on. This packing method corresponds to Fig. 26.

Note that from the definition of p_j in (A.47) and Fig. 23, vertical ordering π_v in Definition 3 first chooses p_1 points on line l_1 , then chooses p_2 points on line l_2 , and so on. Thus, π_v achieves optimal packing in Fig. 26, which maximizes the running sum $S_t(\pi)$. Therefore, vertical ordering is a running

Fig. 27: The optimal selection vector s_h and the optimal ordering vector π_v (for $n = 15, k = 8, L = 3$ case)

sum maximizer, i.e., $\pi_v \in \Pi_r$. Combining Steps 1 and 2, we conclude that π_v minimizes $L(s, \pi)$ among $\pi \in \Pi(s)$ for arbitrary $s \in S$. \square

Now, we define a special selection vector called the *horizontal selection vector*, which is shown to be the optimal selection vector which minimizes $L(s, \pi_v)$.

Definition 4. The horizontal selection vector $s_h = [s_1, \dots, s_L] \in \mathcal{S}$ is defined as:

$$s_i = \begin{cases} n_I, & i \leq \lfloor \frac{k}{n_I} \rfloor \\ (k \bmod n_I), & i = \lfloor \frac{k}{n_I} \rfloor + 1 \\ 0, & i > \lfloor \frac{k}{n_I} \rfloor + 1. \end{cases}$$

The graphical illustration of the horizontal selection vector is on the left side of Fig. 27, in the case of $n = 15, k = 8, L = 3$. The following Lemma states that the horizontal selection vector minimizes $L(s, \pi_v)$.

Lemma 4. Consider applying the vertical ordering vector π_v . Then, the horizontal selection vector s_h minimizes the lower bound $L(s, \pi)$ on the min-cut. In other words, $L(s_h, \pi_v) \leq L(s, \pi_v) \forall s \in \mathcal{S}$.

Proof. From the proof of Lemma 3, the optimal ordering vector turns out to be the vertical ordering vector, where the corresponding $\omega_i(\pi_v)$ sequence is illustrated in Fig. 26. Depending on the selection vector $s = [s_1, \dots, s_L]$, the number p_j of points on each line l_j changes.

Consider an arbitrary selection vector s . Define a point vector $p(s) = [p_1, \dots, p_{n_I}]$ where p_j is the number of points on l_j , as defined in (A.47). Similarly, define $p(s_h) = [p_1^*, \dots, p_{n_I}^*]$. Using Definition 4 and (A.47), we have

$$p_j^* = \begin{cases} \lfloor \frac{k}{n_I} \rfloor + 1, & j \leq (k \bmod n_I) \\ \lfloor \frac{k}{n_I} \rfloor & \text{otherwise} \end{cases} \quad (\text{A.50})$$

Now, we prove

$$\forall t \in [n_I], \sum_{j=1}^t p_j^* \leq \sum_{j=1}^t p_j. \quad (\text{A.51})$$

The proof is divided into two steps: *base case* and *inductive step*.

Base Case: We wish to prove that $p_1^* \leq p_1$. Suppose $p_1^* > p_1$ (i.e., $p_1 \leq p_1^* - 1$). Then,

$$\sum_{l=1}^{n_I} p_l \leq \sum_{l=1}^{n_I} p_1 \leq \sum_{l=1}^{n_I} (p_1^* - 1) \quad (\text{A.52})$$

where the first inequality is from (A.49). Note that if $(k \bmod n_I) = 0$, then

$$\sum_{l=1}^{n_I} p_l^* = \sum_{l=1}^{n_I} p_l^* > \sum_{l=1}^{n_I} (p_1^* - 1). \quad (\text{A.53})$$

Otherwise,

$$\begin{aligned} \sum_{l=1}^{n_I} p_l^* &= \sum_{l=1}^{(k \bmod n_I)} p_l^* + \sum_{l=(k \bmod n_I)+1}^{n_I} p_l^* \\ &= \sum_{l=1}^{(k \bmod n_I)} (\lfloor \frac{k}{n_I} \rfloor + 1) + \sum_{l=(k \bmod n_I)+1}^{n_I} \lfloor \frac{k}{n_I} \rfloor \\ &> \sum_{l=1}^{n_I} \lfloor \frac{k}{n_I} \rfloor = \sum_{l=1}^{n_I} (p_1^* - 1). \end{aligned} \quad (\text{A.54})$$

Therefore, combining (A.52), (A.53) and (A.54) results in $\sum_{l=1}^{n_I} p_l < \sum_{l=1}^{n_I} p_l^* = k$, which contradicts (A.48). Therefore, $p_1^* \leq p_1$ holds.

Inductive Step: Assume that $\sum_{l=1}^{l_0} p_l^* \leq \sum_{l=1}^{l_0} p_l$ for arbitrary $l_0 \in [n_I - 1]$. Now we prove that $\sum_{l=1}^{l_0+1} p_l^* \leq \sum_{l=1}^{l_0+1} p_l$ holds. Suppose not. Then,

$$p_{l_0+1}^* - \Theta - 1 \geq p_{l_0+1} \quad (\text{A.55})$$

holds where

$$\Theta = \sum_{l=1}^{l_0} (p_l - p_l^*). \quad (\text{A.56})$$

Using (A.49) and (A.55), we have

$$\begin{aligned} \sum_{l=l_0+1}^{n_I} p_l &\leq \sum_{l=l_0+1}^{n_I} p_{l_0+1} \leq \sum_{l=l_0+1}^{n_I} (p_{l_0+1}^* - 1 - \Theta) \\ &\leq \sum_{l=l_0+1}^{n_I} (p_{l_0+1}^* - 1) - \Theta \end{aligned} \quad (\text{A.57})$$

where equality holds for the last inequality iff $l_0 = n_I - 1$. Using analysis similar to (A.53) and (A.54) for the *base case*, we can find that $\sum_{l=l_0+1}^{n_I} (p_{l_0+1}^* - 1) < \sum_{l=l_0+1}^{n_I} p_l^*$. Combining with (A.57), we get

$$\sum_{l=l_0+1}^{n_I} p_l < \sum_{l=l_0+1}^{n_I} p_l^* - \Theta. \quad (\text{A.58})$$

Equations (A.56) and (A.58) imply $\sum_{l=1}^{n_I} p_l < \sum_{l=1}^{n_I} p_l^* = k$, which contradicts (A.48). Therefore, (A.51) holds.

