Sparse Collective Operations for MPI

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Abstract—We discuss issues in designing sparse (nearest-neighbor) collective operations for communication and reduction operations in small neighborhoods for the Message Passing Interface (MPI). We propose three such operations, namely a sparse gather operation, a sparse all-to-all, and a sparse reduction operation in both regular and irregular (vector) variants. By two simple experiments we show a) that a collective handle for message scheduling and communication optimization is necessary for any such interface, b) that the possibly different amount of communication between neighbors need to be taken into account by the optimization, and c) illustrate the improvements that are possible by schedules that possess global information compared to implementations that can rely on only local information. We discuss different forms the interface and optimization handles could take. The paper is inspired by current discussion in the MPI Forum.

I. INTRODUCTION

The Message Passing Interface Standard (MPI) [1] provides different ways to realize communication patterns between processes in a communication universe (communicator). One way is to implement each pattern with individual send/receive operations between pairs of processes. This can be tedious and error-prone because the user has the full responsibility of optimizing the communication pattern to particular network topologies, ensuring correctness, and preventing deadlocks. The use of such point-to-point schemes therefore often results in suboptimal algorithms for common communication patterns (such as a linear reduction instead of a tree-based reduction).

To alleviate these drawbacks and support parallel programming at a higher, more portable level, MPI offers a set of (16) collective operations. These embody common patterns and operations such as broadcast, all-to-all personalized exchange, scatter/gather and several parallel data reduction operations. Most of these operations come in both regular and irregular (vector) variants, the latter enabling communication of different amounts of data between processes in the collective pattern. The collective operations all require participation of all processes in the given communicator.

This set of predefined, dense communication patterns cover a wide range of practical applications. However, parallel scientific applications often communicate in a localized neighborhood, e.g., with their neighbors in a regular or irregular mesh. In MPI, such sparse communication is currently not supported by collective operations, and must instead be implemented by the application (or by application specific libraries such as PETSc [2]) by means of point-to-point communication operations. However, the operations often have enough common structure that could conveniently be captured by a set of additional sparse collective operations.

Some sparse collective operations, e.g., sparse, personalized all-to-all exchange where all processes exchange data with each of their neighbors, can be expressed by existing MPI collectives, e.g., a dense, irregular (vector), personalized all-to-all exchange, in which no data are exchanged between processes that are not neighbors (in the neighborhood of the application). This has several disadvantages. First, it is not a natural abstraction for applications with a very small local neighborhood (e.g., 9-neighbor stencil in a 2-dimensional mesh) compared to the total number of processes. This will tend to detract users from collective operations that might otherwise have given them a performance or portability benefit. A second drawback is that such a solution is not scalable, e.g., the major part of the arguments to the MPI_Alltoallv call will be zeroes, that will nevertheless have to be read an interpreted by the underlying MPI implementation. Furthermore, because MPI_Alltoallv is a (most) general collective operations, the optimizations (if any!) that are applied by the MPI library may be weaker (or more time-consuming) than what would be possible given the knowledge that communication takes place only in small neighborhoods. Finally, as we will see, not all natural, sparse collective operations are easily and efficiently expressible with the existing MPI collectives.

To address these issues, and in order to reflect current application needs, we define three new sparse collective operations, in both regular and irregular (vector) variants. We discuss several design possibilities to make the proposal fit the current MPI standard. More concretely, we propose a sparse gather operation, a sparse, personalized all-to-all operation, and a sparse reduction operation (the latter being an example of an operation that is not efficiently expressible in terms of existing MPI collectives), and we discuss alternatives for specifying the neighborhoods of processes. By means of two simple experiments, we first show that scheduling of communication can indeed have an effect on the overall performance (time to completion) of sparse collectives, and thereby argue that a global, collective handle is required for performing such scheduling optimizations. Second, we show that for the irregular sparse collectives, the actual amount of data communication between different neighbors needs to be
taken into account in this optimization. These observations set some natural constraints on the design of the interface, which we elaborate on in this paper.

For the discussion of optimization/schedules we make the simplifying, sometimes problematic assumption that processes arrive at the sparse collective more or less at the same time. If the processes arrive in a very unbalanced fashion other algorithms/approaches than discussed here must be employed. A preliminary discussion of such algorithms for the (dense) \texttt{MPI\_Bcast} collective can be found in [3]. Another alternative is to define the (sparse) collectives to be \textit{nonblocking}, which is touched briefly upon below.

