

Entropy Maximization in Sparse Matrix by Vector Multiplication

ABHISHEK JAIN, ISMAIL BUSTANY, and PAOLO D'ALBERTO

The peak performance of any SpMV accelerator depends primarily on the available DRAM memory bandwidth and the capability of the accelerator to effectively use it. Because SpMV is memory-bound, a more important metric than peak performance alone is the fraction of bandwidth utilized, which captures the overall efficiency of the architecture. GPUs along with some DSA ASIC's and new FPGA architectures exhibit very high bandwidth: utilizing this much bandwidth efficiently is difficult for large scale and highly sparse matrices due to very high random access pattern and workload imbalance. We propose a matrix permutation pre-processing step that aims to maximize the entropy of the distribution of the nonzero elements. We conjecture this would be most effective for matrices with no dense rows or columns, as preconditioning, thus justified when the matrix is reused. Unlike matrix ordering schemes that seek to reduce fill, we seek a permutation that uniformly distributes the non-zero elements' distribution, thereby generating a SpMV problem that is amenable to work load balancing or to speed up sort algorithms. We shall show that randomization is an optimization that any architecture may take advantage although in different ways. Most importantly, any developer can consider and deploy. We shall present cases where we can improve performance by 15% on AMD-based systems.

ACM Reference Format:

Abhishek Jain, Ismail Bustany, and Paolo D'Alberto. 2020. Entropy Maximization in Sparse Matrix by Vector Multiplication . 1, 1 (July 2020), 27 pages.

1 INTRODUCTION

To define the scope of this work, the obvious questions to ask are: first, what is randomization (or entropy maximization) in the context of sparse matrices; second, why would we use it; third, when does it work. We shall provide formal definitions in the following sections. Specifically, we will randomly permute the rows and columns of a sparse matrix before multiplying it with a (dense) vector (SpMV) with the aim of speeding this operation. Undoubtedly, this scheme requires some restrictions about the matrix structure, one among them is that it has no or few dense columns or rows. In the case, where there are dense columns or rows, a sparse/dense partitioning scheme should be used. For the remainder of this manuscript, we shall assume the former nonzero structure. We use randomization because it is the poor man's way for preconditioning SpMV (in our restricted context), and we do not mean it in a pejorative sense.

Preconditioning speeds up the convergence rate of an iterative linear solver by linearly transforming the associated matrix into a form that affords a faster reduction of the residual error at every iteration. The cost of this transformation is justified by the runtime reduction it affords. Likewise, we foresee randomization playing a similar role for SpMV in the context of iterative linear solvers and other methods (e.g in convolutions) where the matrix is reused.

Since sparse linear algebra (and GraphBLAS) kernels are memory bound, there is a common thread of focus in the scientific computing community is to develop acceleration libraries mostly for multi-core systems. These predominantly include multi-core processors and GPUs. The main goal is a balanced work distribution and, when applicable, minimal

Authors' address: Abhishek Jain; Ismail Bustany; Paolo D'Alberto.

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than ACM must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.

© 2020 Association for Computing Machinery.

Manuscript submitted to ACM

Manuscript submitted to ACM

communication [3, 4]. When storage strategy and algorithms must be considered together then GPUs provide the work horse for abundant thrust in research [1]. These works aim at optimal solutions and strive for a clear and complete understanding/exploitation of the software-hardware interface; usually the hardware is composed of symmetric computational units. Interestingly, the SpMV's space and time complexity, which are small, may not warrant more performance because we typically end up utilizing only one-thousandth fraction of the available hardware capacity.

The peak performance of any SpMV accelerator depends primarily on the available memory bandwidth (i.e., DRAM such as DDR or HBM) and the capability of the accelerator to effectively use it. Because SpMV is memory-bound, a more important metric than peak performance alone is the fraction of bandwidth utilized, which captures the overall efficiency of the architecture. GPU platforms exhibit very high bandwidth, see the experimental Section 8: Ellesmere DDR5 224GB/s, Fiji HBM 512GB/s, and Vega 20 HBM 1TB/s. Although utilizing this much bandwidth efficiently is difficult for large scale and highly sparse matrices due to very high random access pattern. Custom architectures based on FPGA or ASIC devices can maximize bandwidth utilization by highly customized data-paths and memory hierarchy designs MISSING CITATION []. Most of the existing accelerators saturate the relatively low memory bandwidth available on FPGA platforms (less than 80 GB/s) MISSING CITATION []. Modern FPGA platforms have multiple HBM stacks to provide large memory bandwidth. However, there is no implementation (currently available) that saturates all of the available DRAM bandwidth for SpMV kernel on HBM-enabled FPGA platforms. Scalability of accelerator design remains a major concern, and it is an active area of research.

FPGA platforms used in early works exhibit low peak performance due to the scarcity of external memory bandwidth. For example, Microsoft's implementation of SpMV uses an FPGA platform which only has 2 DDR2-400 memory banks with a resulting bandwidth of 6.4 GB/s MISSING CITATION []. The accelerator is running at 100 MHz, it reads 64 Bytes of data every cycle, which corresponds to 5 non-zeros at every cycle (a non-zero is about 12 Bytes). At best, the peak performance is 10 double precision operations every cycle at 100 MHz, which is 1 GFLOPS (only). In 2009, Convey systems Inc. released the Convey HC-1 FPGA platform. It has 16 DDR2-677 memories resulting in overall 80 GB/s memory bandwidth MISSING CITATION []. The accelerator logic runs at 150 MHz. It consumes 512 Bytes of data every cycle, which corresponds to around 40 non-zeros every cycle. At best, the peak performance is 80 double precision operations every cycle at 150 MHz, which is 12 GFLOPS.

One of the key building blocks for custom architecture solutions is a multi-ported buffer used to storing vector entries. During execution, multiple column indices are used as addresses to read corresponding vector entries; we shall provide more details in Section 2. Designing a buffer with a very large number of read ports is challenging. One solution is *banking* as a mechanism to store partitioned vector entries. Although banking could allow very high throughput indexing unless the same entry is required multiple times and its reads are purely sequential causing loss of bandwidth. For example, hashing techniques and data duplication are possible solutions for this problem. However, another issue arises: When we distribute SpMV computations across p -nodes, some of the nodes, say k , finish later than the rest because of unbalanced work loads (ie. number of nonzero element) in row/column major traversal. This is a common phenomena for matrices where few rows or columns are dense. These k nodes are referred to as *laggard nodes*. By applying random permutation of columns/rows, we are attempting to balance the loads across all p workers so that there is are no laggards. From this hardware vantage point, randomization or maximizing the entropy of the non-zero element distribution is an optimization transform and provides a clear context for our work.

Clearly, optimally accelerating SpMV is a hard many parameters optimization problem dependent on the choice of algorithm, data structures, and dedicated hardware (CPU, GPUs, FPGA's, Custom ASIC's). Rather, our goal is to provide a tool, we may say a naive tool, to help understand how the structure of the matrix may impact the HW-SW solution.

Row or column shuffling is already used by custom hardware to re-organize the data flow to reduce communications and computational bottlenecks. We will study various forms of random permutations and their impact on performance if at all.

For the readers in the field of algorithms, SpMV can be mapped into a sorting algorithm. Bare with us, Sorting is a method to find if an element is in a list with no prior or limited knowledge of its contents. Sorting is used to prepare the matrix and to find elements in between sparse matrices and sparse vectors. In custom architectures, sorting networks are used to route matrix and vector elements to functional units. Interestingly, the best sorting algorithm is a function of the distribution of elements. In a sense, If one is stuck with a sorting algorithm and a poor distribution, randomization may alter the distribution and throttle performance,

We organize this work as follows: In Section 2, we define the matrix by vector operation; in Section 3, we define what we mean by randomization (or entropy maximization). We use randomization to create a uniform distribution in Section 5 and measure uniformity by entropy in Section 4. We present how we drive our experiments to show the effects of randomization in Section 6. In the last sections, we present a summary of the results: we present our task work loads for the given benchmarks in Section 7, and the complete set of measures for an AMD CPU and GPUs systems in Section 8.

2 BASIC NOTATIONS

Let us start by describing the basic notations so we can clear the obvious (or not). A Sparse-matrix by vector multiplication *SpMV* on an (semi) ring based on the operations $(+, *)$ is defined as $\mathbf{y} = \mathbb{M}\mathbf{x}$ so that $y_i = \sum_j M_{i,j} * x_j$ where $M_{i,j}=0$ are not represented nor stored. Most of the experimental results in Section 8 are based on the classic addition $(+)$ and multiplication $(*)$ in floating point precision using 64 bits (i.e., double floating point precision) albeit are extensible to other semi-rings. For instance, it is well known that SpMV defined on the semi-ring $(\min, +)$ is a kernel in computing an all-pairs shortest paths starting with a graph adjacency matrix, and in using a Boolean algebra we can check if two nodes are connected, which is slightly simpler.

We identify a sparse matrix \mathbb{M} of size $M \times N$ as having $O(M + N)$ non-zero elements, number of non zero nnz . Thus the complexity of $\mathbb{M}\mathbf{x}$ is $O(M + N) \approx 2nnz$. Of course, the definition of sparsity may vary. We represent the matrix \mathbb{M} by using the coordinate list *COO* or and the compressed sparse row *CSR*¹ formats. The COO represents the non-zero of a matrix by a triplet (i, j, v) ; very often there are three identical-in-size vectors for the ROW, COLUMN, and VALUE. The COO format takes $3 \times nnz$ space and two consecutive elements in the value array are not bound to be neither in the same row nor column. In fact, we know only that $VALUE[i] = M_{ROW[i], COLUMN[i]}$.

The CSR format stores elements in the same row and with increasing column values consecutively. There are three arrays V, COL, and ROW. The ROW is sorted in increasing order. Its size is M , and $ROW[i]$ is an index in V and COL describing where i -th row starts (i.e., if row i exists). Accordingly, $M_{i,*}$ is stored in $V[ROW[i] : ROW[i + 1]]$. The column indices are stored at $COL[ROW[i] : ROW[i + 1]]$ and sorted increasingly. The CSR format takes $2 \times nnz + M$ space and a row vector of the matrix can be found in $O(1)$.

The computation $y_i = \sum_j M_{i,j} * x_j$ is a sequence of scalar products and, using the CSR format, is computed as follows:

$$Index = ROW[i] : ROW[i + 1]$$

$$y_i = \sum_{\ell \in Index} V[\ell] * x_{COL[\ell]}$$

¹a.k.a. Compressed row storage CRS.

The matrix row is contiguous (in memory) and rows are stored in increasing order. While access of the (dense) vector \mathbf{x} has no particular pattern.

The COO format can be endowed with certain properties. For example, we can sort the array by row and add row information to achieve the same properties of CSR. In contrast, transposing a "sorted" COO matrix simply entails swapping of the arrays ROW and COL. Think about matrix multiply. Each scalar product achieves peak performance if the reads of the vector \mathbf{x} are streamlined as much as possible and so the reads of the vector V . If we have multiple cores, each could compute a subset of the y_i and a clean data load balancing can go a long way. If we have few functional units, we would like to have a constant stream of independent $*$ and $+$ operations but with data already in registers. That is, data pre-fetch will go a long way especially for $x_{COL[i]}$, which may have an irregular pattern.

3 RANDOMIZATION (OR ENTROPY MAXIMIZATION)

We define *Randomization* as row or column permutation transform of the matrix \mathbb{M} (thus a permutation of \mathbf{y} and \mathbf{x}), and we choose these by a pseudo-random process. The obvious question to ask is why should we seek randomization (or entropy maximizing) transform? The sparsity of a given matrix \mathbb{M} has a non-zero element distribution induced by the nature of the original problem or by some imposed ordering on the respective nodes of its associated graph. This distribution may be computationally incompatible with the chosen algorithm or architecture. For instance, it can induce some load imbalance in the computation. We could break this load imbalance by seeking to maximize entropy for this distribution. Our conjecture is that would favor the average case performance rather than the worse case when operating on the "max-entropy transformed" matrix.

For linear system solvers, if we know the matrix \mathbb{M} , and we know the architecture, preconditioning (when affordable) is a better solution. Well, it is. If we run experiments long enough, we choose the best permutation(s) for the architecture, permute \mathbb{M} , and go on testing the next. On one end, preconditioning exerts a full understanding of both the matrix (the problem) and how the final solution will be computed (architecture). This is the culminating point of knowing, and we must strive to it. On the other end, the simplicity of a random permutation requires no information about the matrix, the vector, and the architecture. Such a simplicity can be exploited directly in Hardware. We are after an understanding when randomization is just enough: We seek to let the hardware do its best with the least effort, or at least with the appearance to be effortless.

Interestingly, this work stems from a sincere surprise about randomization efficacy and its application on custom SpMV. Here, we wish to study this problem systematically so that to help future hardware designs. Intuitively, if we can achieve a uniform distribution of the rows of matrix \mathbb{M} we can have provable expectation of its load balancing across multiple cores. If we have a uniform distribution of accesses on \mathbf{x} we could exploit column load balancing and exploit better sorting algorithms. In practice, the reading of $x_{COL[i]}$ can be reduced to a sorting, and there we know that different sparsity may require different algorithms. This may be lot to unpack but it translates to a better performance of the sequential algorithm without changing the algorithm or to improved bandwidth utilization.