Now define

$$f_i = \min\{s \in [n_I] : \sum_{l=1}^s p_l \geq i\} \quad (\text{A.59})$$

$$h_i = \min\{s \in [n_I] : \sum_{l=1}^s p_l^* \geq i\} \quad (\text{A.60})$$

for $i \in [k]$. Then,

$$\forall i \in [k], h_i \geq f_i \quad (\text{A.61})$$

holds directly from (A.51). Note that since p_i^* in (A.50) is

identical to g_i in (7), h_i can be written as

$$h_i = \min\{s \in [n_I] : \sum_{l=1}^s g_l \geq i\} \quad (\text{A.62})$$

Consider $\pi_v(s)$, the vertical ordering vector for a given selection vector s . Recall that as in Fig. 26, vertical ordering packs the leftmost p_1 points on line l_1 , packs the next p_2 points on line l_2 , and so on. Using (A.45), we can write

$$\omega_i = \begin{cases} (n_I - 1)\beta_I + (n - i - n_I + 1)\beta_c, & \text{if } i \in [p_1] \\ (n_I - 2)\beta_I + (n - i - n_I + 2)\beta_c, & \text{if } i - p_1 \in [p_2] \\ \vdots \\ 0 \cdot \beta_I + (n - i)\beta_c, & \text{if } i - \sum_{t=1}^{n_I-1} p_t \in [p_{n_I}] \end{cases}$$

Therefore, using (A.59), we further write

$$\omega_i(\pi_v(s)) = (n_I - f_i)\beta_I + (n - i - n_I + f_i)\beta_c. \quad (\text{A.63})$$

Similarly,

$$\omega_i(\pi_v(s_h)) = (n_I - h_i)\beta_I + (n - i - n_I + h_i)\beta_c. \quad (\text{A.64})$$

Combining (A.61), (A.63) and (A.64), we have

$$\omega_i(\pi_v(s_h)) \leq \omega_i(\pi_v(s)) \quad \forall i = 1, \dots, k, \forall s \in \mathcal{S},$$

since we assume $\beta_I \geq \beta_c$. Therefore, combining with (A.20), we conclude that $L(s_h, \pi_v) \leq L(s, \pi_v)$ for arbitrary $s \in \mathcal{S}$, which completes the proof of Lemma 4. \square

From Lemmas 3 and 4, we have

$$\forall s \in \mathcal{S}, \forall \pi \in \Pi(s), L(s_h, \pi_v) \leq L(s, \pi).$$

All that remains is to compute $L(s_h, \pi_v)$ and check that it is identical to (A.1).

From (A.20), $L(s_h, \pi_v)$ can be written as

$$L(s_h, \pi_v) = \sum_{i=1}^k \min\{\alpha, \omega_i(\pi_v(s_h))\} \quad (\text{A.65})$$

where $\omega_i(\pi_v(s_h))$ is defined in (A.64). From h_i in (A.62), we have

$$h_i = \begin{cases} 1, & i \in [g_1] \\ 2, & i - g_1 \in [g_2] \\ \vdots \\ n_I, & i - \sum_{t=1}^{n_I-1} g_t \in [g_{n_I}] \end{cases} \quad (\text{A.66})$$

If we define

$$I_m^* = \{i \in [k] : h_i = m\},$$

then $L(s_h, \pi_v)$ in (A.65) can be expressed as

$$\begin{aligned} L(s_h, \pi_v) &= \sum_{i=1}^k \min\{\alpha, (n_I - h_i)\beta_I + (n - n_I - i + h_i)\beta_c\} \\ &= \sum_{m=1}^{n_I} \sum_{i \in I_m^*} \min\{\alpha, (n_I - m)\beta_I + (n - n_I - i + m)\beta_c\} \\ &= \sum_{m=1}^{n_I} \sum_{i \in I_m^*} \min\{\alpha, \rho_m \beta_I + (n - \rho_m - i)\beta_c\} \end{aligned} \quad (\text{A.67})$$

where ρ_m is defined in (6).

Using (A.66), we have

$$I_m^* = \left\{ \sum_{t=1}^{m-1} g_t + 1, \dots, \sum_{t=1}^{m-1} g_t + g_m \right\}.$$

for $m \in [n_I]$. Therefore, $i \in I_m^*$ can be represented as

$$i = \sum_{t=1}^{m-1} g_t + l$$

for $l \in [g_m]$. Using this notation, (A.67) can be written as

$$L(\mathbf{s}_h, \boldsymbol{\pi}_v) = \sum_{m=1}^{n_I} \sum_{l=1}^{g_m} \min\{\alpha, \rho_m \beta_I + (n - \rho_m - s_m^{(l)}) \beta_c\} \quad (\text{A.68})$$

where $s_m^{(l)} = \sum_{t=1}^{m-1} g_t + l$. This expression reduces to (A.1). This completes the proof of Part II-2. Therefore, the storage capacity of clustered DSS is as stated in Theorem 1.

APPENDIX B PROOF OF THEOREM 3

We begin with introducing properties of the parameters z_t and h_t defined in (25) and (26).

Proposition 4.

$$h_k = n_I, \quad (\text{B.1})$$

$$z_k = (n - k)\epsilon. \quad (\text{B.2})$$

Proof. Since we consider $k > n_I$ case as stated in (3), we have

$$g_i \geq 1 \quad \forall i \in [n_I]$$

for $\{g_i\}_{i=1}^{n_I}$ defined in (7). Combining with (9) and (26), we can conclude that $h_k = n_I$. Finally, $z_k = (n - k)\epsilon$ is from (25) and (B.1). \square

First, consider the $\epsilon \geq \frac{1}{n-k}$ case. From (20), data \mathcal{M} can be reliably stored with node storage $\alpha = \mathcal{M}/k$ if the repair bandwidth satisfies $\gamma \geq \gamma^*$, where

$$\begin{aligned} \gamma^* &= \frac{\mathcal{M} - (k-1)\mathcal{M}/k}{s_{k-1}} = \frac{\mathcal{M}}{k} \frac{1}{s_{k-1}} \\ &= \frac{\mathcal{M}}{k} \frac{(n-k)\epsilon}{(n_I-1) + (n-n_I)\epsilon} \end{aligned}$$

where the last equality is from (23) and (B.2). Thus, $\alpha = \mathcal{M}/k$ is achievable with finite γ , when $\epsilon \geq \frac{1}{n-k}$.

Second, we prove that it is impossible to achieve $\alpha = \mathcal{M}/k$ for $0 \leq \epsilon < \frac{1}{n-k}$, in order to reliably store file \mathcal{M} . Recall that the minimum storage for $0 \leq \epsilon < \frac{1}{n-k}$ is

$$\alpha = \frac{\mathcal{M}}{\tau + \sum_{i=\tau+1}^k z_i} \quad (\text{B.3})$$

from (28). From (22) and (B.2), we have $z_i < 1$ for $i = \tau + 1, \tau + 2, \dots, k$. Therefore,

$$\tau + \sum_{i=\tau+1}^k z_i < \tau + (k - (\tau + 1) + 1) = k$$

holds, which result in

$$\frac{\mathcal{M}}{\tau + \sum_{i=\tau+1}^k z_i} > \frac{\mathcal{M}}{k}. \quad (\text{B.4})$$

Thus, the $0 \leq \epsilon \leq \frac{1}{n-k}$ case has the minimum storage α greater than \mathcal{M}/k , which completes the proof of Theorem 3.