\section{Related Work}

Many algorithms, for example weather prediction [4] and computational fluid dynamics [5], naturally exhibit sparse communications among neighboring elements or zones. Additionally many practical domain decompositions [6] result in nearest neighbor communication patterns. Such sparse communication patterns are very important for applications such as Qbox [7], TDQDF/Octopus [8], QCD codes [9], POP [10] and many more. Also libraries such as PETSc [11] or ScaLAPACK [12], that use MPI to implement several numerical methods and solvers, often exhibit sparse communication patterns.

Efficient implementation of sparse communication patterns is most important for large-scale applications. Most large-scale parallel computers support only sparse communication efficiently. For example, the 3d-torus Blue Gene/L [13] and Cray XT 4 communication networks only supports direct communication with six neighboring processors. The QC-DOC supercomputer [14] also optimizes for nearest neighbor communication. For such architectures, which exhibit a very low effective bisection bandwidth, the mapping from logical communication paths to physical channels is most important. It is also rather clear that future massively parallel systems can not support high bisection bandwidth for every communication pattern [15]. Thus, the use of sparse communication techniques and proper mapping will gain more importance in the near future.

We assume that many such algorithms and applications would benefit from a higher-level description of their communication operations. A previous study with Octopus [16] shows that the implementation complexity can be reduced by applying collective semantics to sparse communication patterns.

\section{Sparse Collective Operations}

We propose three different collective operations that are defined on process neighborhoods. Process neighborhoods are represented by the communicator on which the collectives are called. How neighborhoods can get associated with communicators will be discussed in Section IV. A process neighborhood is a set of local neighborhoods that for each process \(i\) consists of a list of \(k\) target processes \([t_0, t_1, \ldots, t_{k-1}]\) and a list of \(\ell\) not necessarily different source processes.

\begin{verbatim}
MPI\_Neighbor\_gather(sendbuf,sendcount,sendtype,
recvbuf,recvcount,recvtype,
comm)
\end{verbatim}

Listing 1. Sparse gather collective function prototype.

\begin{figure}[h]
\centering
\includegraphics[width=0.5\textwidth]{fig1.png}
\caption{The sparse gather operation on a local neighborhood with 6 source and 4 target processes. As indicated the size of the block sent to the target processes may be different from the size of the blocks received from the source processes. In the regular \texttt{MPI\_Neighbor\_gather} operation the received blocks all have the same size and type signature.}
\end{figure}

In each of the sparse collective operations, process \(i\) sends some data to its target processes, and receives some data from its source processes. Note that a process can be both a target and a source neighbor of itself. It is also not required that processes are unique in the source and target lists.

As for the standard MPI collectives, data to be sent and received are stored in send and receive buffers relative to some start address. The order of data is given by the order of the neighbors in the target and source lists. Data are described by a datatype and a repetition count. The usual semantic constraints shall apply, i.e., the datatype signature between neighbors where data are sent and/or received must match.

\textit{a) Gather:} In the sparse gather operation each process \(i\) receives a block of data from each of its source processes \([s_0, s_1, \ldots, s_{r-1}]\), and stores the block in that order relative to the \texttt{recvbuf} address. All received blocks are of the same size. Process \(i\) sends the same block of data from its \texttt{sendbuf} to its target processes \([t_0, t_1, \ldots, t_{k-1}]\). This is depicted in Figure 1. The function prototype is given in Listing 1. Note that the size of the data sent must equal the size of the data received by each of the target processes. If a process is source and target of itself, this implies that the size of the data sent and received must be equal. More generally, all processes lying on a cycle in the process neighborhood must send and receive the same amount of data.

\textit{b) All-to-all:} The sparse all-to-all personalized exchange operation extends the sparse gather operation in that personalized data is sent to each target process. Thus, instead of a just single block the \texttt{sendbuf} holds \(k\) blocks of data (of the same size). The function prototype is shown in Listing 2.
 MPI_Neighbor_alltoall(sendbuf,sendcount,sendtype, recvbuf,recvcount,recvtype, comm)

Listing 2. Sparse all-to-all collective function prototype.