We will show that (different) randomness affects architectures and algorithms differently, making randomization a suitable optimization transform especially when the application and hardware are at odds: Hardware (unless programmable) is difficult to change and the matrix sparsity is simple to change. We want to show that there is a randomness hierarchy that we can distinguish as global and local. There are simple-to-find cases where the sparsity breaks randomness optimization. For instance, matrices with dense rows or columns are better partitioned into sparse and dense components and operated on separately.

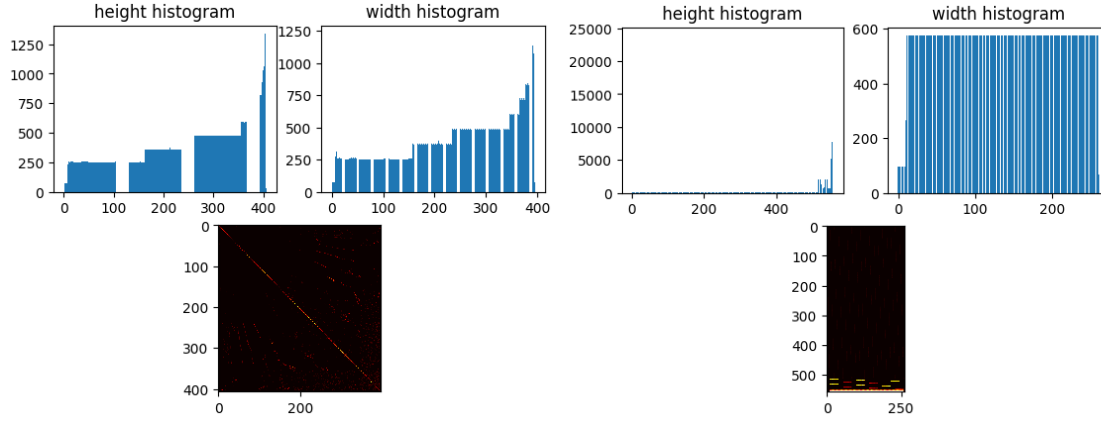


Fig. 1. Left: OPF 3754. Right: LP OSA 07. These are histograms where we represent normalized buckets and counts

4 ENTROPY

Patterns in sparse matrices are often visually pleasing, see Figure 1 where we present the height histogram, the width histograms and a two-dimensional histogram as heat map. We will let someone else using AI picture classification. Intuitively, we would like to express a measure of uniform distribution and here we apply the basics: *Entropy*. Given an histogram $i \in [0, M - 1]$ $h_i \in \mathbb{N}$, we define $S = \sum_{i=0}^{M-1} h_i$ and thus we have a probability distribution function $p_i = \frac{h_i}{S}$. The *information* of bin i is defined as $I(i) = -\log_2 p_i$. If we say that the stochastic variable X has PDF p_i than the entropy of X is defined as.

$$H(x) = - \sum_{i=0}^{M-1} p_i \log_2 p_i = \sum_{i=0}^{M-1} p_i I(i) = E[I_x] \quad (1)$$

The maximum entropy is when $\forall i, p_i = p = \frac{1}{M}$; that is, we are observing a uniform distributed event. There is no conceptual difference when the PDF represents a two dimensional distribution. Thus our randomization should aim at higher entropy numbers. The entropy for matrix LP OSA 07 is 8.41 and for OPF 3754 is 8.39. We use the entropy specified in the Scipy stats module. A single number is concise and satisfying. If you are pondering why they are so close contrary to their sparsity we discuss this next.

5 UNIFORM DISTRIBUTION

We know that we should **not** compare the entropy numbers of two matrices because entropy does not use any information about the order of the buckets only their probabilities. By construction, the matrices are quite different in sparsity and in shapes, however their entropy numbers are very close. Two matrices with the same number of non-zeros, spaced well enough in the proper number of bin, will have the same entropy. To appreciate their different sparsity, we should compare their entropy distributions by Jensen-Shannon measure (which is a symmetric measure, please do not use Kullback-Leibler KL divergence) [2]. Or we could use a representation of a hierarchical 2d-entropy, see Figure 2, where the entropy is split into 2x2, 4x4 and 8x8 (or fewer if the distribution is not square). We have a hierarchical entropy heat maps.

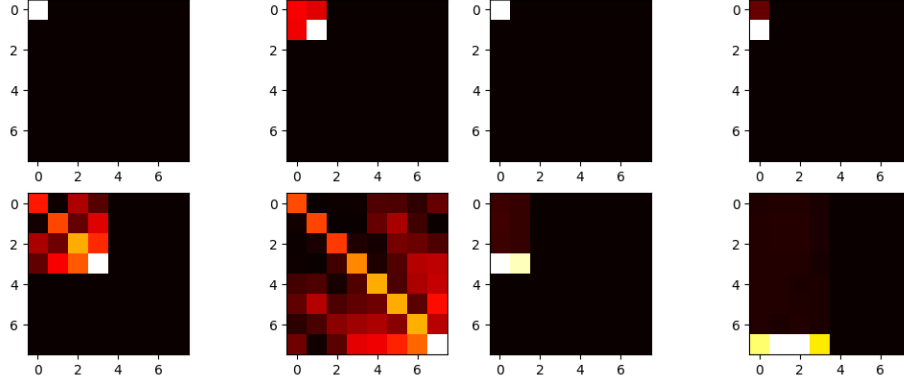


Fig. 2. Hierarchical 2D entropy for OPF 3754 (left) and LP OSA 07 (right).

169 We can see that a granular entropy summarizes better the nature of the matrix because it keep some spatial
 170 information. In this work, the entropy vector is used mostly for visualization purpose more than for comparison purpose.
 171 Of course, we can appreciate how the matrix LP OSA 07 has a few very heavy rows and they are clustered. This matrix
 172 will help us showing how randomization need some tips. Now we apply row and column random permutation once
 173 by row and one by column: Figure 3: OPF has now entropy 11.27 and LP 9.26. The numerical difference is significant.
 174 The good news is that for entropy, being an expectation, we can use simple techniques like bootstrap to show that the
 175 difference is significant or we have shown that Jensen-Shannon can be used and a significance level is available. What
 176 we like to see is the the hierarchical entropy heat map is becoming *more* uniform for at least one of the matrix.

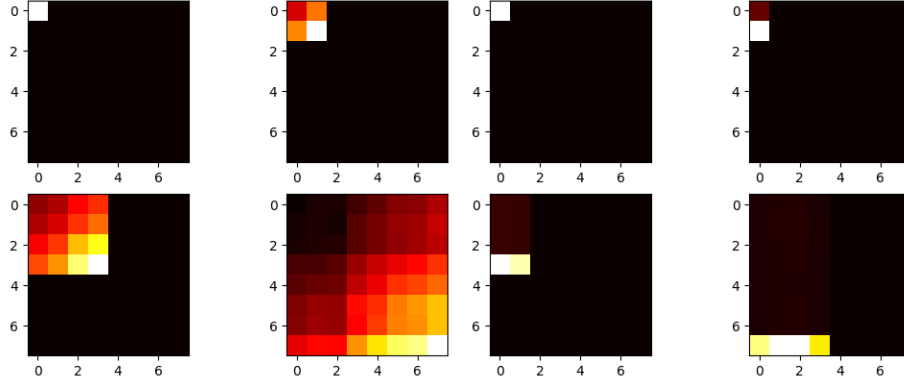


Fig. 3. Hierarchical 2D entropy after row and column random permutation for OPF 3754 (left) and LP OSA 07 (right).

177 In practice, permutations need some help especially for relatively large matrices. As you can see, the permutation
 178 affects locally the matrix. Of course, it depends on the implementation of the random permutation (we use numpy for
 179 this) but it is reasonable a slightly modified version of the original is still a random selection but unfortunately they seem
 180 more likely than they should. We need to compensate or help the randomization so that this current implementation
 181 does not get too lazy.

If we are able to identify the row and column that divide high and low density, we could use them as pivot for a shuffle like in a quick-sort algorithm. We could apply a sorting algorithm but its complexity will be the same of SpMV. We use a gradients operations to choose the element with maximum steepness, Figure 4 and 5

LP achieves entropy 8.67 and 9.58 and OPF achieves 10.47 and 11.40.

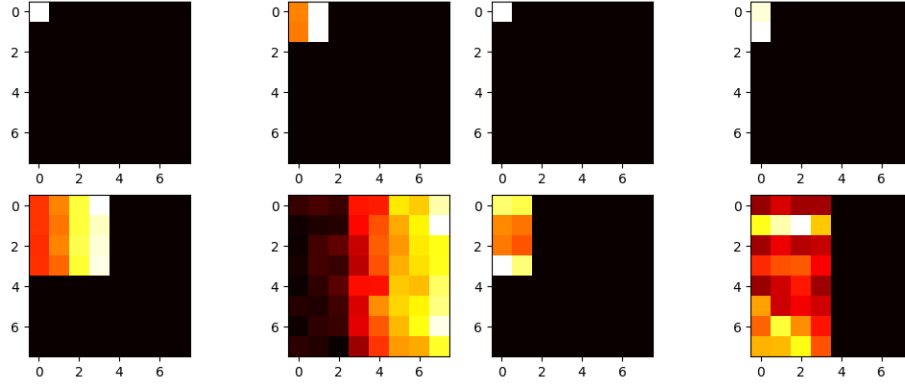


Fig. 4. Hierarchical 2D entropy after height gradient based shuffle and row random permutation for OPF 3754 (left) and LP OSA 07 (right).

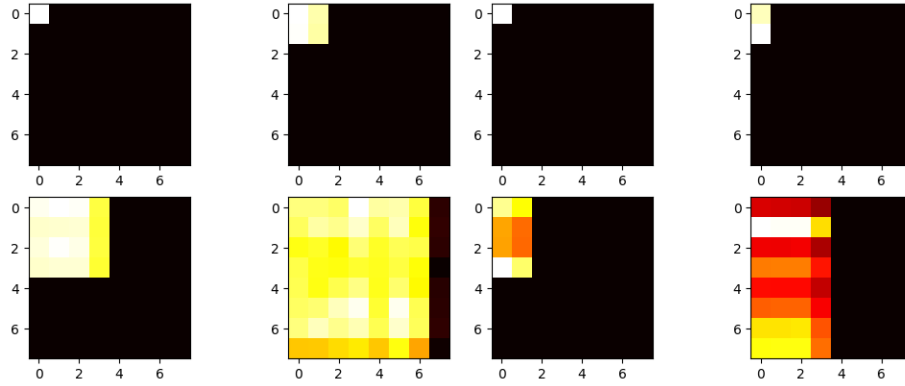


Fig. 5. Hierarchical 2D entropy after height and width gradient shuffle and row and column random permutation for OPF 3754 (left) and LP OSA 07 (right).

If the goal is to achieve a uniformly sparse matrix, it seems that we have the tools to compute and to measure such a sparsity. We admit that we do not try to find the best permutation. But our real goal is to create a work bench where randomization can be tested on different architectures and different algorithms. A randomization with a measurable uniform distribution is preferable than just random. We are interested to find out when random is enough or not enough. Also, consider that to achieve a uniform distribution, we do not need a random transformation and any permutation balancing the number of non-zero is possible, but for now not looked for.

6 MEASURING THE RANDOMIZATION EFFECTS

Whether or not this ever applied to the reader, when we have timed algorithms (i.e., measure execution time), we came to expect variation. The introduction of randomization may hide behind the ever present variance, after all these are algorithms on *small* inputs and small error can be comparable to the overall execution time. Here, we must address this concern even before describing the experiments.

First, we execute every algorithm between 1000 and 5000 times. The time of each experiment is in the seconds, providing a granularity for which we are confident the measuring time error is under control. Thus, for each experiment we provide an average execution time: we measure the time and we divide by the number of trials. Cold starts, the first iteration, are still accounted. To make the measure portable across platform we present GFLOPS, that is, Giga (10^{12}) floating operations per second: $2 * nnz$ divided by the average time in seconds.

Then we repeat the same experiment 32 times. Permutations in *numpy* Python uses a seed that is time sensitive: thus every experiment is independent from the previous. The number 32 is an old statistic trick and it is a minimum number of independent trials to approximate a normal distribution. In practice, they are not but the number is sufficient for most of the cases and it is an excellent starting point.

A short hand legend: **Reg** is the matrix without any permutation and thus is the regular; **R** stands for random Row permutation; **G-R** stands for gradient-based row shuffle and random row permutation; **G-C** stands for gradient-based column shuffle and random column permutation; **R-C** stands for random row and column permutation. This legend is used in the pictures to be concise, in the tables in the following sections, we use a verbose description. We shall clarify the gradient based approach in the experimental results section 8. Intuitively, we help the random permutation by a quick targeting of high and low volume of the histogram (and thus the matrix).