APPENDIX C PROOF OF THEOREM 4

First, we prove (30). To begin with, we obtain the expression of $\alpha_{msr}^{(\epsilon)}$, for $\epsilon = 0, 1$. From (28), we obtain

$$\begin{aligned} \alpha_{msr}^{(0)} &= \frac{\mathcal{M}}{\tau + \sum_{i=\tau+1}^k z_i}, \\ \alpha_{msr}^{(1)} &= \frac{\mathcal{M}}{k}. \end{aligned} \quad (\text{C.1})$$

We further simplify the expression for $\alpha_{msr}^{(0)}$ as follows. Recall

$$z_t = n_I - h_t \quad (\text{C.2})$$

for $t \in [k]$ from (25), when $\epsilon = 0$ holds. Note that we have

$$z_t = \begin{cases} 0, & t \geq k - \lfloor \frac{k}{n_I} \rfloor + 1 \\ 1, & t = k - \lfloor \frac{k}{n_I} \rfloor \end{cases} \quad (\text{C.3})$$

from the following reason. First, from (26) and (C.2), $z_t = 0$ holds for

$$t \geq \sum_{l=1}^{n_I-1} g_l + 1 = \sum_{l=1}^{n_I} g_l - g_{n_I} + 1 = k - \lfloor \frac{k}{n_I} \rfloor + 1$$

where the last equality is from (9) and (7). Similarly, we can prove that $z_t = 1$ holds for $t = k - \lfloor \frac{k}{n_I} \rfloor$. From (C.3) and (22), we obtain

$$\tau = k - \lfloor \frac{k}{n_I} \rfloor \quad (\text{C.4})$$

when $\epsilon = 0$. Combining (C.1), (C.3) and (C.4), we have

$$\alpha_{msr}^{(0)} = \frac{\mathcal{M}}{k - \lfloor \frac{k}{n_I} \rfloor}. \quad (\text{C.5})$$

Then, using $R = k/n$ and $\sigma = L^2/n$,

$$\begin{aligned} \frac{\alpha_{msr}^{(0)}}{\alpha_{msr}^{(1)}} &= \frac{k}{k - \lfloor \frac{k}{n_I} \rfloor} = \frac{nR}{nR - \lfloor RL \rfloor} \\ &= \frac{nR}{nR - \lfloor R\sqrt{n\sigma} \rfloor} = \frac{R}{R - \lfloor R\sqrt{n\sigma} \rfloor/n}. \end{aligned}$$

Thus, for arbitrary fixed R and σ ,

$$\lim_{n \rightarrow \infty} \frac{\alpha_{msr}^{(0)}}{\alpha_{msr}^{(1)}} = 1.$$

Therefore, $\alpha_{msr}^{(0)}$ is asymptotically equivalent to $\alpha_{msr}^{(1)}$.

Second, we prove (31). Note that from (29), $\alpha_{mbr}^{(\epsilon)} = \gamma_{mbr}^{(\epsilon)}$ holds for arbitrary $0 \leq \epsilon \leq 1$. Therefore, all we need to prove is

$$\gamma_{mbr}^{(0)} \rightarrow \gamma_{mbr}^{(1)}.$$

To begin with, we obtain the expression for $\gamma_{mbr}^{(\epsilon)}$, when $\epsilon = 0, 1$. For $\epsilon = 1$, z_t in (25) is

$$z_t = n - t \quad (\text{C.6})$$

for $t \in [k]$. Moreover, from (23),

$$s_0 = \frac{\sum_{i=1}^k z_i}{n-1} \quad (\text{C.7})$$

for $\epsilon = 1$. Therefore, from (29), (C.6) and (C.7),

$$\gamma_{mbr}^{(1)} = \frac{\mathcal{M}}{s_0} = \frac{(n-1)\mathcal{M}}{\sum_{i=1}^k (n-i)} = \frac{\mathcal{M}}{k} \frac{2(n-1)}{2n-k-1}. \quad (\text{C.8})$$

Now we focus on the case of $\epsilon = 0$. First, let q and r be

$$q := \lfloor \frac{k}{n_I} \rfloor, \quad (\text{C.9})$$

$$r := (k \bmod n_I), \quad (\text{C.10})$$

which represent the quotient and remainder of k/n_I . Note that

$$qn_I + r = k. \quad (\text{C.11})$$

Then, we have

$$\begin{aligned} \sum_{t=1}^{n_I} t g_t &= \sum_{t=1}^r (q+1)t + \sum_{t=r+1}^{n_I} qt = q \sum_{t=1}^{n_I} t + \sum_{t=1}^r t \\ &= q \frac{n_I(n_I+1)}{2} + \frac{r(r+1)}{2} = \frac{1}{2}(qn_I^2 + r^2 + k) \end{aligned} \quad (\text{C.12})$$

where the last equality is from (C.11). From (C.2) and (A.66), we have

$$\begin{aligned} \sum_{i=1}^k z_i &= \sum_{t=1}^{n_I} (n_I - t) g_t = n_I k - \frac{1}{2}(qn_I^2 + r^2 + k) \\ &= (n_I - 1)k - \frac{1}{2}(qn_I^2 + r^2 - k) \end{aligned} \quad (\text{C.13})$$

where the second last equality is from (9) and (C.12). Moreover, using (C.11), we have

$$\begin{aligned} qn_I^2 + r^2 - k &= qn_I^2 + r^2 - qn_I - r \\ &= (qn_I + r)(n_I - 1) - r(n_I - r) \\ &\leq (qn_I + r)(n_I - 1) = k(n_I - 1) \end{aligned} \quad (\text{C.14})$$

where the equality holds if and only if $r = 0$. Furthermore,

$$s_0 = \frac{\sum_{i=1}^k z_i}{n_I - 1} \quad (\text{C.15})$$

for $\epsilon = 0$ from (23). Combining (29), (C.13), (C.14) and (C.15) result in

$$\gamma_{mbr}^{(0)} = \frac{\mathcal{M}}{s_0} \leq \frac{2\mathcal{M}}{k}. \quad (\text{C.16})$$

From (C.8) and (C.16), we have

$$\begin{aligned} \gamma_{mbr}^{(0)} - \gamma_{mbr}^{(1)} &\leq \frac{\mathcal{M}}{k} \left(2 - \frac{2(n-1)}{2n-k-1} \right) = \frac{\mathcal{M}}{k} \frac{2(n-k)}{2n-k-1} \\ &= \frac{\mathcal{M}}{nR} \frac{2n(1-R)}{n(2-R)-1} \end{aligned}$$

where $R = k/n$. Thus, for arbitrary n ,

$$\gamma_{mbr}^{(0)} \rightarrow \gamma_{mbr}^{(1)}$$

as $R \rightarrow 1$. This completes the proof of (31). Finally, (C.8) and (C.16) provides

$$\frac{\gamma_{mbr}^{(0)}}{\gamma_{mbr}^{(1)}} \leq \frac{2n-k-1}{n-1} = 2 - \frac{k-1}{n-1},$$

which completes the proof of (32).

APPENDIX D PROOF OF THEOREM 5

Recall the definition of an $(n, l_0, m_0, \mathcal{M}, \alpha)$ -LRC which appear right before Theorem 5. Moreover, recall that the *repair locality* of a code is defined as the number of nodes to be contacted in the node repair process [32]. Since each cluster contains n_I nodes, every node in a DSS with $\epsilon = 0$ has the repair locality of

$$l_0 = n_I - 1. \quad (\text{D.1})$$

Moreover, note that for any code with minimum distance m , the original file \mathcal{M} can be retrieved by contacting $n-m+1$ coded symbols [38]. Since the present paper considers DSSs such that contacting any k nodes can retrieve the original file \mathcal{M} , we have the minimum distance of

$$m_0 = n - k + 1. \quad (\text{D.2})$$

Thus, the intra-cluster repairable code defined in Section IV-C is a $(n, l_0, m_0, \mathcal{M}, \alpha)$ -LRC.