 MPI_Neighbor_reduce(sendbuf,sendcount,sendtype, recvbuf,recvcount,recvtype, comm)


c) Reduce: In the sparse reduction operation each process gathers data from each of its source processes, and reduces these data into a single block using an MPI binary reduction operator (either pre- or user-defined). Each process sends the same data block to each of its target processes. The prototype of this function is shown in Listing 3.

The sparse reduction operation cannot easily be expressed in terms of existing MPI collectives. The current reduction collectives all perform a reduction on contributions from all processes of the communicator, whereas the sparse operation produces a value for each process computed from contributions from the local neighborhoods. The alternative is to revert to a general MPI_Alltoallv operation, followed by local, sequential reductions by the processes of the data from their neighborhoods.

A. Irregular (vector) variants

For user convenience, in analogy with the existing MPI collectives, we propose an irregular (vector) variant for each of the three sparse collectives.

For the all-to-all operation this is straightforward. Each process can send a different amount of data to each of its target processes, now addressed by a senddispls displacement relative to the sendbuf, and receive a different amount of data from each of its source processes. We also propose an MPI_Alltoallv-like operation where each block to be sent and received may have its own datatype. As will be seen in Section II-D this is useful when the blocks have different memory layouts.

The irregular, sparse gather operation allows that a block of different size can be received from each source process, whereas the same block is still sent to each target process. Likewise, the irregular, sparse reduction operation relaxes the constraint that the same block (of the same size) is sent for reduction to the target processes. Instead, an individual block can be specified for each neighbor. The proposed function interfaces are shown in Listing 4.

B. Semantics

The proposed operations are collective and need involvement of the processes of the communicator. Whereas the existing MPI collectives require that all processes in the communicator call the collective at the same time (i.e., with no other collective calls in-between), it is possible to define meaningfully a more relaxed semantics for the sparse collectives. For correctness we will always require that if process

j is in the target list of process i (with multiplicity r), then process i is in the source list of process j (with multiplicity r).

For each sparse collective, we propose/require that if process i is calling sparse collective A, then each process j \in \{t_0, t_1, \ldots, t_k\} \cup \{s_0, s_1, \ldots, s_{\ell - 1}\} must eventually call A with no other collective call (on the same communicator) in-between. This means that if processes i and j are not connected by a path in the communication neighborhood (see below) their calls to sparse collectives can be independent of each other. Since it is perhaps not always obvious for the user that these conditions, including the requirements of matching block sizes, are fulfilled, it is worth noting that they can be automatically verified (by similar collective operations), and thus incorporated into a verification interface as described in [17], [18].

The relaxed calling conditions can give more flexibility to applications with disconnected neighborhoods. Processes in one neighborhood need not ensure that sparse collective calls follow in the same order or with the same frequency as sparse collective calls in another disconnected neighborhood. The number of iterations in loops with sparse collective calls need thus not be the same in all neighborhoods of the communicator.

We note that this definition excludes optimizations in which processes not actually in the neighborhood of some process helps with routing or computation in the collective operation. It can be shown that this can sometimes reduce the number of communication rounds, e.g., for irregular all-to-all communication [19].

C. Nonblocking variants

Nonblocking versions of the proposed sparse collective operations are possible. This would enable overlap of communication and computation during the communication phase. Such benefits of nonblocking nearest neighbor communication on a graph communicator were investigated in [16]. Another, more wide-ranging possibility that is not discussed further here is to introduce a partial completion function to indicate
neighbors for which data have already arrived. This would allow finer control of the communication while retaining the higher abstraction level and message scheduling possibilities.

D. An example: ghost cell updates

Applications that use ghost cell regions to introduce more communication slackness update these by patterns that can be captured by the sparse \texttt{MPI\_Neighbor\_alltoall} operation. In Figure 2 each processor in a mesh maintains a border of ghost cells (shaded) that have to be exchanged with its 8 neighbors. This can be expressed as an \texttt{MPI\_Neighbor\_alltoall} sparse collective communication operation. Horizontal and vertical $x$ blocks are exchanged with one neighbor only, but may typically have different layout in memory and thus different MPI datatypes. Each smaller $y$ block is sent to three neighbors (horizontally, vertically and diagonally), thus the \texttt{MPI\_Neighbor\_alltoall} operation must allow overlapping displacements. For the exchange of each $y$, $x$, $y$ border with a horizontal or vertical neighbor, each such neighbor appears three times in source and target lists.