In Figure 6, We show CPU performance using COO and CSR SpMV algorithms for the matrix OPF 3754. We can see that the CSR algorithms are consistent and the Regular (i.e., the original) has always the best performance. For the COO, permutations introduce long tails, thus performance advantage.

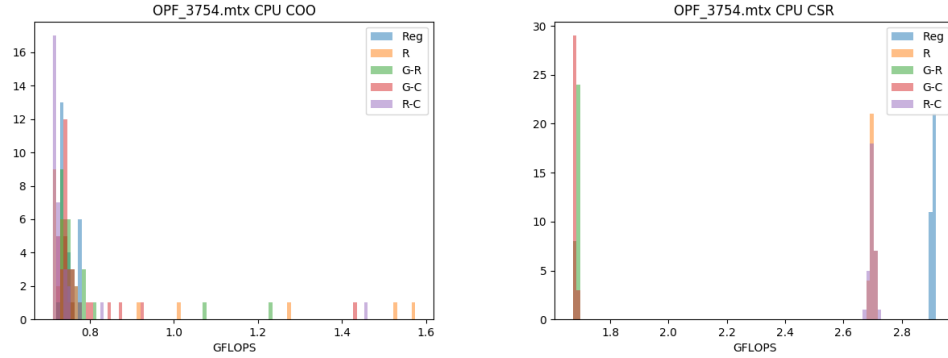


Fig. 6. CPU COO (left) and CPU CSR (left) for OPF 3754

In Figure 7, 8 and 9, randomization is harmful to the GPU implementation. The OPF 375 matrix is mostly diagonal, thus the vector \mathbf{x} is read in close quarters, randomization breaks it. If the load balance is fixed (i.e., by dividing the matrix by row and in equal row), randomization is beneficial.

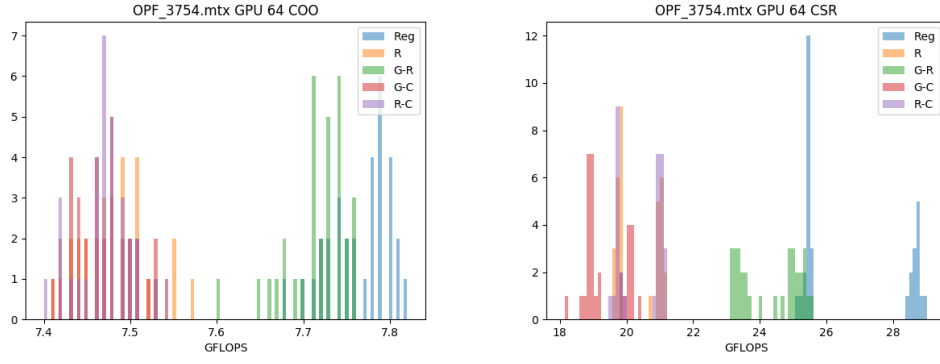


Fig. 7. Vega 20, GPU 64bits COO (left) and GPU CSR (right) for OPF 3754

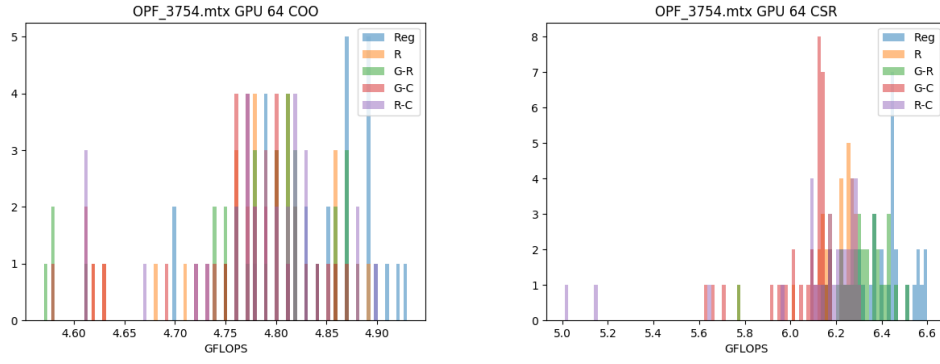


Fig. 8. Ellesmere, GPU 64bits COO (left) and GPU CSR (right) for OPF 3754

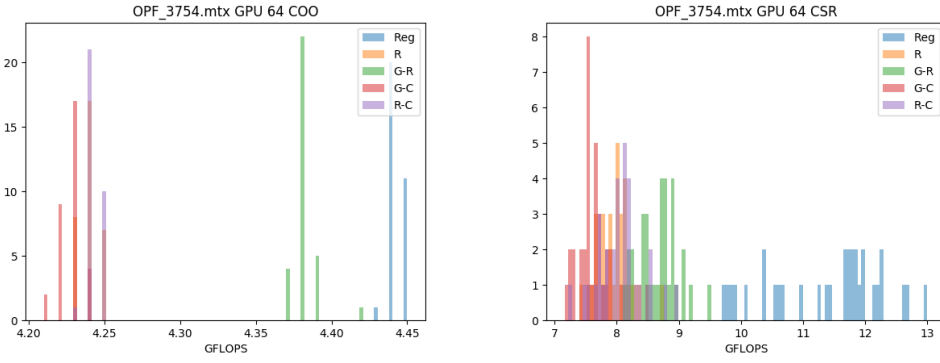


Fig. 9. Fiji, GPU 64bits COO (left) and GPU CSR (right) for OPF 3754

218 If we take the original matrix and split into part having the same number of rows, and execute them in parallel using
 219 different cores, we can see in Figure 10 that randomization is quite useful.

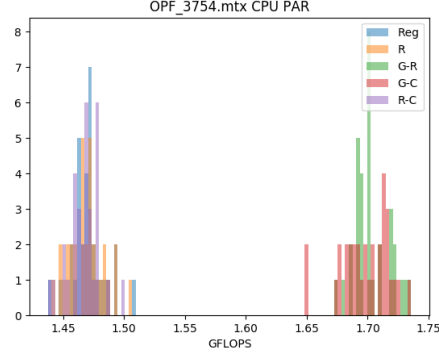


Fig. 10. Parallel CPU CSR for OPF 3754

219

220 For matrix LP OSA 07, randomization helps clearly only for CPU CSR as we show in Figure 11

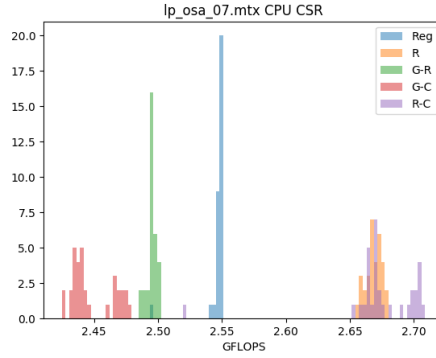


Fig. 11. CPU CSR for LP OSA 07

221 In Figure 12, 13, and 14, we can see that randomization is harmful but for one GPU, we can show that a single
 222 exception is possible (40% improvement).

223 An example, the matrix MULT DCOP 01, is where randomization is useful for the CPU, GPU, and the parallel version
 224 Figure 15, 16 - 19 and the gains can be up to 10-15%. Consider, we can achieve these improvements without any insights
 225 to the architecture, the algorithms and their relationships.

226 What does it mean when randomization does not work? The matrices we use in this work are not chosen randomly
 227 (pun not intended), they are the matrices that are difficult to handle in our custom SpMV engines using a combination
 228 of sorting networks and systolic arrays. If randomization does not work in our simplified work bench, will not work in
 229 our specialized architecture because the reorganization of the matrix or the input and output vector does not have
 230 the necessary parallelism, data locality, and data streaming. We need to do something else. In this case disrupting the
 231 memory pattern is not sufficient. Thus, if we cannot beat the pattern, we must exploit it, well not in this work.