Now we show that (34) holds. Note that from Fig. 10, we obtain $\alpha \geq \alpha_{msr}^{(0)}$ for $\epsilon = 0$, where

$$\alpha_{msr}^{(0)} = \frac{\mathcal{M}}{k - \lfloor \frac{k}{n_I} \rfloor} \quad (\text{D.3})$$

holds according to (C.1). Thus, (34) is proven by showing

$$m_0 \leq n - \left\lceil \frac{\mathcal{M}}{\alpha_{msr}^{(0)}} \right\rceil - \left\lceil \frac{\mathcal{M}}{l_0 \alpha_{msr}^{(0)}} \right\rceil + 2. \quad (\text{D.4})$$

By plugging (D.1), (D.2) and (D.3) into (D.4), we have

$$\begin{aligned} n - k + 1 &\leq n - \left\lceil k - \left\lfloor \frac{k}{n_I} \right\rfloor \right\rceil - \left\lceil \frac{k - \lfloor \frac{k}{n_I} \rfloor}{n_I - 1} \right\rceil + 2 \\ &= n - k + \left\lceil \frac{k}{n_I} \right\rceil - \left\lceil \frac{k - \lfloor \frac{k}{n_I} \rfloor}{n_I - 1} \right\rceil + 2. \end{aligned}$$

Therefore, all we need to prove is

$$0 \leq \left\lceil \frac{k}{n_I} \right\rceil - \left\lceil \frac{k - \lfloor \frac{k}{n_I} \rfloor}{n_I - 1} \right\rceil + 1, \quad (\text{D.5})$$

which is proved as follows. Using q and r defined in (C.9) and (C.10), the right-hand-side (RHS) of (D.5) is

$$\begin{aligned} \text{RHS} &= q - \left\lceil \frac{qn_I + r - q}{n_I - 1} \right\rceil + 1 \\ &= \begin{cases} q - (q+1) + 1 = 0, & r \neq 0 \\ q - q + 1 = 1, & r = 0 \end{cases} \end{aligned}$$

Thus, (D.5) holds, where the equality condition is $r \neq 0$, or equivalently $(k \bmod n_I) \neq 0$. Therefore, (34) holds, where the equality condition is $\alpha = \alpha_{msr}^{(0)}$ and $(k \bmod n_I) \neq 0$. This completes the proof of Theorem 5.

APPENDIX E PROOF OF THEOREM 6

According to (A.20) and (A.68) in Appendix B, the capacity can be expressed as

$$\mathcal{C} = \sum_{i=1}^k \min\{\alpha, \omega_i(\boldsymbol{\pi}_v(\mathbf{s}_h))\}. \quad (\text{E.1})$$

Using (A.64) and (A.66), $\omega_i(\boldsymbol{\pi}_v(\mathbf{s}_h))$ in (E.1), or simply ω_i has the following property:

$$\omega_{i+1} = \begin{cases} \omega_i - \beta_I, & i \in I_G \\ \omega_i - \beta_c, & i \in [k] \setminus I_G \end{cases} \quad (\text{E.2})$$

where $I_G = \{g_m\}_{m=1}^{n_I-1}$. Note that $g_{n_I} = \lfloor \frac{k}{n_I} \rfloor$ from (7). Therefore, k_0 in (37) can be expressed as

$$k_0 = k - \lfloor \frac{k}{n_I} \rfloor = k - g_{n_I} \leq k - 1 \quad (\text{E.3})$$

where the last inequality is from (3). Combining (26) and (E.3) result in

$$h_{k_0} = n_I - 1. \quad (\text{E.4})$$

From (A.64), (E.3) and (E.4), we have

$$\begin{aligned} \omega_{k_0} &= (n_I - h_{k_0})\beta_I + (n - k_0 - n_I + h_{k_0})\beta_c \\ &= \beta_I + (n - k_0 - 1)\beta_c \geq \beta_I + (n - k)\beta_c \geq \beta_I = \alpha. \end{aligned} \quad (\text{E.5})$$

where the last equality holds due to the assumption of $\beta_I = \alpha$ in the setting of Theorem 6. Since $(\omega_i)_{i=1}^k$ is a decreasing sequence from (E.2), the result of (E.5) implies that

$$\omega_i \geq \alpha, \quad 1 \leq i \leq k_0. \quad (\text{E.6})$$

Thus, the capacity expression in (E.1) can be expressed as

$$\mathcal{C} = \begin{cases} k_0\alpha + \sum_{i=k_0+1}^k \omega_i, & \omega_{k_0+1} \leq \alpha \\ m\alpha + \sum_{i=m+1}^k \omega_i, & \omega_{m+1} \leq \alpha < \omega_m \\ & (k_0 + 1 \leq m \leq k - 1) \\ k\alpha, & \alpha < \omega_k \end{cases} \quad (\text{E.7})$$

Note that from (A.64) and (A.66), we have $\omega_i = (n - i)\beta_c$ for $i = k_0 + 1, k_0 + 2, \dots, k$. Therefore, \mathcal{C} in (E.7) is

$$\mathcal{C} = \begin{cases} k_0\alpha + \sum_{i=k_0+1}^k (n - i)\beta_c, & 0 \leq \beta_c \leq \frac{\alpha}{n - k_0 - 1} \\ m\alpha + \sum_{i=m+1}^k (n - i)\beta_c, & \frac{\alpha}{n - m} < \beta_c \leq \frac{\alpha}{n - m - 1} \\ & (k_0 + 1 \leq m \leq k - 1) \\ k\alpha, & \frac{\alpha}{n - k} < \beta_c, \end{cases} \quad (\text{E.8})$$

which is illustrated as a piecewise linear function of β_c in Fig. 28. Based on (E.8), the sequence $(T_m)_{m=k_0}^k$ in this figure has

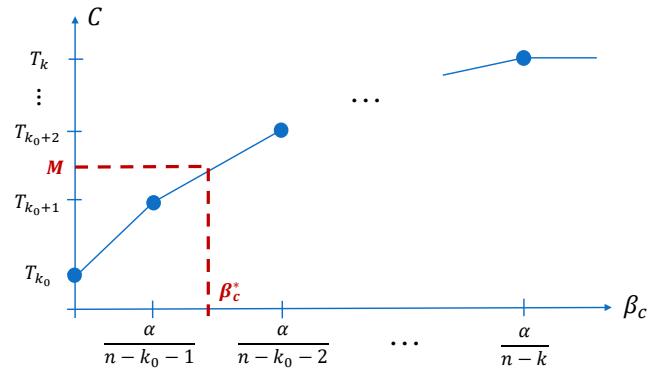


Fig. 28: Capacity as a function of β_c

the following expression:

$$T_m = \begin{cases} k_0\alpha, & m = k_0 \\ (m + \frac{\sum_{i=m+1}^k (n-i)}{n-m})\alpha, & k_0 + 1 \leq m \leq k - 1 \\ k\alpha, & m = k \end{cases} \quad (\text{E.9})$$

From Fig. 28, we can conclude that $\mathcal{C} \geq \mathcal{M}$ holds if and only if $\beta_c \geq \beta_c^*$ where

$$\beta_c^* = \begin{cases} 0, & \mathcal{M} \in [0, T_{k_0}] \\ \frac{\mathcal{M} - m\alpha}{\sum_{i=m+1}^k (n-i)}, & \mathcal{M} \in (T_m, T_{m+1}] \\ & (m = k_0, k_0 + 1, \dots, k - 1) \\ \infty, & \mathcal{M} \in (T_k, \infty). \end{cases} \quad (\text{E.10})$$

Using T_m in (E.9) and f_m in (36), (E.10) reduces to (35), which completes the proof.