The common optimization for saving diagonal communication, sending each $y$ block first in the horizontal direction, combining it with the $y$ block from this neighbor, and then sending both blocks in the vertical direction (see e.g., [20]) would be automatically taken care of by a good implementation of \texttt{MPI\_Neighbor\_alltoall}.

III. IMPLEMENTATION AND PERFORMANCE

We now consider one of the simplest process communication topologies in practical use [21], [22], namely a $n$-dimensional mesh or torus (we chose two dimensions for simplicity). Each process has a local neighborhood consisting of 4 neighbors (excluding itself) as shown in Figure 3, and sends and receives (the same amount of) data to and from all neighbors. For this simple communication topology we give two implementations of the \texttt{MPI\_Neighbor\_alltoall} collective.

A straightforward implementation queries the communicator for source and target lists and posts the corresponding nonblocking send and receive calls for all source and target processes. This is the way that many applications currently implement the sparse exchange pattern (cf. Section I-A). The implementation is shown in Listing 5.

Since there is no control of the order in which the send and receive operations are started by the underlying MPI implementation, this implementation could suffer from contention by several source processes trying to send data to the same target process at the same time. Furthermore, nonblocking operations typically incur a certain overhead that could grow considerably for larger neighborhoods than in the simple mesh case.

By exploiting the knowledge of the global mesh topology, a possibly more efficient implementation of the sparse all-to-all operation would schedule communication in dimension order, and use combined, blocking send-receive operations. If processes can be assumed to arrive at the collective more or less at the same time, this implementation will not suffer from contention, and can possibly more efficiently take advantage of bidirectional communication capabilities of the underlying network (even in the case where the size of a dimension is odd). This implementation is sketched in Listing 6.
int MPI_Neighbor_alltoall(sendbuf, sendcount, sendtype,
    recvbuf, recvcount, recvtype, comm)
{
    i = 0;
    for (d=0; d<dim; d++) {
        MPI_Cart_shift(comm, d, 1, &down, &up);
        MPI_Sendrecv(sendbuf+i*sendcount+sendextent,...,
            up,...,
            recvbuf+i*recvcount+recvextent,...,
            down,...,comm, MPI_STATUS_IGNORE);
        i++;
        MPI_Sendrecv(sendbuf+i*sendcount+sendextent,...,
            up,...,
            recvbuf+i*recvcount+recvextent,...,
            down,...,comm, MPI_STATUS_IGNORE);
        i++;
    }
    // next pair of neighbors
}

Listing 6. Scheduled sparse all-to-all implementation for Cartesian meshes
and tori.

Both implementations send and receive the same amount
of data without any combining or fancy rerouting, and
therefore have the same message complexity. The first, generic
implementation may suffer from contention, and possibly has
a higher overhead due to the use of nonblocking operations, but
is generic in that it does not rely on global knowledge of the
communication topology. The second implementation works
strictly for meshes or similar, regular topologies. Posting
blocking send-receive operations on a local neighborhood
without any knowledge of the order in which the other
processes perform the send-receive operations will deadlock
in most cases. Alone for this reason, global knowledge is
necessary for scheduling blocking communication for general
sparse collective operations, unless one is satisfied with the
generic solution of Listing 5.

We use a simple benchmark for measuring the time to
completion of the two alternatives. Results on a single shared-
memory node are given in Figure 4 and a results for a hybrid
x86 cluster with InfiniBand interconnect are shown in Figure 5.
We see that the generic, naive implementation (Listing 5)
can be about 10% slower than the more carefully scheduled
implementation (Listing 6).

A. Irregular

We now use the dimension-scheduled implementation of
MPI_Neighbor_alltoall also for solving the irregular variant
of the problem. For the benchmark we distinguish between
communication light and heavy edges, and consider the two
different exchange patterns shown in Figure 6. We refer
to these as horizontal (left) and circular (right) exchanges,
respectively.

The two patterns obviously have the same message com-
plexity (each process sends and receives two heavy and two
light messages), but whereas the horizontal pattern has all
communication in only one dimension, and can thus complete
in only two heavy rounds (right-to-left followed by left-to-
right), the circular pattern requires four heavy rounds (right-
to-left sends or receives on a heavy edge, and likewise left-to-
right sends or receives on a heavy edge. Also the two up-down
communication rounds are both heavy). It is obvious that a
different schedule could easily be used to solve the circular
problem also in two heavy rounds.