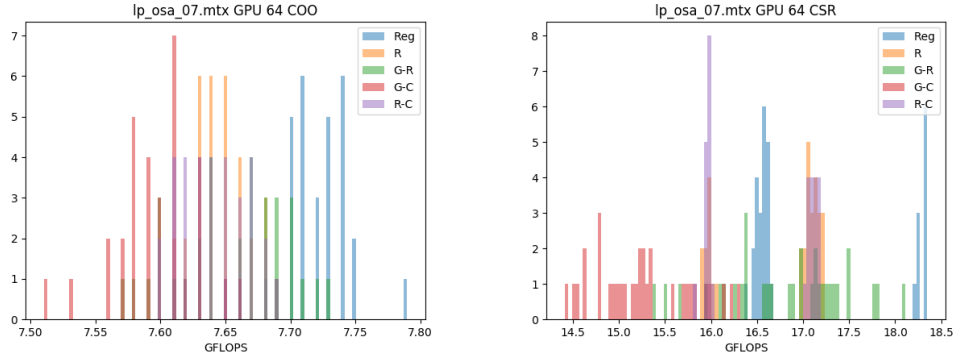


Fig. 12. Vega 20, GPU 64bits COO (left) and GPU CSR (right) for OPF 3754

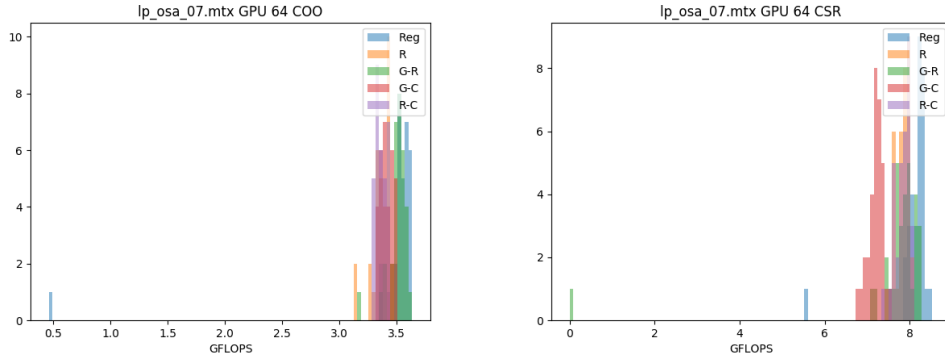


Fig. 13. Ellesmere, GPU 64bits COO (left) and GPU CSR (right) for OPF 3754

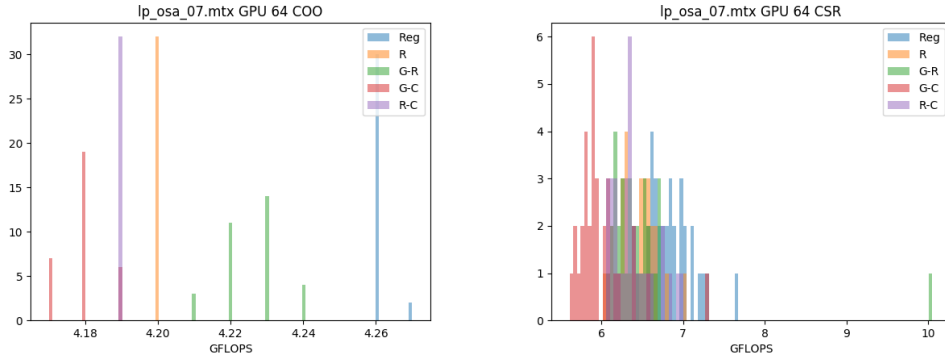


Fig. 14. Fiji, GPU 64bits COO (left) and GPU CSR (right) for OPF 3754

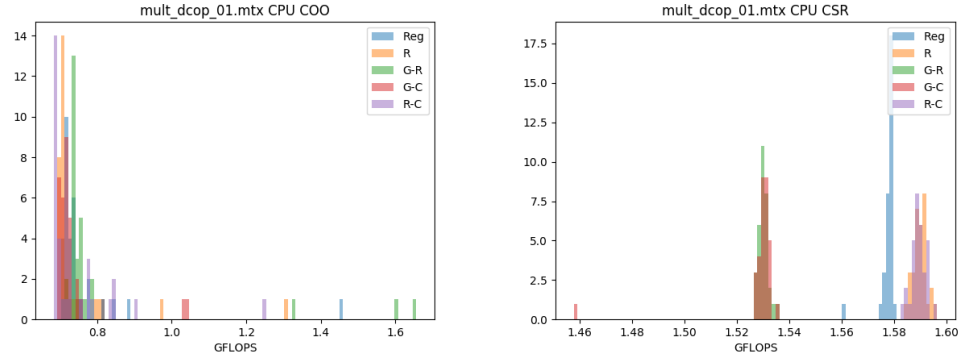


Fig. 15. CPU COO (left) and CPU CSR (right) for MULT DCOP 01

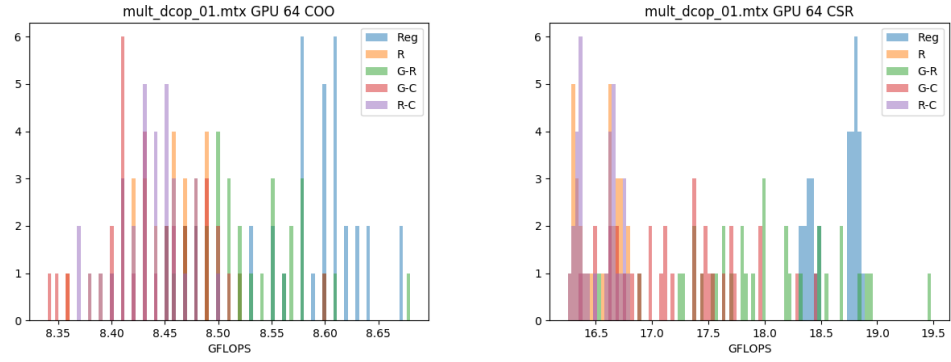


Fig. 16. Vega 20, GPU 64bits COO (left) and GPU CSR (right) for MULT DCOP 01

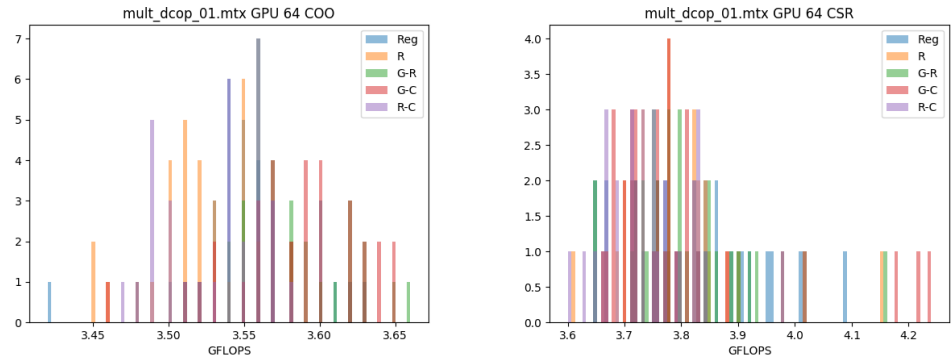


Fig. 17. Ellesmere, GPU 64bits COO (left) and GPU CSR (right) for MULT DCOP 01

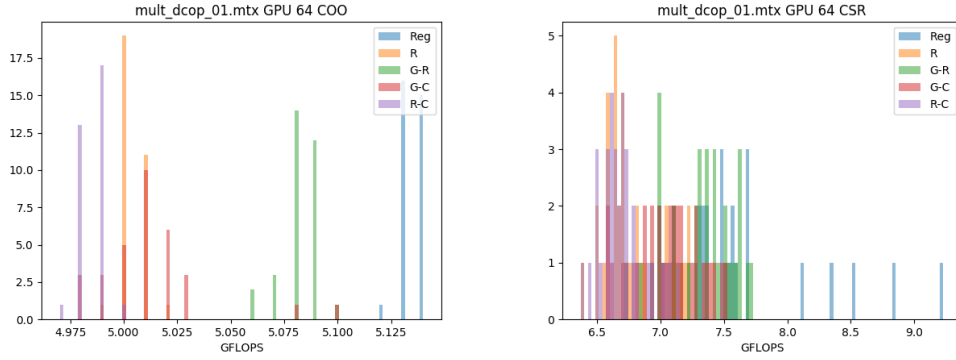


Fig. 18. Fiji, GPU 64bits COO (left) and GPU CSR (right) for MULT DCOP 01

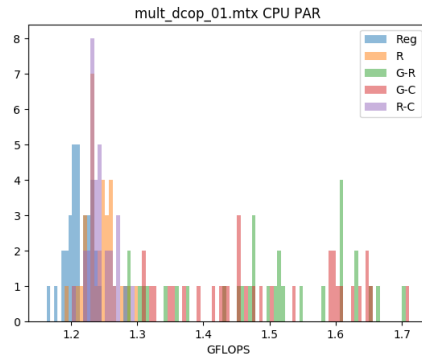


Fig. 19. Parallel CPU CSR for MULT DCOP 01

7 WORKLOADS

In the previous sections, we defined what we mean for randomization and we present our tools of tricks for the measure of the effects of randomization. Here we describe the work loads, the applications, we use to test the effects of the randomization.

7.1 Python COO and CSR algorithms

The simplicity to compute the SpMV by the code $z = A * b$ in Python is very rewarding. By change of the matrix storage format, $A = A.tocsr(); z = A * b$, we have a different algorithm. The performance exploitation is moved to the lower level. The CSR implementation is often two times faster but there are edge cases where the COO and COO with randomization can go beyond and be surprisingly better: MUL DCOP 03 is an example where COO can do well.

Intuitively, Randomization can affect the performance because the basic implementation is a sorting algorithm and it is a fixed algorithm. There are many sorting algorithms and each can be optimal for a different initial distribution. If we knew what is the sorting algorithm we could tailor the input distribution. Here we just play with it.

244 In Section 8, we present all the results for CPU and GPUS. Keep in mind that these problems are hard, in the sense
 245 they do not have fancy performance sheets (these architectures can achieve Tera FLOPs sustained performance for
 246 dense computations). If we go through diligently, we can see that there is a 15x performance difference between the
 247 single thread CPU and Vega 20 GPU (i.e, 3 vs 40 GFLOPS).

248 7.2 Parallel CSR using up to 16 cores

249 Python provides the concept of Pool to exploit a naive parallel computation. We notice that work given to a Pool is split
 250 accordingly to the number of elements to separate HW cores. We also noticed that the work load move from a core
 251 to another, thus not ideal. Also we notice that Pool introduce a noticeable overhead: a Pool of 1, never achieves the
 252 performance of the single thread $z = A * b$. Using Pool allows us to investigate how a naive row partitioning without
 253 counting can scale up with number of cores. We tested by splitting the rows to 1–16 cores evenly (one thread per core)
 254 and we present the performance for only the best configuration. The randomization goal is to distribute the work
 255 uniformly: a balanced work distribution avoid the unfortunate case where a single core does all the work. We are
 256 pleased by the simplicity of the benchmark and we know we can do better.

257 7.3 GPU COO and CSR algorithms

258 In this work, we use AMD GPUs and *rocSPARSE* is their current software. The software has a few glitches but overall
 259 can be used for different generation of AMD GPUs. We use the COO and CSR algorithms and we provide performance
 260 measure for double precision only. The ideas of using different GPUs: it is important to verify that the randomization
 261 can be applied independently of the HW. We are not here to compare performance across GPUs and CPUs. Often the
 262 limitation is the software, how the software can exploit the hardware or how the software will make easy to use a
 263 specific GPU. For example, the Fiji architecture is clearly superior to the Ellesmere, however the latter have better
 264 support and the system overall is more stable and user friendly.

265 The performance of the CSR algorithm is about two times faster than the COO. Most of the algorithms count the
 266 number of sparse elements in a row and thus they can decide the work load partition accordingly. Counting give you
 267 an edge but without changing the order of the computation there could be cases where the work load is not balanced
 268 and a little randomization could help and it does.

269 7.4 Randomization sometimes works

270 For the majority of the cases we investigated and reported in the following sections, Randomization does not work.
 271 However, there are cases where randomization does work and does work for different algorithms and architectures. If
 272 you are in the business of preconditioning, permutations are pretty cheap. If you can find a good one just consider like
 273 a preconditioning matrix, which it is.

274 This shows also that HW has to be more conscious, well the HW designer should, and accept that there are options
 275 at software level, at matrix level and beyond.

276 8 EXPERIMENTAL RESULTS

277 The main hardware setup is a AMD Threadripper with 16 cores. We have three Radeon GPUs: Vega 20 7nm, Pro 2xFiji,
 278 and Pro 2xEllesmere.

279 Vega 20 can deliver 3.5TFLOPS in double precision and it has 1TB/s HBM memory. Each Fiji provides 0.5 TFLOPS in
 280 double precision and has 512GB/s HBM, the card has two chips. The Ellesmere provides 0.3TFLOPS in double precision

and has 224GB/s DDR5, the card has two chips. In the performance plots presented earlier and in the following, you will notice that the performance gap between these GPUs is not so marked. We can safely state that $vega \sim 2 \times Fiji$ and $Fiji \sim 2 \times ellesmere$

There are 4 basic randomization formats:

- **Random Row Permutation**, we take the original matrix and permute the rows.
- **Random Row and Column Permutation**, we take the original matrix and permute the rows and the columns.
- **Gradient based row permutation**, we compute the row histogram and we compute the gradient: $h_{i+1} - h_i$. We find a single point where the gradient is maximum, this is the pivot for a shuffle like a magician would shuffle a deck of cards. Then we permute the two parts randomly.
- **Gradient based row and column permutation**, As above but also for the columns.

For large matrices (large number of columns and rows) a permutation tends to be a close variation of the original, still a random permutation. The gradient allows us to describe two area of the original matrix where there is a clear and de-marked density variation: for example, there are two uniform distributed sub matrices but one denser than the other. A shuffle redistribute every other sample/card to different parts and these can be permuted locally.

We report in the following the performance results, we introduce a * following the best performance. This is tedious to read and, we assure, to write. The code and the results are available as software repository.

9 VEGA VII AND THREADRIPPER

mult_dcop_03.mtx

Regular

CPU COO	min	0.728	max	0.880	mean	0.757
CPU CSR	min	1.563	max	1.581	mean	1.577
GPU 64 COO	min	8.540	max*	8.670	mean	8.619
CSR	min	18.320	max	18.930	mean	18.620
CPU PAR	min	1.170	max	1.269	mean	1.226
H	min	9.689	max	9.689	mean	9.689

Row-Premute

CPU COO	min	0.710	max	0.845	mean	0.724
CPU CSR	min	1.549	max*	1.597	mean	1.589
GPU 64 COO	min	8.360	max	8.540	mean	8.442
CSR	min	16.260	max	16.780	mean	16.551
CPU PAR	min	1.205	max	1.319	mean	1.263
H	min	10.737	max	10.742	mean	10.740

Row-Gradient

CPU COO	min	0.706	max	1.603	mean	0.806
CPU CSR	min	1.493	max	1.534	mean	1.528
GPU 64 COO	min	8.430	max	8.610	mean	8.527
CSR	min	17.070	max*	18.970	mean	18.115
CPU PAR	min	1.331	max	1.695	mean	1.513
H	min	10.576	max	10.585	mean	10.580

Column-Gradient

CPU COO	min	0.694	max*	1.632	mean	0.797
CPU CSR	min	1.491	max	1.534	mean	1.529
GPU 64 COO	min	8.350	max	8.520	mean	8.429
CSR	min	15.970	max	18.180	mean	17.124
CPU PAR	min	1.321	max*	1.728	mean	1.514
H	min	10.826	max*	10.840	mean	10.833

Row-Column-Permute

CPU COO	min	0.688	max	0.757	mean	0.696
CPU CSR	min	1.490	max	1.595	mean	1.584
GPU 64 COO	min	8.380	max	8.500	mean	8.445
CSR	min	16.230	max	16.780	mean	16.513
CPU PAR	min	1.192	max	1.274	mean	1.237
H	min	10.737	max	10.742	mean	10.740

mult_dcop_01.mtx

Regular

CPU COO	min	0.710	max	1.453	mean	0.761
CPU CSR	min	1.561	max	1.581	mean	1.578
GPU 64 COO	min	8.520	max	8.670	mean	8.597
CSR	min	18.320	max	18.870	mean	18.636
CPU PAR	min	1.163	max	1.246	mean	1.212
H	min	9.689	max	9.689	mean	9.689

Row-Premute

CPU COO	min	0.699	max	1.305	mean	0.745
CPU CSR	min	1.585	max	1.597	mean	1.590
GPU 64 COO	min	8.360	max	8.520	mean	8.446
CSR	min	16.260	max	16.780	mean	16.528
CPU PAR	min	1.192	max	1.298	mean	1.242
H	min	10.738	max	10.742	mean	10.740

Row-Gradient

CPU COO	min	0.709	max*	1.656	mean	0.819
CPU CSR	min	1.527	max	1.535	mean	1.530
GPU 64 COO	min	8.450	max*	8.680	mean	8.527
CSR	min	16.520	max*	19.480	mean	17.984
CPU PAR	min	1.280	max	1.704	mean	1.485
H	min	10.572	max	10.585	mean	10.581

Column-Gradient

CPU COO	min	0.698	max	1.042	mean	0.737
CPU CSR	min	1.458	max	1.536	mean	1.528
GPU 64 COO	min	8.340	max	8.600	mean	8.443
CSR	min	16.360	max	18.450	mean	17.247
CPU PAR	min	1.307	max*	1.712	mean	1.494
H	min	10.823	max*	10.841	mean	10.835

Row-Column-Permute

CPU COO	min	0.683	max	1.247	mean	0.749
CPU CSR	min	1.583	max*	1.595	mean	1.590
GPU 64 COO	min	8.370	max	8.500	mean	8.435
CSR	min	16.250	max	16.780	mean	16.518
CPU PAR	min	1.206	max	1.291	mean	1.243
H	min	10.738	max	10.742	mean	10.740

mult_dcop_02.mtx

Regular

CPU COO	min	1.615	max*	1.677	mean	1.652
CPU CSR	min	1.539	max	1.579	mean	1.575
GPU 64 COO	min	8.530	max*	8.700	mean	8.614
CSR	min	18.290	max	18.890	mean	18.597
CPU PAR	min	1.120	max	1.248	mean	1.211
H	min	9.689	max	9.689	mean	9.689