APPENDIX F PROOFS OF COROLLARIES

A. Proof of Corollary 1

From the proof of Theorem 1, the capacity expression is equal to (A.67), which is

$$\mathcal{C} = \sum_{i=1}^k \min\{\alpha, (n_I - h_i)\beta_I + (n - n_I - i + h_i)\beta_c\}.$$

where h_i is defined in (A.60). Using $\epsilon = \beta_c/\beta_I$ and (2), this can be rewritten as

$$\mathcal{C} = \sum_{i=1}^k \min\{\alpha, \frac{(n - n_I - i + h_i)\epsilon + (n_I - h_i)}{(n - n_I)\epsilon + (n_I - 1)}\gamma\}. \quad (\text{F.1})$$

Using $\{z_t\}$ and $\{y_t\}$ defined in (25) and (24), the capacity expression reduces to

$$\mathcal{C}(\alpha, \gamma) = \sum_{t=1}^k \min\{\alpha, \frac{\gamma}{y_t}\}, \quad (\text{F.2})$$

which is a continuous function of γ .

Remark 1. $\{z_t\}$ in (25) is a decreasing sequence of t . Moreover, $\{y_t\}$ in (24) is an increasing sequence.

Proof. Note that from (A.62),

$$h_{t+1} = \begin{cases} h_t + 1, & t \in T \\ h_t, & t \in [k-1] \setminus T \end{cases}$$

where $T = \{g_1, g_1 + g_2, \dots, \sum_{m=1}^{n_I-1} g_m\}$. Therefore, $\{z_t\}$ in (25) is a decreasing function of t , which implies that $\{y_t\}$ is an increasing sequence. \square

Moreover, note that $\beta_I \leq \alpha$ holds from the definition of β_I and α in Table I. Thus, combined with $\epsilon = \beta_I/\beta_c$, it is shown that γ in (2) is lower-bounded as

$$\begin{aligned} \gamma &= (n_I - 1)\beta_I + (n - n_I)\beta_c \\ &= \{n_I - 1 + (n - n_I)\epsilon\}\beta_I \leq \{n_I - 1 + (n - n_I)\epsilon\}\alpha. \end{aligned}$$

Here, we define

$$\bar{\gamma} = \{n_I - 1 + (n - n_I)\epsilon\}\alpha.$$

Then, the valid region of γ is expressed as $\gamma \leq \bar{\gamma}$, as illustrated in Figs. 29 and 30. The rest of the proof depends on the range of ϵ values; we first consider the $\frac{1}{n-k} \leq \epsilon \leq 1$ case, and then consider the $0 \leq \epsilon < \frac{1}{n-k}$ case.

1) If $\frac{1}{n-k} \leq \epsilon \leq 1$: Using (B.2), $z_k = (n - k)\epsilon \geq 1$ holds. Combining with (24), we have $y_k \leq n_I - 1 + \epsilon(n - n_I)$, or equivalently, $y_k\alpha \leq \bar{\gamma}$. If $y_t\alpha < \gamma \leq y_{t+1}\alpha$ for some $t \in [k-1]$, then (F.2) can be expressed as

$$\begin{aligned} \mathcal{C}(\alpha, \gamma) &= t\alpha + \sum_{m=t+1}^k \frac{\gamma}{y_m} \\ &= t\alpha + \frac{\gamma (\sum_{m=t+1}^k z_m)}{(n_I - 1) + \epsilon(n - n_I)} = t\alpha + s_t\gamma \end{aligned}$$

where $\{s_t\}$ is defined in (23). If $0 \leq \gamma \leq y_1\alpha$, then

$$\mathcal{C}(\alpha, \gamma) = \sum_{m=1}^k \frac{\gamma}{y_m} = \frac{\gamma (\sum_{m=1}^k z_m)}{(n_I - 1) + \epsilon(n - n_I)} = s_0\gamma.$$

If $y_k\alpha < \gamma \leq \bar{\gamma}$, then $\mathcal{C}(\alpha, \gamma) = \sum_{m=1}^k \alpha = k\alpha$. In summary, capacity is

$$\mathcal{C}(\alpha, \gamma) = \begin{cases} s_0\gamma, & 0 \leq \gamma \leq y_1\alpha \\ t\alpha + s_t\gamma, & y_t\alpha < \gamma \leq y_{t+1}\alpha \\ & (t = 1, 2, \dots, k-1) \\ k\alpha, & y_k\alpha < \gamma \leq \bar{\gamma} \end{cases} \quad (\text{F.3})$$

which is illustrated in Fig. 29. Since $\{z_t\}$ is a decreasing sequence from Remark 1, we have $z_t \geq z_k = (n - k)\epsilon > 0$ for $t \in [k]$. Thus, $\{s_t\}_{t=1}^k$ defined in (23) is a monotonically decreasing, non-negative sequence. This implies that the curve in Fig. 29 is a monotonic increasing function of γ .

From Fig. 29, it is shown that $\mathcal{C}(\alpha, \gamma) \geq \mathcal{M}$ holds if and only if $\gamma \geq \gamma^*(\alpha)$. From (F.3), the threshold value $\gamma^*(\alpha)$ can be expressed as

$$\gamma^*(\alpha) = \begin{cases} \frac{\mathcal{M}}{s_0}, & \mathcal{M} \in [0, E_1] \\ \frac{\mathcal{M} - t\alpha}{s_t}, & \mathcal{M} \in (E_t, E_{t+1}] \\ & (t = 1, 2, \dots, k-1) \\ \infty, & \mathcal{M} \in (E_k, \infty). \end{cases} \quad (\text{F.4})$$