The results from the benchmark show the expected dif-
fERENCE in performance of about a factor two on an NEC
SX-8, see Figure 7. Figure 8 shows the same benchmark
for an x86 cluster with InfiniBand. We see that horizontal
communication is faster for all homogeneous communica-
Fig. 7. Running times for horizontal and circular patterns on an NEC SX-8 node with 8 processes.

Fig. 8. Communication times for different mapping options for an x86 cluster system with InfiniBand. Processes are either mapped in a 5x6 grid on 32 nodes with 1 process per node using InfiniBand (IB) to communicate or an 11x11 grid on 32 nodes using IB and Shared Memory (SM) with 4 processes per node. The 2x4 example uses only shared memory.

IV. SPECIFYING NEIGHBORHOODS

So far we have assumed that the local neighborhoods, i.e., the lists of source and target processes for each process have been associated with the communicator. We now have to discuss how this can be done. From the discussion and the results of the previous section it is clear that a handle through which the processes can collectively provide their local neighborhood and communication amount to the MPI library is required for correct, deadlock-free and efficient communication scheduling. This collective handle would be responsible for computing and distributing knowledge about the global communication topology to each process, thereby allowing it to make efficient and correct scheduling decisions. Although the handle needs to be collective, this does not necessarily imply that a global communication graph has to be explicitly constructed in full by any one process. Distributed algorithms (e.g., for graph coloring [23]) may be possible that allow for computation of enough information for each process to make the correct scheduling and optimization decisions.

In the following we discuss two solutions to the problem.

A. Handles taking local information

The straightforward alternative would be to introduce a collective operation in which each process contributes its local neighborhood in the form of source and target lists. These lists would get associated with the communicator used in the call, and can later be queried locally. At this point, schedules and other optimizations can be decided (locally) for the processes. However, since the three sparse collectives described in Section II may use different local neighborhoods in the application, and since the scheduling and other optimization criteria may be different for the three collectives, it seems that a specific handle for each type of collective would be necessary. Thus either three handles would have to be introduced, as shown in Listing 7, or a composite handle as in Listing 8 in which additional information on which collective the source and target lists pertain to is given in the first argument.

The operation argument for the second possibility could be a bit-vector of values MPI_NEIGHBOR_GATHER, MPI_NEIGHBOR_ALLTOALL, and MPI_NEIGHBOR_REDUCE that could thus be given in any combination.

For both possibilities an MPI info object is introduced to convey information of optimization criteria, process arrival patterns and other information that could be relevant to the MPI implementation. The weight arguments should reflect (approximately) the amount of communication with neighbors, and can be used by the MPI library to find a good schedule for the underlying hardware architecture. Note that this is decoupled from the actual communication amounts (given by the send and receive counts and datatype arguments in the actual, sparse collective calls), and there is no requirement that the two be identical. If a user makes a sparse collective call with completely different communication amounts from what was specified in the neighborhood handle call, suboptimal

Listing 7. Collective handle for attaching local neighborhoods to communicator (for MPI_Alltoall).

MPI_Neighbor_alltoall_set(sources,sourceweights, targets,targetweights, info,comm)

Listing 8. Combined collective handle for attaching local neighborhoods to communicator.

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performance may be expected. Correctness must, however, not be compromised. Thus, communication weights and info object are only hints to the library as to what can be expected.

In MPI lists (ordered sets) of processes are represented by process groups. The source and target list arguments should thus be given as process groups, although many users consider this construct tedious. An alternative might be simply to supply simple lists of process ranks.

B. Using the MPI virtual topology functionality

The set of all local neighborhoods, that is the source and target lists introduced in Section II, together comprise a directed communication graph. In MPI there is already a mechanism for using such communication graphs to improve communication performance. This is the virtual topology functionality [1, Chapter 7]. It is therefore a natural alternative to use this functionality also for fixing the process neighborhoods for the sparse collective operations.

The Cartesian topology mechanism allows explicit specification of simple meshes, tori (and hypercubes). Each process has neighbors along the dimensions. This neighborhood communication pattern is probably too restricted for many actual applications (that use e.g., 9-neighbor stencils in the 2-dimensional case), and it further limits the sparse collectives to only symmetric exchange patterns. For using this, otherwise convenient functionality, extensions that give more flexibility would need to be considered.