Row-Premute

CPU COO	min	0.684	max	0.780	mean	0.705
CPU CSR	min	1.558	max*	1.596	mean	1.588
GPU 64 COO	min	8.360	max	8.490	mean	8.433
CSR	min	16.240	max	16.750	mean	16.552
CPU PAR	min	1.182	max	1.277	mean	1.242
H	min	10.737	max	10.742	mean	10.740

Row-Gradient

CPU COO	min	0.704	max	1.373	mean	0.790
CPU CSR	min	1.518	max	1.535	mean	1.529
GPU 64 COO	min	8.420	max	8.590	mean	8.517
CSR	min	16.680	max*	19.550	mean	17.907
CPU PAR	min	1.328	max*	1.713	mean	1.484
H	min	10.572	max	10.585	mean	10.581

Column-Gradient

CPU COO	min	0.697	max	1.460	mean	0.742
CPU CSR	min	1.517	max	1.534	mean	1.527
GPU 64 COO	min	8.330	max	8.490	mean	8.420
CSR	min	16.020	max	18.390	mean	17.303
CPU PAR	min	1.321	max	1.709	mean	1.557
H	min	10.823	max*	10.843	mean	10.835

Row-Column-Permute

CPU COO	min	0.691	max	0.746	mean	0.698
CPU CSR	min	1.568	max	1.595	mean	1.587
GPU 64 COO	min	8.350	max	8.500	mean	8.436
CSR	min	16.250	max	16.780	mean	16.517
CPU PAR	min	1.187	max	1.280	mean	1.228
H	min	10.739	max	10.743	mean	10.740

lp_fit2d.mtx

Regular

CPU COO	min	0.774	max	0.804	mean	0.793
CPU CSR	min	2.538	max	2.550	mean	2.547
GPU 64 COO	min	7.060	max	7.170	mean	7.101
CSR	min	15.650	max*	18.700	mean	18.031
CPU PAR	min	1.537	max	1.645	mean	1.590
H	min	11.109	max	11.109	mean	11.109

Row-Premute

CPU COO	min	0.740	max	0.776	mean	0.746
CPU CSR	min	3.302	max*	3.328	mean	3.317
GPU 64 COO	min	7.040	max*	7.180	mean	7.098
CSR	min	15.690	max	18.580	mean	16.732
CPU PAR	min	1.327	max	1.482	mean	1.422
H	min	11.098	max	11.105	mean	11.101

Row-Gradient

CPU COO	min	0.739	max*	2.092	mean	1.091
CPU CSR	min	2.539	max	2.546	mean	2.543
GPU 64 COO	min	7.040	max	7.150	mean	7.100
CSR	min	15.520	max	18.560	mean	17.547
CPU PAR	min	1.401	max	1.661	mean	1.525
H	min	11.109	max	11.109	mean	11.109

Column-Gradient

CPU COO	min	0.726	max	2.065	mean	1.011
CPU CSR	min	2.539	max	2.550	mean	2.546
GPU 64 COO	min	6.800	max	7.140	mean	7.080
CSR	min	15.480	max	18.560	mean	16.866
CPU PAR	min	1.391	max*	1.737	mean	1.563
H	min	11.329	max	11.333	mean	11.331

Row-Column-Permute

CPU COO	min	0.746	max	0.782	mean	0.754
CPU CSR	min	3.310	max	3.324	mean	3.318
GPU 64 COO	min	7.030	max	7.160	mean	7.100
CSR	min	15.730	max	18.530	mean	17.362
CPU PAR	min	1.340	max	1.451	mean	1.401
H	min	11.099	max	11.104	mean	11.102

bloweya.mtx

Regular

444		CPU COO	min	0.727	max*	1.815	mean	0.892	518		GPU 64 COO	min	11.340	max*	11.860	mean	11.441
445		CPU CSR	min	2.867	max*	2.936	mean	2.917	519		CSR	min	36.010	max*	40.960	mean	38.048
446		GPU 64 COO	min	0.000	max	0.000	mean	0.000	520		CPU PAR	min	2.019	max	2.204	mean	2.130
447		CSR	min	0.000	max	0.000	mean	0.000	521		H	min	8.228	max	8.228	mean	8.228
448		CPU PAR	min	1.680	max*	1.751	mean	1.719	522	Row-Premute							
449		H	min	7.205	max	7.205	mean	7.205	523		CPU COO	min	0.718	max	0.751	mean	0.732
450	Row-Premute								524		CPU CSR	min	2.488	max	2.507	mean	2.498
451		CPU COO	min	0.678	max	1.483	mean	0.746	525		GPU 64 COO	min	10.810	max	11.090	mean	10.949
452		CPU CSR	min	2.311	max	2.326	mean	2.320	526		CSR	min	24.860	max	26.410	mean	25.527
453		GPU 64 COO	min	6.840	max*	7.270	mean	6.930	527		CPU PAR	min	1.978	max	2.290	mean	2.135
454		CSR	min	15.650	max	16.800	mean	16.233	528		H	min	11.836	max	11.840	mean	11.838
455		CPU PAR	min	1.649	max	1.730	mean	1.682	529	Row-Gradient							
456		H	min	11.026	max	11.031	mean	11.029	530		CPU COO	min	0.722	max	1.794	mean	0.769
457	Row-Gradient								531		CPU CSR	min	2.407	max	2.421	mean	2.416
458		CPU COO	min	0.708	max	1.209	mean	0.779	532		GPU 64 COO	min	11.210	max	11.480	mean	11.317
459		CPU CSR	min	1.648	max	1.735	mean	1.709	533		CSR	min	31.920	max	34.690	mean	33.246
460		GPU 64 COO	min	6.920	max	7.080	mean	7.015	534		CPU PAR	min	2.184	max*	2.302	mean	2.232
461		CSR	min	16.950	max	19.500	mean	17.794	535		H	min	10.742	max	10.757	mean	10.748
462		CPU PAR	min	1.497	max	1.743	mean	1.608	536	Column-Gradient							
463		H	min	10.298	max	10.304	mean	10.301	537		CPU COO	min	0.720	max	0.916	mean	0.742
464	Column-Gradient								538		CPU CSR	min	2.395	max	2.410	mean	2.402
465		CPU COO	min	0.709	max	1.536	mean	0.817	539		GPU 64 COO	min	10.840	max	11.070	mean	10.946
466		CPU CSR	min	1.705	max	1.753	mean	1.735	540		CSR	min	24.340	max	26.140	mean	25.393
467		GPU 64 COO	min	6.800	max	7.120	mean	6.865	541		CPU PAR	min	2.184	max	2.272	mean	2.223
468		CSR	min	15.480	max*	17.710	mean	16.470	542		H	min	11.873	max	11.882	mean	11.878
469		CPU PAR	min	1.446	max	1.718	mean	1.591	543	Row-Column-Permute							
470		H	min	10.880	max	10.886	mean	10.883	544		CPU COO	min	0.707	max	0.748	mean	0.714
471	Row-Column-Permute								545		CPU CSR	min	2.458	max	2.511	mean	2.506
472		CPU COO	min	0.670	max	1.024	mean	0.706	546		GPU 64 COO	min	10.880	max	11.070	mean	10.957
473		CPU CSR	min	2.199	max	2.340	mean	2.326	547		CSR	min	24.890	max	26.490	mean	25.642
474		GPU 64 COO	min	6.800	max	6.980	mean	6.933	548		CPU PAR	min	2.209	max	2.282	mean	2.240
475		CSR	min	15.610	max	16.900	mean	16.227	549		H	min	11.834	max*	11.840	mean	11.838
476		CPU PAR	min	1.598	max	1.668	mean	1.632	550	brainpc2.mtx							
477		H	min	11.025	max*	11.032	mean	11.029	551	Regular							
478	lp_osa_07.mtx								552		CPU COO	min	0.732	max	0.751	mean	0.744
479	Regular								553		CPU CSR	min	2.885	max*	2.916	mean	2.909
480		CPU COO	min	0.715	max	1.798	mean	0.885	554		GPU 64 COO	min	0.000	max	0.000	mean	0.000
481		CPU CSR	min	2.495	max	2.551	mean	2.547	555		CSR	min	0.000	max	0.000	mean	0.000
482		GPU 64 COO	min	7.650	max*	7.790	mean	7.718	556		CPU PAR	min	1.276	max	1.299	mean	1.286
483		CSR	min	16.390	max*	18.350	mean	17.093	557		H	min	7.478	max	7.478	mean	7.478
484		CPU PAR	min	0.963	max	1.012	mean	0.995	558	Row-Premute							
485		H	min	8.412	max	8.412	mean	8.412	559		CPU COO	min	0.727	max	0.855	mean	0.736
486	Row-Premute								560		CPU CSR	min	2.385	max	2.411	mean	2.397
487		CPU COO	min	0.720	max*	2.078	mean	1.104	561		GPU 64 COO	min	8.120	max	8.410	mean	8.206
488		CPU CSR	min	2.656	max*	2.679	mean	2.669	562		CSR	min	18.670	max	19.960	mean	19.536
489		GPU 64 COO	min	7.610	max	7.690	mean	7.647	563		CPU PAR	min	1.293	max	1.340	mean	1.314
490		CSR	min	15.910	max	17.210	mean	16.750	564		H	min	9.809	max	9.813	mean	9.811
491		CPU PAR	min	0.890	max	0.940	mean	0.918	565	Row-Gradient							
492		H	min	9.255	max	9.258	mean	9.256	566		CPU COO	min	0.696	max*	1.546	mean	0.785
493	Row-Gradient								567		CPU CSR	min	1.361	max	1.420	mean	1.411
494		CPU COO	min	0.725	max	2.078	mean	1.041	568		GPU 64 COO	min	8.190	max*	8.550	mean	8.302
495		CPU CSR	min	2.487	max	2.502	mean	2.495	569		CSR	min	18.700	max*	21.000	mean	19.890
496		GPU 64 COO	min	7.570	max	7.730	mean	7.655	570		CPU PAR	min	1.435	max	1.666	mean	1.549
497		CSR	min	15.370	max	18.100	mean	16.803	571		H	min	9.721	max	9.727	mean	9.723
498		CPU PAR	min	1.435	max	1.796	mean	1.592	572	Column-Gradient							
499		H	min	8.637	max	8.678	mean	8.672	573		CPU COO	min	0.698	max	1.467	mean	0.746
500	Column-Gradient								574		CPU CSR	min	1.377	max	1.423	mean	1.414
501		CPU COO	min	0.724	max	1.990	mean	1.000	575		GPU 64 COO	min	8.110	max	8.290	mean	8.187
502		CPU CSR	min	2.425	max	2.477	mean	2.448	576		CSR	min	18.090	max	20.190	mean	19.217
503		GPU 64 COO	min	7.510	max	7.660	mean	7.596	577		CPU PAR	min	1.345	max*	1.681	mean	1.518
504		CSR	min	14.410	max	16.290	mean	15.267	578		H	min	10.369	max*	10.372	mean	10.370
505		CPU PAR	min	1.238	max	1.774	mean	1.534	579	Row-Column-Permute							
506		H	min	9.447	max*	9.603	mean	9.576	580		CPU COO	min	0.698	max	1.390	mean	0.788
507	Row-Column-Permute								581		CPU CSR	min	2.387	max	2.410	mean	2.399
508		CPU COO	min	0.738	max	1.950	mean	1.071	582		GPU 64 COO	min	8.120	max	8.260	mean	8.191
509		CPU CSR	min	2.522	max	2.709	mean	2.675	583		CSR	min	18.530	max	19.960	mean	19.307
510		GPU 64 COO	min	7.600	max	7.690	mean	7.641	584		CPU PAR	min	1.295	max	1.347	mean	1.319
511		CSR	min	15.820	max	17.190	mean	16.572	585		H	min	9.809	max	9.813	mean	9.811
512		CPU PAR	min	0.891	max	0.944	mean	0.924	586	shermanACB.mtx							
513		H	min	9.255	max	9.258	mean	9.256	587	Regular							
514	ex19.mtx								588		CPU COO	min	0.712	max	1.201	mean	0.756
515	Regular								589		CPU CSR	min	1.558	max	1.601	mean	1.596
516		CPU COO	min	0.732	max*	1.837	mean	1.076	590		GPU 64 COO	min	7.080	max*	7.370	mean	7.184
517		CPU CSR	min	2.563	max*	2.586	mean	2.577	591		CSR	min	17.580	max*	19.480	mean	18.770