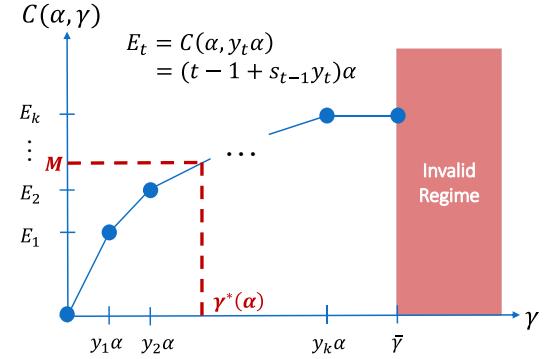


Fig. 29: Capacity as a function of γ , for $\frac{1}{n-k} \leq \epsilon \leq 1$

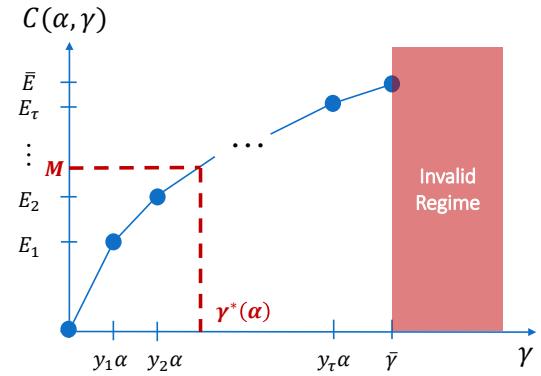


Fig. 30: Capacity as a function of γ , for $0 \leq \epsilon < \frac{1}{n-k}$ case

where

$$E_t = \mathcal{C}(\alpha, y_t\alpha) = (t - 1 + s_{t-1}y_t)\alpha \quad (\text{F.5})$$

for $t \in [k]$. The threshold value $\gamma^*(\alpha)$ in (F.4) can be expressed as (20), which completes the proof.

2) Otherwise (if $0 \leq \epsilon < \frac{1}{n-k}$): Using (B.2),

$$z_k = (n - k)\epsilon < 1 \quad (\text{F.6})$$

holds. Since $\{z_t\}$ is a decreasing sequence from Remark 1, there exists $\tau \in \{0, 1, \dots, k-1\}$ such that $z_{\tau+1} < 1 \leq z_\tau$ holds, or equivalently, $y_\tau\alpha \leq \bar{\gamma} < y_{\tau+1}\alpha$.

Using the analysis similar to the $\frac{1}{n-k} \leq \epsilon \leq 1$ case, we obtain

$$\mathcal{C}(\alpha, \gamma) = \begin{cases} s_0\gamma, & 0 \leq \gamma \leq y_1\alpha \\ t\alpha + s_t\gamma, & y_t\alpha < \gamma \leq y_{\tau+1}\alpha \\ & (t = 1, 2, \dots, \tau-1) \\ \tau\alpha + s_\tau\gamma, & y_\tau\alpha < \gamma \leq \bar{\gamma} \end{cases} \quad (\text{F.7})$$

which is illustrated in Fig. 30.

From Fig. 30, it is shown that $\mathcal{C}(\alpha, \gamma) \geq \mathcal{M}$ holds if and only if $\gamma \geq \gamma^*(\alpha)$. From (F.7), the threshold value $\gamma^*(\alpha)$ can

be expressed as

$$\gamma^*(\alpha) = \begin{cases} \frac{\mathcal{M}}{s_0}, & \mathcal{M} \in [0, E_1] \\ \frac{\mathcal{M}-t\alpha}{s_t}, & \mathcal{M} \in (E_t, E_{t+1}] \\ & (t = 1, 2, \dots, \tau - 1) \\ \frac{\mathcal{M}-\tau\alpha}{s_\tau}, & \mathcal{M} \in (E_\tau, \bar{E}] \\ \infty, & \mathcal{M} \in (\bar{E}, \infty). \end{cases} \quad (\text{F.8})$$

where $\{E_t\}$ is defined in (F.5), and

$$\bar{E} = \mathcal{C}(\alpha, \bar{\gamma}) = \tau\alpha + s_\tau\alpha\{n_I - 1 + (n - n_I)\epsilon\}.$$

The threshold value $\gamma^*(\alpha)$ in (F.8) can be expressed as (21), which completes the proof.

B. Proof of Corollary 2

First, we focus on the MSR point illustrated in Fig. 9. From (20), the MSR point for $\frac{1}{n-k} \leq \epsilon \leq 1$ is

$$\begin{aligned} (\alpha_{msr}^{(\epsilon)}, \gamma_{msr}^{(\epsilon)}) &= \left(\frac{\mathcal{M}}{k + s_k y_k}, \frac{\mathcal{M} - (k-1)\alpha_{msr}^{(\epsilon)}}{s_{k-1}} \right) \\ &= \left(\frac{\mathcal{M}}{k}, \frac{\mathcal{M}}{k} \frac{1}{s_{k-1}} \right) \end{aligned} \quad (\text{F.9})$$

where the last equality is from $s_k = 0$ in (23). Moreover, from (21), the MSR point for $0 \leq \epsilon < \frac{1}{n-k}$ is

$$\begin{aligned} (\alpha_{msr}^{(\epsilon)}, \gamma_{msr}^{(\epsilon)}) &= \left(\frac{M}{\tau + \sum_{i=\tau+1}^k z_i}, \frac{\mathcal{M} - \tau\alpha_{msr}^{(\epsilon)}}{s_\tau} \right) \\ &= \left(\frac{M}{\tau + \sum_{i=\tau+1}^k z_i}, \frac{M}{\tau + \sum_{i=\tau+1}^k z_i} \frac{\sum_{i=\tau+1}^k z_i}{s_\tau} \right). \end{aligned} \quad (\text{F.10})$$

Equations (F.9) and (F.10) proves (28). The expression (29) for the MBR point is directly obtained from Corollary 1 and Fig. 9.

APPENDIX G PROOFS OF PROPOSITIONS

A. Proof of Proposition 1

As in (A.23), capacity \mathcal{C} for maximum d_I, d_c setting ($d_I = n_I - 1, d_c = n - n_I$) is expressed as

$$\mathcal{C} = \min_{\mathbf{s}, \boldsymbol{\pi} \in \Pi(\mathbf{s})} L(\mathbf{s}, \boldsymbol{\pi}) \quad (\text{G.1})$$

where

$$\begin{aligned} L(\mathbf{s}, \boldsymbol{\pi}) &= \sum_{i=1}^k \min\{\alpha, \omega_i(\boldsymbol{\pi})\}, \\ \omega_i(\boldsymbol{\pi}) &= \gamma - e_i(\boldsymbol{\pi})\beta_I - (i-1 - e_i(\boldsymbol{\pi}))\beta_c, \\ e_i(\boldsymbol{\pi}) &= \sum_{j=1}^{i-1} \mathbb{1}_{\pi_j=\pi_i}, \end{aligned} \quad (\text{G.2})$$

as in (A.20), (A.21) and (A.19).