The general, graph topology interface gives full flexibility in describing neighborhood, since communication graphs are not required by the MPI standard [1] to be symmetric. Unfortunately, in the current interface all processes are required to supply the full communication graph. This may not be known, and it would therefore entail global, collective communication by the user to build this knowledge. Furthermore, the existing functionality has room neither for communication edge weights, nor for an info object for providing information to the MPI library. This is, however, likely to be extended with new, more flexible functionality in upcoming versions of the MPI standard. In order to get the list of local neighbors that is needed to pack and access data in the communication buffers, additional convenience functionality is needed for the Cartesian topology functionality.

The virtual topology functionality creates a new communicator with possibly a new process to processor mapping that can have been improved for the communication pattern implied by the user supplied communication graph. If used as a handle for sparse collective operations, this would also have the effect of optimizing for these patterns. However, as discussed above, the same neighborhood would be fixed for all three collective operations. Furthermore, any change in neighborhood would force the user to create a new virtual topology communicator, and this might be rather expensive. The solution discussed in the previous section is more flexible in this respect.

In addition to the advantage of reusing existing (but extended) MPI functionality, the major advantage of this solution is that process reordering (for improved point-to-point communication) and optimization of sparse collective patterns is not separated. The first alternative suffers from this drawback.

C. Scheduling communication and other optimizations

For the regular, sparse all-to-all collective, the experiments showed exchange in dimension-order to be beneficial, and this was an example of a more general scheduling optimization.

For homogeneous, single-ported systems both the regular and the irregular all-to-all problem can be solved by graph edge-coloring. A communication multi-graph is constructed where the number of edges between any pair of nodes is proportional to the communication amount between the corresponding processes. An edge coloring with colors $0 \leq i < c$ where $c - 1$ is the largest color used gives a deadlock-free schedule for the communication in $c$ communication rounds. In round $i$ processes sends and receives on edges with color $i$. This is a common solution, see e.g., [19], with many variations. We were deliberately vague about how to handle directed graphs and uni- or bidirectional communication capabilities. The general edge-coloring problem is NP-complete, but good approximation schemes exist, so that this is a viable course for finding good schedules. Also, depending on the communication model sometimes the problem to be solved is a bipartite edge coloring problem (or other variant), that can be solved in polynomial time. For non-homogeneous systems, like SMP-clusters, this approach is not likely to produce good results. For such cases, optimizations that combine messages to save on communication start-ups over weak connections are likely to pay off. Such are often implemented by users, e.g., sending the data to a vertical and diagonal neighbor that reside on a process on a different SMP node in one message. Here it is important that the interface definitions of Section II do not preclude such optimizations.

Figure 9 finally illustrates the sensitivity of the communication schedules to process mapping on an SMP system. The benchmark of Figure 6 was used on a 4-node SX-8 system with 8 processes per node. We compared the cases of horizontal heavy edges, vertical heavy edges, and the circular pattern on the MPI_COMM_WORLD communicator. With MPI’s row major ordering, the horizontal pattern has the most heavy edges crossing nodes, and thus performs the worst, whereas the vertical pattern performs best, with circular in between. We note that process reordering (which is done by NEC’s MPI/SX implementation [24]) cannot improve the communication in any of the cases, because the (current) MPI topology functionality does not permit specification of communication amounts between neighbors.

V. Conclusions

Sparse collective operations are (together with other collective enhancements) currently under discussion in MPI Forum for future MPI versions. In this paper we proposed three such sparse collective communication and reductions operations, each in a regular and an irregular (vector) variant. We proposed
two alternative ways of informing the MPI library of the local neighborhoods of the processes. Collective operations and collective handles for specifying neighborhoods were designed to capture patterns in actual applications, and so as not to exclude any of the optimizations that are typically carried out by users, e.g., combination of messages and scheduling of communication. One exception was made. The relaxed collective semantics do not require that all processes in the communicator always take part in a call, and this excludes certain types of rerouting via otherwise idle processes.

By experiments with one of the simplest sparse communication topologies it was shown that messages scheduling is necessary for performance, especially for the irregular operations and that global knowledge is necessary also for correctness (deadlock-freedom). We think that these are the side-constraints that any design for sparse collectives for MPI must obey.

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