Manuscript submitted to ACM

740		CPU CSR	min	2.358	max	2.413	mean	2.392	814		CSR	min	19.960	max	21.190	mean	20.696
741		GPU 64 COO	min	11.430	max	11.770	mean	11.549	815		CPU PAR	min	1.303	max	1.371	mean	1.345
742		CSR	min	24.470	max	25.580	mean	24.785	816		H	min	10.059	max	10.062	mean	10.061
743		CPU PAR	min	1.758	max	1.896	mean	1.829	817	Row-Gradient							
744		H	min	11.872	max	11.877	mean	11.875	818		CPU COO	min	0.723	max	0.984	mean	0.753
745	Row-Gradient								819		CPU CSR	min	1.781	max	1.809	mean	1.803
746		CPU COO	min	0.716	max	0.775	mean	0.739	820		GPU 64 COO	min	9.380	max	9.660	mean	9.464
747		CPU CSR	min	1.651	max	1.689	mean	1.675	821		CSR	min	15.770	max	19.090	mean	18.037
748		GPU 64 COO	min	12.100	max	12.410	mean	12.205	822		CPU PAR	min	1.775	max	1.924	mean	1.868
749		CSR	min	31.670	max	34.910	mean	33.370	823		H	min	10.205	max	10.233	mean	10.219
750		CPU PAR	min	2.079	max	2.286	mean	2.207	824	Column-Gradient							
751		H	min	11.111	max	11.116	mean	11.113	825		CPU COO	min	0.715	max	0.926	mean	0.757
752	Column-Gradient								826		CPU CSR	min	1.729	max	1.802	mean	1.791
753		CPU COO	min	0.715	max	1.021	mean	0.743	827		GPU 64 COO	min	9.080	max	9.270	mean	9.158
754		CPU CSR	min	1.655	max	1.674	mean	1.666	828		CSR	min	13.980	max	15.780	mean	14.938
755		GPU 64 COO	min	11.340	max	11.560	mean	11.463	829		CPU PAR	min	1.751	max	1.906	mean	1.846
756		CSR	min	23.770	max	25.470	mean	24.489	830		H	min	11.213	max	11.232	mean	11.222
757		CPU PAR	min	2.056	max	2.172	mean	2.118	831	Row-Column-Permute							
758		H	min	12.040	max	12.047	mean	12.043	832		CPU COO	min	0.732	max	1.598	mean	0.785
759	Row-Column-Permute								833		CPU CSR	min	2.594	max	2.602	mean	2.599
760		CPU COO	min	0.677	max	0.785	mean	0.687	834		GPU 64 COO	min	9.340	max	9.460	mean	9.394
761		CPU CSR	min	2.325	max	2.434	mean	2.369	835		CSR	min	19.950	max	21.500	mean	20.544
762		GPU 64 COO	min	11.450	max	11.650	mean	11.538	836		CPU PAR	min	1.326	max	1.374	mean	1.354
763		CSR	min	24.330	max	25.560	mean	25.008	837		H	min	10.059	max	10.062	mean	10.061
764		CPU PAR	min	1.631	max	1.776	mean	1.709	838	mhd4800a.mtx							
765		H	min	11.873	max	11.877	mean	11.875	839	Regular							
766	OPF_3754.mtx								840		CPU COO	min	0.759	max	0.795	mean	0.780
767	Regular								841		CPU CSR	min	2.479	max	2.565	mean	2.557
768		CPU COO	min	0.726	max	0.774	mean	0.747	842		GPU 64 COO	min	5.490	max	5.650	mean	5.552
769		CPU CSR	min	2.898	max	2.919	mean	2.908	843		CSR	min	16.700	max	19.460	mean	18.004
770		GPU 64 COO	min	7.680	max	7.820	mean	7.766	844		CPU PAR	min	1.456	max	1.523	mean	1.492
771		CSR	min	25.070	max	29.030	mean	26.756	845		H	min	7.132	max	7.132	mean	7.132
772		CPU PAR	min	1.437	max	1.508	mean	1.471	846	Row-Premute							
773		H	min	8.393	max	8.393	mean	8.393	847		CPU COO	min	0.695	max	0.943	mean	0.726
774	Row-Premute								848		CPU CSR	min	2.480	max	2.488	mean	2.485
775		CPU COO	min	0.714	max	1.574	mean	0.817	849		GPU 64 COO	min	5.410	max	5.490	mean	5.453
776		CPU CSR	min	2.686	max	2.711	mean	2.699	850		CSR	min	15.700	max	17.520	mean	16.678
777		GPU 64 COO	min	7.410	max	7.570	mean	7.484	851		CPU PAR	min	1.422	max	1.514	mean	1.474
778		CSR	min	19.600	max	21.190	mean	20.307	852		H	min	10.959	max	10.966	mean	10.963
779		CPU PAR	min	1.443	max	1.505	mean	1.469	853	Row-Gradient							
780		H	min	11.267	max	11.272	mean	11.269	854		CPU COO	min	0.723	max	2.029	mean	0.990
781	Row-Gradient								855		CPU CSR	min	2.411	max	2.427	mean	2.421
782		CPU COO	min	0.723	max	1.232	mean	0.775	856		GPU 64 COO	min	5.490	max	5.560	mean	5.534
783		CPU CSR	min	1.672	max	1.691	mean	1.685	857		CSR	min	16.350	max	19.560	mean	17.784
784		GPU 64 COO	min	7.600	max	7.760	mean	7.716	858		CPU PAR	min	1.441	max	1.509	mean	1.477
785		CSR	min	23.160	max	25.590	mean	24.304	859		H	min	9.512	max	9.526	mean	9.520
786		CPU PAR	min	1.675	max	1.736	mean	1.703	860	Column-Gradient							
787		H	min	10.463	max	10.472	mean	10.468	861		CPU COO	min	0.721	max	1.802	mean	0.871
788	Column-Gradient								862		CPU CSR	min	2.393	max	2.408	mean	2.404
789		CPU COO	min	0.726	max	1.431	mean	0.778	863		GPU 64 COO	min	5.410	max	5.480	mean	5.453
790		CPU CSR	min	1.671	max	1.685	mean	1.679	864		CSR	min	15.680	max	17.870	mean	16.540
791		GPU 64 COO	min	7.410	max	7.530	mean	7.467	865		CPU PAR	min	1.429	max	1.488	mean	1.468
792		CSR	min	18.140	max	20.350	mean	19.315	866		H	min	10.931	max	10.945	mean	10.938
793		CPU PAR	min	1.650	max	1.736	mean	1.699	867	Row-Column-Permute							
794		H	min	11.393	max	11.401	mean	11.397	868		CPU COO	min	0.728	max	1.646	mean	1.037
795	Row-Column-Permute								869		CPU CSR	min	2.472	max	2.488	mean	2.480
796		CPU COO	min	0.711	max	1.458	mean	0.751	870		GPU 64 COO	min	5.410	max	5.480	mean	5.449
797		CPU CSR	min	2.678	max	2.717	mean	2.700	871		CSR	min	15.760	max	17.560	mean	16.654
798		GPU 64 COO	min	7.400	max	7.540	mean	7.471	872		CPU PAR	min	1.428	max	1.513	mean	1.474
799		CSR	min	19.560	max	21.150	mean	20.453	873		H	min	10.959	max	10.967	mean	10.963
800		CPU PAR	min	1.440	max	1.499	mean	1.467	874	gen4.mtx							
801		H	min	11.266	max	11.272	mean	11.269	875	Regular							
802	c-47.mtx								876		CPU COO	min	0.737	max	1.977	mean	1.431
803	Regular								877		CPU CSR	min	2.674	max	2.688	mean	2.681
804		CPU COO	min	0.754	max	1.829	mean	1.204	878		GPU 64 COO	min	5.900	max	6.000	mean	5.954
805		CPU CSR	min	2.610	max	2.624	mean	2.618	879		CSR	min	13.650	max	15.410	mean	14.657
806		GPU 64 COO	min	9.530	max	9.870	mean	9.640	880		CPU PAR	min	1.468	max	1.521	mean	1.491
807		CSR	min	23.990	max	25.910	mean	24.992	881		H	min	9.234	max	9.234	mean	9.234
808		CPU PAR	min	1.311	max	1.380	mean	1.357	882	Row-Premute							
809		H	min	8.364	max	8.364	mean	8.364	883		CPU COO	min	0.740	max	2.048	mean	1.121
810	Row-Premute								884		CPU CSR	min	2.777	max	2.798	mean	2.790
811		CPU COO	min	0.740	max	0.885	mean	0.755	885		GPU 64 COO	min	5.910	max	5.970	mean	5.944
812		CPU CSR	min	2.574	max	2.611	mean	2.597	886		CSR	min	13.700	max	15.370	mean	14.541
813		GPU 64 COO	min	9.320	max	9.510	mean	9.397	887		CPU PAR	min	1.468	max	1.546	mean	1.502

888		H	min 10.250 max 10.255 mean 10.252	962	CPU COO	min 0.735 max 1.806 mean 0.878
889	Row-Gradient			963	CPU CSR	min 2.706 max 2.744 mean 2.726
890		CPU COO	min 0.740 max 1.790 mean 0.994	964	GPU 64 COO	min 6.390 max 6.500 mean 6.433
891		CPU CSR	min 2.663 max 2.682 mean 2.674	965	CSR	min 19.780 max 22.870 mean 20.936
892		GPU 64 COO	min 5.890 max* 6.160 mean 5.946	966	CPU PAR	min 1.710 max 1.865 mean 1.785
893		CSR	min 13.780 max*17.520 mean 15.601	967	H	min 10.251 max 10.267 mean 10.257
894		CPU PAR	min 1.479 max* 1.619 mean 1.569	968	Column-Gradient	
895		H	min 9.939 max 9.955 mean 9.948	969	CPU COO	min 0.728 max 1.792 mean 0.986
896	Column-Gradient			970	CPU CSR	min 2.521 max 2.720 mean 2.703
897		CPU COO	min 0.743 max 1.991 mean 0.981	971	GPU 64 COO	min 6.280 max 6.370 mean 6.327
898		CPU CSR	min 2.620 max 2.654 mean 2.646	972	CSR	min 18.000 max 19.720 mean 19.040
899		GPU 64 COO	min 5.840 max 5.910 mean 5.885	973	CPU PAR	min 1.649 max 1.741 mean 1.702
900		CSR	min 13.130 max 17.040 mean 15.008	974	H	min 11.113 max 11.121 mean 11.117
901		CPU PAR	min 1.477 max 1.607 mean 1.559	975	Row-Column-Permute	
902		H	min 10.858 max*10.876 mean 10.864	976	CPU COO	min 0.714 max 1.525 mean 0.957
903	Row-Column-Permute			977	CPU CSR	min 2.876 max 2.892 mean 2.884
904		CPU COO	min 0.742 max 2.010 mean 1.124	978	GPU 64 COO	min 6.280 max 6.370 mean 6.322
905		CPU CSR	min 2.789 max* 2.800 mean 2.795	979	CSR	min 17.960 max 19.670 mean 18.670
906		GPU 64 COO	min 5.900 max 5.980 mean 5.941	980	CPU PAR	min 1.667 max 1.754 mean 1.710
907		CSR	min 13.640 max 15.410 mean 14.556	981	H	min 11.162 max*11.168 mean 11.165
908		CPU PAR	min 1.462 max 1.540 mean 1.504	982	TSOPF_RS_b39_c7.mtx	
909		H	min 10.250 max 10.253 mean 10.252	983	Regular	
910	Maragal_6.mtx			984	CPU COO	min 0.771 max 0.793 mean 0.780
911	Regular			985	CPU CSR	min 3.219 max* 3.232 mean 3.227
912		CPU COO	min 0.725 max 0.741 mean 0.729	986	GPU 64 COO	min 11.070 max*11.200 mean 11.142
913		CPU CSR	min 2.345 max 2.409 mean 2.372	987	CSR	min 37.050 max*42.100 mean 39.040
914		GPU 64 COO	min 18.200 max 18.770 mean 18.357	988	CPU PAR	min 1.910 max 2.027 mean 1.982
915		CSR	min 38.310 max*40.240 mean 39.477	989	H	min 7.304 max 7.304 mean 7.304
916		CPU PAR	min 0.789 max 0.813 mean 0.797	990	Row-Permute	
917		H	min 9.930 max 9.930 mean 9.930	991	CPU COO	min 0.701 max 0.722 mean 0.707
918	Row-Permute			992	CPU CSR	min 2.931 max 2.952 mean 2.942
919		CPU COO	min 0.709 max 0.779 mean 0.715	993	GPU 64 COO	min 10.860 max 11.030 mean 10.928
920		CPU CSR	min 2.675 max 2.715 mean 2.696	994	CSR	min 28.730 max 30.880 mean 29.483
921		GPU 64 COO	min 17.810 max 18.030 mean 17.935	995	CPU PAR	min 1.760 max 1.922 mean 1.851
922		CSR	min 29.650 max 30.580 mean 30.109	996	H	min 10.537 max 10.541 mean 10.539
923		CPU PAR	min 0.857 max 0.940 mean 0.904	997	Row-Gradient	
924		H	min 10.777 max 10.779 mean 10.778	998	CPU COO	min 0.747 max 0.808 mean 0.757
925	Row-Gradient			999	CPU CSR	min 2.606 max 2.648 mean 2.624
926		CPU COO	min 0.710 max* 1.566 mean 0.755	1000	GPU 64 COO	min 10.850 max 11.120 mean 10.999
927		CPU CSR	min 2.042 max 2.159 mean 2.120	1001	CSR	min 33.910 max 37.600 mean 35.909
928		GPU 64 COO	min 18.460 max*18.960 mean 18.665	1002	CPU PAR	min 2.154 max* 2.245 mean 2.203
929		CSR	min 25.650 max 27.330 mean 26.549	1003	H	min 9.636 max 9.646 mean 9.642
930		CPU PAR	min 2.257 max 2.612 mean 2.416	1004	Column-Gradient	
931		H	min 11.251 max 11.301 mean 11.285	1005	CPU COO	min 0.718 max* 1.693 mean 0.802
932	Column-Gradient			1006	CPU CSR	min 2.502 max 2.585 mean 2.547
933		CPU COO	min 0.711 max 0.743 mean 0.725	1007	GPU 64 COO	min 10.700 max 10.990 mean 10.804
934		CPU CSR	min 2.036 max 2.161 mean 2.110	1008	CSR	min 27.230 max 29.380 mean 28.488
935		GPU 64 COO	min 17.840 max 18.860 mean 18.149	1009	CPU PAR	min 2.128 max 2.227 mean 2.172
936		CSR	min 19.410 max 20.690 mean 20.066	1010	H	min 11.131 max*11.222 mean 11.208
937		CPU PAR	min 2.174 max* 2.546 mean 2.349	1011	Row-Column-Permute	
938		H	min 12.011 max*12.072 mean 12.052	1012	CPU COO	min 0.709 max 0.726 mean 0.716
939	Row-Column-Permute			1013	CPU CSR	min 2.917 max 2.958 mean 2.940
940		CPU COO	min 0.712 max 0.971 mean 0.737	1014	GPU 64 COO	min 10.840 max 11.030 mean 10.930
941		CPU CSR	min 2.732 max* 2.751 mean 2.743	1015	CSR	min 28.780 max 30.810 mean 29.578
942		GPU 64 COO	min 17.720 max 18.070 mean 17.911	1016	CPU PAR	min 1.757 max 1.834 mean 1.792
943		CSR	min 29.600 max 30.500 mean 29.961	1017	H	min 10.537 max 10.540 mean 10.539
944		CPU PAR	min 0.827 max 0.954 mean 0.913			
945		H	min 10.776 max 10.778 mean 10.777			
946	aft01.mtx			1018	10 ELLESMERE	
947	Regular			1019	aft01.mtx	
948		CPU COO	min 0.735 max* 2.079 mean 1.069	1020	Regular	
949		CPU CSR	min 3.132 max* 3.154 mean 3.145	1021	GPU 64 COO	min 4.080 max* 4.280 mean 4.186
950		GPU 64 COO	min 6.390 max* 6.610 mean 6.457	1022	CSR	min 9.660 max*12.660 mean 11.485
951		CSR	min 19.990 max*23.250 mean 21.820	1023	H	min 7.811 max 7.811 mean 7.811
952		CPU PAR	min 1.746 max* 1.865 mean 1.812	1024	Row-Permute	
953		H	min 7.811 max 7.811 mean 7.811	1025	GPU 64 COO	min 3.860 max 4.090 mean 4.001
954	Row-Permute			1026	CSR	min 9.520 max 10.340 mean 9.936
955		CPU COO	min 0.714 max 1.648 mean 0.840	1027	H	min 11.161 max 11.167 mean 11.165
956		CPU CSR	min 2.864 max 2.892 mean 2.883	1028	Row-Gradient	
957		GPU 64 COO	min 6.280 max 6.380 mean 6.329	1029	GPU 64 COO	min 4.010 max 4.240 mean 4.135
958		CSR	min 17.980 max 19.700 mean 19.105	1030	CSR	min 5.890 max 11.350 mean 6.882
959		CPU PAR	min 1.729 max 1.850 mean 1.782	1031	H	min 10.246 max 10.262 mean 10.256
960		H	min 11.162 max 11.168 mean 11.165	1032	Column-Gradient	
961	Row-Gradient					