Consider a general d_I, d_c setting, where each newcomer node is helped by d_I nodes in the same cluster, receiving β_I information from each node, and d_c nodes in other clusters, receiving β_c information from each node. Under this setting,

the coefficient of β_I in (G.2) cannot exceed d_I . Similarly, the coefficient of β_c in (G.2) cannot exceed d_c . Thus, the capacity for general d_I, d_c is expressed as

$$\mathcal{C}(d_I, d_c) = \min_{\mathbf{s} \in S, \boldsymbol{\pi} \in \Pi(\mathbf{s})} L(d_I, d_c, \mathbf{s}, \boldsymbol{\pi}) \quad (\text{G.3})$$

where

$$\begin{aligned} L(d_I, d_c, \mathbf{s}, \boldsymbol{\pi}) &= \sum_{i=1}^k \min\{\alpha, \omega_i(d_I, d_c, \mathbf{s}, \boldsymbol{\pi})\}, \\ \omega_i(d_I, d_c, \mathbf{s}, \boldsymbol{\pi}) &= \gamma - \min\{d_I, e_i(\boldsymbol{\pi})\}\beta_I \\ &\quad - \min\{d_c, i-1 - e_i(\boldsymbol{\pi})\}\beta_c, \\ e_i(\boldsymbol{\pi}) &= \sum_{j=1}^{i-1} \mathbb{1}_{\pi_j=\pi_i}. \end{aligned} \quad (\text{G.4})$$

Consider arbitrary fixed $\mathbf{s}, \boldsymbol{\pi}$ and d_c . Since γ and $\gamma_c = d_c\beta_c$ are fixed in the basic setting of Proposition 1, only d_I and β_I are variables in (G.4), while other parameters are constants. Then, (G.4) can be expressed as

$$\begin{aligned} \omega_i(d_I, d_c, \mathbf{s}, \boldsymbol{\pi}) &= C_1 - \min\{d_I, e_i(\boldsymbol{\pi})\}\beta_I \\ &= C_1 - \frac{\min\{d_I, e_i(\boldsymbol{\pi})\}}{d_I} C_2 \end{aligned} \quad (\text{G.5})$$

where $C_1 = \gamma - \min\{d_c, i-1 - e_i(\boldsymbol{\pi})\}\beta_c$ and $C_2 = \gamma_I = \gamma - \gamma_c$ are constants. Note that

$$\frac{\min\{d_I, e_i(\boldsymbol{\pi})\}}{d_I} = \begin{cases} 1, & \text{if } d_I \leq e_i(\boldsymbol{\pi}), \\ \frac{e_i(\boldsymbol{\pi})}{d_I}, & \text{otherwise} \end{cases} \quad (\text{G.6})$$

is a non-increasing function of d_I . Thus, $\omega_i(d_I, d_c, \mathbf{s}, \boldsymbol{\pi})$ in (G.5) is a non-decreasing function of d_I for arbitrary fixed $\mathbf{s}, \boldsymbol{\pi}, d_c$ and $i \in [k]$. Since the maximum d_I value is $n_I - 1$, we have

$$\begin{aligned} L(d_I, d_c, \mathbf{s}, \boldsymbol{\pi}) &= \sum_{i=1}^k \min\{\alpha, \omega_i(d_I, d_c, \mathbf{s}, \boldsymbol{\pi})\} \\ &\leq \sum_{i=1}^k \min\{\alpha, \omega_i(n_I - 1, d_c, \mathbf{s}, \boldsymbol{\pi})\} \\ &= L(n_I - 1, d_c, \mathbf{s}, \boldsymbol{\pi}) \end{aligned} \quad (\text{G.7})$$

for $d_I \in [n_I - 1]$. In other words, for all $\mathbf{s}, \boldsymbol{\pi}, d_c$, we have

$$\arg \max_{d_I \in [n_I - 1]} L(d_I, d_c, \mathbf{s}, \boldsymbol{\pi}) = n_I - 1.$$

Similarly, for all $\mathbf{s}, \boldsymbol{\pi}, d_I$,

$$\arg \max_{d_c \in [n - n_I]} L(d_I, d_c, \mathbf{s}, \boldsymbol{\pi}) = n - n_I$$

holds. Therefore, for all $\mathbf{s}, \boldsymbol{\pi}$,

$$\arg \max_{[d_I, d_c]} L(d_I, d_c, \mathbf{s}, \boldsymbol{\pi}) = [n_I - 1, n - n_I]. \quad (\text{G.8})$$

Let

$$[\mathbf{s}^*, \boldsymbol{\pi}^*] = \arg \min_{\mathbf{s} \in S, \boldsymbol{\pi} \in \Pi(\mathbf{s})} L(n_I - 1, n - n_I, \mathbf{s}, \boldsymbol{\pi}). \quad (\text{G.9})$$

Then, from (G.3), (G.8) and (G.9),

$$\begin{aligned}\mathcal{C}(d_I, d_c) &= \min_{\mathbf{s} \in S, \boldsymbol{\pi} \in \Pi(\mathbf{s})} L(d_I, d_c, \mathbf{s}, \boldsymbol{\pi}) \\ &\leq L(d_I, d_c, \mathbf{s}^*, \boldsymbol{\pi}^*) \leq L(n_I - 1, n - n_I, \mathbf{s}^*, \boldsymbol{\pi}^*) \\ &= \min_{\mathbf{s} \in S, \boldsymbol{\pi} \in \Pi(\mathbf{s})} L(n_I - 1, n - n_I, \mathbf{s}, \boldsymbol{\pi}) \\ &= \mathcal{C}(n_I - 1, n - n_I)\end{aligned}\quad (\text{G.10})$$

for all $d_I \in [n_I - 1]$ and $d_c \in [n - n_I]$. Therefore, choosing $d_I = n_I - 1$ and $d_c = n - n_I$ maximizes storage capacity when the available resources, γ and γ_c , are given.

B. Proof of Proposition 2

First, we prove (8). Recall ρ_i and g_m defined in (6) and (7). Consider the support set S , which is defined as

$$S = \{i \in [n_I] : g_i \geq 1\}. \quad (\text{G.11})$$

Then, we have

$$\rho_i = n_I - i \leq n_I - 1, \quad (\text{G.12})$$

$$\sum_{m=1}^{i-1} g_m \geq i - 1 \quad (\text{G.13})$$

for every $i \in S$. Therefore, by combining (G.13) and (6),

$$\begin{aligned}n - \rho_i - j - \sum_{m=1}^{i-1} g_m &\leq n - (i - 1) - j - \rho_i \\ &= n - n_I - (j - 1) \leq n - n_I\end{aligned}\quad (\text{G.14})$$

holds for every $i \in S, j \in [g_i]$. Combining (2), (G.12) and (G.14) results in

$$\rho_i \beta_I + (n - \rho_i - j - \sum_{m=1}^{i-1} g_m) \beta_c \leq (n_I - 1) \beta_I + (n - n_I) \beta_c = \gamma \quad (\text{G.15})$$

for arbitrary $i \in S, j \in [g_i]$. Since $[g_i] = \emptyset$ holds for $i \in [n_I] \setminus S$, we conclude that (G.15) holds for (i, j) with $i \in [n_I], j \in [g_i]$.

Second, we prove (9). Using q and r in (C.9) and (C.10),

$$g_i = \begin{cases} q + 1, & i \leq r \\ q, & \text{otherwise} \end{cases} \quad (\text{G.16})$$

Therefore, $\sum_{i=1}^{n_I} g_i = (q + 1)r + q(n_I - r) = r + qn_I = k$, where the last equality is from (C.11).