1033		GPU 64 COO min 3.850 max 4.100 mean 4.012	1107		H min 7.380 max 7.380 mean 7.380
1034		CSR min 5.460 max 8.790 mean 6.005	1108	Row-Premute	
1035		H min 11.112 max 11.122 mean 11.117	1109		GPU 64 COO min 4.820 max 4.940 mean 4.859
1036	Row-Column-Permute		1110		CSR min 5.080 max 6.520 mean 6.342
1037		GPU 64 COO min 3.850 max 4.080 mean 3.990	1111		H min 10.042 max 10.047 mean 10.044
1038		CSR min 5.420 max 6.760 mean 5.977	1112	Row-Gradient	
1039		H min 11.162 max*11.169 mean 11.165	1113		GPU 64 COO min 4.810 max* 4.940 mean 4.876
1040	bloweya.mtx		1114		CSR min 6.100 max* 6.560 mean 6.307
1041	Regular		1115		H min 9.681 max 9.704 mean 9.694
1042		GPU 64 COO min 0.000 max 0.000 mean 0.000	1116	Column-Gradient	
1043		CSR min 0.000 max 0.000 mean 0.000	1117		GPU 64 COO min 4.810 max 4.930 mean 4.869
1044		H min 7.205 max 7.205 mean 7.205	1118		CSR min 4.820 max 6.460 mean 6.208
1045	Row-Premute		1119		H min 10.554 max*10.661 mean 10.638
1046		GPU 64 COO min 3.800 max 3.940 mean 3.875	1120	Row-Column-Permute	
1047		CSR min 3.710 max 4.570 mean 4.399	1121		GPU 64 COO min 4.810 max 4.940 mean 4.864
1048		H min 11.025 max 11.031 mean 11.028	1122		CSR min 5.930 max 6.520 mean 6.379
1049	Row-Gradient		1123		H min 10.041 max 10.047 mean 10.044
1050		GPU 64 COO min 3.800 max* 4.120 mean 3.962	1124	cvxqp3.mtx	
1051		CSR min 4.340 max* 4.670 mean 4.546	1125	Regular	
1052		H min 10.296 max 10.307 mean 10.300	1126		GPU 64 COO min 3.350 max* 3.590 mean 3.483
1053	Column-Gradient		1127		CSR min 5.430 max* 9.260 mean 8.333
1054		GPU 64 COO min 3.880 max 4.100 mean 3.978	1128		H min 8.646 max 8.646 mean 8.646
1055		CSR min 4.240 max 4.570 mean 4.412	1129	Row-Premute	
1056		H min 10.881 max 10.886 mean 10.883	1130		GPU 64 COO min 3.230 max 3.480 mean 3.371
1057	Row-Column-Permute		1131		CSR min 7.560 max 8.220 mean 7.900
1058		GPU 64 COO min 3.800 max 3.980 mean 3.885	1132		H min 11.027 max 11.033 mean 11.030
1059		CSR min 4.130 max 4.540 mean 4.399	1133	Row-Gradient	
1060		H min 11.025 max*11.033 mean 11.029	1134		GPU 64 COO min 3.240 max 3.510 mean 3.396
1061	brainpc2.mtx		1135		CSR min 6.990 max 7.890 mean 7.574
1062	Regular		1136		H min 11.060 max 11.069 mean 11.064
1063		GPU 64 COO min 0.000 max 0.000 mean 0.000	1137	Column-Gradient	
1064		CSR min 0.000 max 0.000 mean 0.000	1138		GPU 64 COO min 3.240 max 3.480 mean 3.374
1065		H min 7.478 max 7.478 mean 7.478	1139		CSR min 6.980 max 7.900 mean 7.557
1066	Row-Premute		1140		H min 11.126 max*11.134 mean 11.130
1067		GPU 64 COO min 3.840 max* 6.750 mean 4.110	1141	Row-Column-Permute	
1068		CSR min 4.260 max* 4.500 mean 4.437	1142		GPU 64 COO min 3.110 max 3.470 mean 3.365
1069		H min 9.809 max 9.813 mean 9.811	1143		CSR min 4.810 max 8.210 mean 7.742
1070	Row-Gradient		1144		H min 11.026 max 11.032 mean 11.030
1071		GPU 64 COO min 0.640 max 4.030 mean 3.864	1145	ex19.mtx	
1072		CSR min 4.270 max 4.470 mean 4.383	1146	Regular	
1073		H min 9.722 max 9.727 mean 9.724	1147		GPU 64 COO min 2.450 max* 2.610 mean 2.564
1074	Column-Gradient		1148		CSR min 4.490 max 4.760 mean 4.714
1075		GPU 64 COO min 0.640 max 4.070 mean 3.898	1149		H min 8.228 max 8.228 mean 8.228
1076		CSR min 4.230 max 4.500 mean 4.386	1150	Row-Premute	
1077		H min 10.368 max*10.372 mean 10.370	1151		GPU 64 COO min 2.000 max 2.040 mean 2.021
1078	Row-Column-Permute		1152		CSR min 4.640 max 4.780 mean 4.733
1079		GPU 64 COO min 3.980 max 4.110 mean 4.027	1153		H min 11.835 max 11.840 mean 11.838
1080		CSR min 4.320 max 4.490 mean 4.437	1154	Row-Gradient	
1081		H min 9.809 max 9.813 mean 9.811	1155		GPU 64 COO min 2.240 max 2.390 mean 2.329
1082	c-47.mtx		1156		CSR min 4.570 max* 4.850 mean 4.807
1083	Regular		1157		H min 10.742 max 10.752 mean 10.747
1084		GPU 64 COO min 3.980 max* 4.080 mean 4.026	1158	Column-Gradient	
1085		CSR min 4.760 max 4.850 mean 4.812	1159		GPU 64 COO min 2.010 max 2.050 mean 2.034
1086		H min 8.364 max 8.364 mean 8.364	1160		CSR min 4.570 max 4.760 mean 4.701
1087	Row-Premute		1161		H min 11.872 max*11.881 mean 11.878
1088		GPU 64 COO min 3.880 max 4.010 mean 3.942	1162	Row-Column-Permute	
1089		CSR min 4.040 max 4.900 mean 4.807	1163		GPU 64 COO min 2.000 max 2.040 mean 2.023
1090		H min 10.059 max 10.063 mean 10.061	1164		CSR min 0.770 max 4.780 mean 4.594
1091	Row-Gradient		1165		H min 11.835 max 11.840 mean 11.838
1092		GPU 64 COO min 3.900 max 4.050 mean 3.976	1166	gen4.mtx	
1093		CSR min 4.380 max 4.740 mean 4.630	1167	Regular	
1094		H min 10.201 max 10.228 mean 10.214	1168		GPU 64 COO min 4.880 max 4.980 mean 4.900
1095	Column-Gradient		1169		CSR min 10.020 max*11.300 mean 10.716
1096		GPU 64 COO min 3.860 max 3.990 mean 3.936	1170		H min 9.234 max 9.234 mean 9.234
1097		CSR min 4.350 max 4.610 mean 4.525	1171	Row-Premute	
1098		H min 11.204 max*11.241 mean 11.222	1172		GPU 64 COO min 4.860 max 4.930 mean 4.890
1099	Row-Column-Permute		1173		CSR min 0.330 max 11.200 mean 10.038
1100		GPU 64 COO min 3.890 max 4.020 mean 3.953	1174		H min 10.249 max 10.254 mean 10.252
1101		CSR min 4.490 max* 4.920 mean 4.840	1175	Row-Gradient	
1102		H min 10.058 max 10.063 mean 10.061	1176		GPU 64 COO min 4.860 max* 4.990 mean 4.908
1103	case9.mtx		1177		CSR min 9.160 max 11.240 mean 10.435
1104	Regular		1178		H min 9.939 max 9.961 mean 9.947
1105		GPU 64 COO min 0.000 max 0.000 mean 0.000	1179	Column-Gradient	
1106		CSR min 0.000 max 0.000 mean 0.000	1180		GPU 64 COO min 4.780 max 4.880 mean 4.816