APPENDIX H PROOFS OF LEMMAS

A. Proof of Lemma 1

Using (2), \underline{C} in (14) can be expressed as

$$\begin{aligned}\underline{C} &= \frac{k}{2} \left((n_I - 1) \beta_I + (n - n_I) \left(1 + \frac{n - k}{n(1 - 1/L)} \right) \beta_c \right) \\ &= \frac{k}{2} \left((n_I - 1) \beta_I + (n - n_I) \left(1 + \frac{n - k}{n - n_I} \right) \beta_c \right) \\ &= \frac{k}{2} \left\{ (n_I - 1) \beta_I + (2n - n_I - k) \beta_c \right\}.\end{aligned}\quad (\text{H.1})$$

According to (A.20) and (A.68) in Appendix B, the capacity can be expressed as

$$\mathcal{C} = L(\mathbf{s}_h, \boldsymbol{\pi}_v) = \sum_{i=1}^k \min\{\alpha, \omega_i(\boldsymbol{\pi}_v(\mathbf{s}_h))\}. \quad (\text{H.2})$$

From (A.21), we have

$$\omega_i(\boldsymbol{\pi}_v(\mathbf{s}_h)) \leq \gamma \quad (\text{H.3})$$

for $i \in [k]$. Therefore, when $\alpha = \gamma$, the capacity expression in (H.2) reduces to

$$\mathcal{C} = \sum_{i=1}^k \omega_i(\boldsymbol{\pi}_v(\mathbf{s}_h)). \quad (\text{H.4})$$

Recall (A.64):

$$\omega_i(\boldsymbol{\pi}_v(\mathbf{s}_h)) = (n_I - h_i) \beta_I + (n - i - n_I + h_i) \beta_c. \quad (\text{H.5})$$

From the expression of $(h_i)_{i=1}^k$ in (A.66), we have

$$\sum_{i=1}^k (n_I - h_i) = \sum_{s=1}^{n_I} g_s (n_I - s) \quad (\text{H.6})$$

since $\sum_{m=1}^k g_m = k$ from (9),

Using (H.5) and (H.6), the capacity expression in (H.4) is expressed as

$$\begin{aligned}\mathcal{C} &= \left(\sum_{i=1}^k (n_I - h_i) \right) \beta_I + \left(\sum_{i=1}^k (n - i - (n_I - h_i)) \right) \beta_c \\ &= A_0 \beta_I + B_0 \beta_c\end{aligned}\quad (\text{H.7})$$

where $A_0 = \sum_{s=1}^{n_I} g_s (n_I - s)$ and

$$B_0 = \sum_{i=1}^k (n - i) - A_0. \quad (\text{H.8})$$

Similarly, \underline{C} in (H.1) can be expressed as

$$\underline{C} = A'_0 \beta_I + B'_0 \beta_c \quad (\text{H.9})$$

where $A'_0 = (n_I - 1) \frac{k}{2}$ and

$$B'_0 = (2n - n_I - k) \frac{k}{2} = \sum_{i=1}^k (n - i) - A'_0. \quad (\text{H.10})$$

First, we show that $\mathcal{C} \geq \underline{C}$ holds. From (H.7), (H.8), (H.9) and (H.10),

$$\begin{aligned}\mathcal{C} - \underline{C} &= (A_0 - A'_0) \beta_I + (B_0 - B'_0) \beta_c \\ &= (A_0 - A'_0) \beta_I - (A_0 - A'_0) \beta_c = (A_0 - A'_0)(\beta_I - \beta_c).\end{aligned}\quad (\text{H.11})$$

Since we consider the $\beta_I \geq \beta_c$ case, all we need to prove is

$$A_0 - A'_0 \geq 0.$$

Using $(g_i)_{i=1}^k$ expression in (G.16), A_0 can be rewritten as

$$\begin{aligned} A_0 &= \sum_{s=1}^{n_I} g_s(n_I - s) = q \sum_{s=1}^{n_I} (n_I - s) + \sum_{s=1}^r (n_I - s) \\ &= q \frac{n_I(n_I - 1)}{2} + \sum_{s=1}^r (n_I - s) \\ &= q \frac{n_I(n_I - 1)}{2} + \frac{r((n_I - 1) + (n_I - r))}{2} \\ &= (qn_I + r) \frac{n_I - 1}{2} + \frac{r(n_I - r)}{2} \\ &= \frac{k(n_I - 1)}{2} + \frac{r(n_I - r)}{2} = A'_0 + \frac{r(n_I - r)}{2}. \end{aligned}$$

Since $0 \leq r < n_I$, we have

$$A_0 - A'_0 = \frac{r(n_I - r)}{2} \geq 0. \quad (\text{H.12})$$

Therefore, $\mathcal{C} \geq \underline{\mathcal{C}}$ holds.

Second, we prove $\mathcal{C} \leq \underline{\mathcal{C}} + n_I^2(\beta_I - \beta_c)/8$. Note that $A_0 - A'_0$ in (H.12) is maximized when $r = \lfloor n_I/2 \rfloor$ holds. Thus, $A_0 - A'_0 \leq \frac{\lfloor n_I/2 \rfloor(n_I - \lfloor n_I/2 \rfloor)}{2} \leq n_I^2/8$. Combining with (H.11),

$$\mathcal{C} - \underline{\mathcal{C}} = (A_0 - A'_0)(\beta_I - \beta_c) \leq n_I^2(\beta_I - \beta_c)/8.$$

B. Proof of Lemma 2

Recall that $\xi = \gamma_c/\gamma$, γ and $R = k/n$ value are all fixed. The expression for $\underline{\mathcal{C}}$ in (14) can be expressed as

$$\begin{aligned} \underline{\mathcal{C}} &= \frac{k}{2} \left(\gamma + \frac{n-k}{n(1-\frac{1}{L})} \gamma_c \right) = \frac{nR}{2} \left(\gamma + \frac{1-R}{1-\frac{1}{L}} \gamma_c \right) \\ &= \gamma \frac{nR}{2} \left(1 + \frac{1-R}{(1-\frac{1}{L})} \xi \right) \end{aligned} \quad (\text{H.13})$$

Note that (H.13) is a monotonic decreasing function of L . Moreover, we consider the $L \geq 2$ case, as mentioned in (4). Thus, $\underline{\mathcal{C}}$ is upper/lower bounded by expressions for $L = 2$ and $L = \infty$, respectively:

$$\gamma \frac{nR}{2} \left(1 + (1-R)\xi \right) < \underline{\mathcal{C}} \leq \gamma \frac{nR}{2} \left(1 + 2(1-R)\xi \right). \quad (\text{H.14})$$

Therefore, $\underline{\mathcal{C}} = \Theta(n)$ holds. Moreover, the expression for δ in (17) is

$$\begin{aligned} \delta &= \frac{n_I^2(\beta_I - \beta_c)}{8} = \frac{n_I^2}{8} \left(\frac{\gamma_I}{n_I - 1} - \frac{\gamma_c}{n - n_I} \right) \\ &= \frac{n_I^2}{8} \left(\frac{\gamma(1-\xi)}{n_I - 1} - \frac{\gamma\xi}{n - n_I} \right) \\ &= \frac{n_I^2\gamma}{8} \frac{(1-\xi)(n - n_I) - \xi(n_I - 1)}{(n_I - 1)(n - n_I)}. \end{aligned} \quad (\text{H.15})$$

Putting $n = n_I L$ into (H.15), we get

$$\delta = \frac{n_I\gamma}{8} \frac{(1-\xi)n_I(L-1) - \xi(n_I-1)}{(n_I-1)(L-1)} = O(n_I).$$

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