1181		CSR min 7.770 max 10.570 mean 9.407	1255	Row-Permute	
1182		H min 10.851 max*10.876 mean 10.864	1256		GPU 64 COO min 4.420 max 4.520 mean 4.445
1183	Row-Column-Permute		1257		CSR min 10.520 max 10.880 mean 10.696
1184		GPU 64 COO min 4.850 max 4.950 mean 4.886	1258		H min 10.960 max*10.968 mean 10.963
1185		CSR min 10.220 max 11.280 mean 10.748	1259	Row-Gradient	
1186		H min 10.250 max 10.255 mean 10.252	1260		GPU 64 COO min 4.570 max 4.690 mean 4.605
1187	lp_fit2d.mtx		1261		CSR min 4.550 max 13.350 mean 12.479
1188	Regular		1262		H min 9.508 max 9.527 mean 9.520
1189		GPU 64 COO min 4.360 max* 4.640 mean 4.515	1263	Column-Gradient	
1190		CSR min 10.080 max 10.900 mean 10.491	1264		GPU 64 COO min 4.430 max 4.530 mean 4.461
1191		H min 11.109 max 11.109 mean 11.109	1265		CSR min 10.250 max 10.940 mean 10.603
1192	Row-Permute		1266		H min 10.934 max 10.945 mean 10.939
1193		GPU 64 COO min 4.170 max 4.630 mean 4.476	1267	Row-Column-Permute	
1194		CSR min 0.910 max 10.910 mean 10.257	1268		GPU 64 COO min 4.420 max 4.520 mean 4.450
1195		H min 11.098 max 11.104 mean 11.101	1269		CSR min 7.380 max 10.900 mean 10.598
1196	Row-Gradient		1270		H min 10.959 max 10.967 mean 10.963
1197		GPU 64 COO min 4.370 max 4.630 mean 4.529	1271	mult_dcop_01.mtx	
1198		CSR min 10.030 max 10.970 mean 10.624	1272	Regular	
1199		H min 11.109 max 11.109 mean 11.109	1273		GPU 64 COO min 3.420 max 3.630 mean 3.555
1200	Column-Gradient		1274		CSR min 3.650 max 4.090 mean 3.814
1201		GPU 64 COO min 4.250 max 4.640 mean 4.499	1275		H min 9.689 max 9.689 mean 9.689
1202		CSR min 8.510 max*11.010 mean 10.505	1276	Row-Permute	
1203		H min 11.328 max*11.333 mean 11.331	1277		GPU 64 COO min 3.450 max 3.580 mean 3.521
1204	Row-Column-Permute		1278		CSR min 3.610 max 4.150 mean 3.785
1205		GPU 64 COO min 4.350 max 4.640 mean 4.511	1279		H min 10.738 max 10.742 mean 10.740
1206		CSR min 10.040 max 10.790 mean 10.468	1280	Row-Gradient	
1207		H min 11.097 max 11.106 mean 11.101	1281		GPU 64 COO min 3.510 max* 3.660 mean 3.579
1208	lp_osa_07.mtx		1282		CSR min 3.650 max 4.160 mean 3.806
1209	Regular		1283		H min 10.576 max 10.585 mean 10.580
1210		GPU 64 COO min 0.460 max* 3.640 mean 3.456	1284	Column-Gradient	
1211		CSR min 5.570 max* 8.530 mean 8.106	1285		GPU 64 COO min 3.460 max 3.650 mean 3.584
1212		H min 8.412 max 8.412 mean 8.412	1286		CSR min 3.660 max* 4.240 mean 3.799
1213	Row-Permute		1287		H min 10.826 max*10.842 mean 10.836
1214		GPU 64 COO min 3.140 max 3.450 mean 3.367	1288	Row-Column-Permute	
1215		CSR min 7.600 max 8.070 mean 7.853	1289		GPU 64 COO min 3.470 max 3.580 mean 3.532
1216		H min 9.255 max 9.258 mean 9.256	1290		CSR min 3.600 max 3.980 mean 3.743
1217	Row-Gradient		1291		H min 10.738 max 10.742 mean 10.740
1218		GPU 64 COO min 3.190 max 3.610 mean 3.509	1292	mult_dcop_02.mtx	
1219		CSR min 0.000 max 8.260 mean 7.597	1293	Regular	
1220		H min 8.583 max 8.678 mean 8.670	1294		GPU 64 COO min 3.390 max 3.660 mean 3.585
1221	Column-Gradient		1295		CSR min 0.960 max 4.330 mean 4.162
1222		GPU 64 COO min 3.330 max 3.500 mean 3.416	1296		H min 9.689 max 9.689 mean 9.689
1223		CSR min 6.730 max 7.540 mean 7.199	1297	Row-Permute	
1224		H min 9.542 max* 9.604 mean 9.581	1298		GPU 64 COO min 3.310 max 3.600 mean 3.488
1225	Row-Column-Permute		1299		CSR min 0.620 max 4.290 mean 4.132
1226		GPU 64 COO min 3.290 max 3.430 mean 3.365	1300		H min 10.738 max 10.743 mean 10.740
1227		CSR min 7.390 max 8.060 mean 7.832	1301	Row-Gradient	
1228		H min 9.255 max 9.258 mean 9.256	1302		GPU 64 COO min 3.310 max* 3.670 mean 3.593
1229	Maragal_6.mtx		1303		CSR min 4.130 max* 4.430 mean 4.331
1230	Regular		1304		H min 10.576 max 10.584 mean 10.580
1231		GPU 64 COO min 4.160 max 4.310 mean 4.217	1305	Column-Gradient	
1232		CSR min 4.940 max 4.960 mean 4.956	1306		GPU 64 COO min 0.550 max 3.660 mean 3.486
1233		H min 9.930 max 9.930 mean 9.930	1307		CSR min 3.890 max 4.410 mean 4.275
1234	Row-Permute		1308		H min 10.831 max*10.843 mean 10.836
1235		GPU 64 COO min 4.220 max 4.240 mean 4.225	1309	Row-Column-Permute	
1236		CSR min 4.750 max*13.040 mean 5.133	1310		GPU 64 COO min 3.470 max 3.590 mean 3.542
1237		H min 10.776 max 10.778 mean 10.777	1311		CSR min 4.190 max 4.290 mean 4.242
1238	Row-Gradient		1312		H min 10.738 max 10.742 mean 10.740
1239		GPU 64 COO min 4.180 max* 4.450 mean 4.245	1313	mult_dcop_03.mtx	
1240		CSR min 4.880 max 4.940 mean 4.915	1314	Regular	
1241		H min 11.259 max*11.302 mean 11.281	1315		GPU 64 COO min 3.360 max* 3.660 mean 3.550
1242	Column-Gradient		1316		CSR min 3.650 max 4.090 mean 3.813
1243		GPU 64 COO min 4.200 max 4.250 mean 4.236	1317		H min 9.689 max 9.689 mean 9.689
1244		CSR min 4.800 max 4.890 mean 4.859	1318	Row-Permute	
1245		H min 12.022 max 12.073 mean 12.051	1319		GPU 64 COO min 3.450 max 3.580 mean 3.521
1246	Row-Column-Permute		1320		CSR min 3.610 max 4.160 mean 3.784
1247		GPU 64 COO min 4.210 max 4.230 mean 4.222	1321		H min 10.738 max 10.743 mean 10.740
1248		CSR min 4.860 max 4.890 mean 4.887	1322	Row-Gradient	
1249		H min 10.776 max 10.778 mean 10.778	1323		GPU 64 COO min 3.470 max 3.660 mean 3.572
1250	mhd4800a.mtx		1324		CSR min 3.640 max 4.190 mean 3.809
1251	Regular		1325		H min 10.572 max 10.584 mean 10.580
1252		GPU 64 COO min 4.570 max* 4.710 mean 4.608	1326	Column-Gradient	
1253		CSR min 12.690 max*13.940 mean 13.369	1327		GPU 64 COO min 3.430 max 3.650 mean 3.562
1254		H min 7.132 max 7.132 mean 7.132	1328		CSR min 3.670 max* 4.290 mean 3.793

1329		H	min 10.828 max*10.840 mean 10.834
1330	Row-Column-Permute		
1331		GPU 64 COO min	3.370 max 3.610 mean 3.502
1332		CSR min	3.610 max 3.970 mean 3.744
1333		H	min 10.738 max 10.741 mean 10.740
1334	OPF_3754.mtx		
1335	Regular		
1336		GPU 64 COO min	4.700 max* 4.930 mean 4.842
1337		CSR min	6.230 max* 6.600 mean 6.411
1338		H	min 8.393 max 8.393 mean 8.393
1339	Row-Premute		
1340		GPU 64 COO min	4.620 max 4.890 mean 4.787
1341		CSR min	5.780 max 6.310 mean 6.192
1342		H	min 11.265 max 11.272 mean 11.269
1343	Row-Gradient		
1344		GPU 64 COO min	4.570 max 4.870 mean 4.776
1345		CSR min	5.770 max 6.510 mean 6.302
1346		H	min 10.464 max 10.473 mean 10.468
1347	Column-Gradient		
1348		GPU 64 COO min	4.580 max 4.870 mean 4.756
1349		CSR min	5.630 max 6.180 mean 6.055
1350		H	min 11.394 max*11.401 mean 11.397
1351	Row-Column-Permute		
1352		GPU 64 COO min	4.610 max 4.900 mean 4.780
1353		CSR min	5.010 max 6.300 mean 6.113
1354		H	min 11.268 max 11.272 mean 11.270
1355	OPF_6000.mtx		
1356	Regular		
1357		GPU 64 COO min	3.780 max* 3.920 mean 3.864
1358		CSR min	4.270 max 4.360 mean 4.332
1359		H	min 8.799 max 8.799 mean 8.799
1360	Row-Premute		
1361		GPU 64 COO min	3.770 max 3.870 mean 3.821
1362		CSR min	3.970 max*11.050 mean 4.439
1363		H	min 11.872 max 11.877 mean 11.875
1364	Row-Gradient		
1365		GPU 64 COO min	3.700 max 3.870 mean 3.795
1366		CSR min	4.330 max 4.440 mean 4.403
1367		H	min 11.109 max 11.116 mean 11.113
1368	Column-Gradient		
1369		GPU 64 COO min	3.690 max 3.870 mean 3.804
1370		CSR min	4.260 max 4.340 mean 4.308
1371		H	min 12.041 max*12.045 mean 12.043
1372	Row-Column-Permute		
1373		GPU 64 COO min	3.780 max 3.860 mean 3.819
1374		CSR min	4.090 max 4.290 mean 4.259
1375		H	min 11.873 max 11.877 mean 11.876
1376	shermanACb.mtx		
1377	Regular		
1378		GPU 64 COO min	2.920 max* 3.140 mean 3.048
1379		CSR min	5.550 max 5.980 mean 5.803
1380		H	min 8.600 max 8.600 mean 8.600
1381	Row-Premute		
1382		GPU 64 COO min	2.760 max 3.020 mean 2.898
1383		CSR min	2.660 max 5.830 mean 5.632
1384		H	min 10.377 max 10.381 mean 10.379
1385	Row-Gradient		
1386		GPU 64 COO min	2.800 max 3.040 mean 2.944
1387		CSR min	5.330 max* 6.020 mean 5.742
1388		H	min 9.919 max 9.925 mean 9.922
1389	Column-Gradient		
1390		GPU 64 COO min	2.720 max 3.010 mean 2.926
1391		CSR min	0.000 max 5.840 mean 5.513
1392		H	min 10.587 max*10.596 mean 10.591
1393	Row-Column-Permute		
1394		GPU 64 COO min	2.780 max 3.030 mean 2.939
1395		CSR min	4.860 max 5.810 mean 5.667
1396		H	min 10.376 max 10.382 mean 10.379
1397	TSOPF_FS_b9_c6.mtx		
1398	Regular		
1399		GPU 64 COO min	0.000 max 0.000 mean 0.000
1400		CSR min	0.000 max 0.000 mean 0.000
1401		H	min 7.380 max 7.380 mean 7.380
1402	Row-Premute		

1403		GPU 64 COO min	4.540 max 4.940 mean 4.874
1404		CSR min	6.280 max 6.520 mean 6.403
1405		H	min 10.042 max 10.047 mean 10.044
1406	Row-Gradient		
1407		GPU 64 COO min	4.830 max 4.930 mean 4.875
1408		CSR min	5.790 max* 6.560 mean 6.289
1409		H	min 9.675 max 9.706 mean 9.692
1410	Column-Gradient		
1411		GPU 64 COO min	4.790 max* 4.960 mean 4.880
1412		CSR min	5.760 max 6.450 mean 6.204
1413		H	min 10.601 max*10.661 mean 10.626
1414	Row-Column-Permute		
1415		GPU 64 COO min	4.330 max 4.950 mean 4.845
1416		CSR min	5.740 max 6.500 mean 6.375
1417		H	min 10.041 max 10.046 mean 10.044
1418	TSOPF_RS_b39_c7.mtx		
1419	Regular		
1420		GPU 64 COO min	4.300 max* 4.430 mean 4.364
1421		CSR min	4.480 max 4.750 mean 4.716
1422		H	min 7.304 max 7.304 mean 7.304
1423	Row-Premute		
1424		GPU 64 COO min	4.260 max 4.400 mean 4.353
1425		CSR min	4.490 max 4.770 mean 4.734
1426		H	min 10.536 max 10.541 mean 10.539
1427	Row-Gradient		
1428		GPU 64 COO min	3.970 max 4.420 mean 4.338
1429		CSR min	4.620 max* 4.820 mean 4.789
1430		H	min 9.638 max 9.644 mean 9.641
1431	Column-Gradient		
1432		GPU 64 COO min	4.240 max 4.430 mean 4.368
1433		CSR min	4.710 max 4.770 mean 4.736
1434		H	min 11.129 max*11.222 mean 11.205
1435	Row-Column-Permute		
1436		GPU 64 COO min	4.260 max 4.410 mean 4.359
1437		CSR min	4.660 max 4.760 mean 4.738
1438		H	min 10.537 max 10.541 mean 10.539

11 FIJI

1439			
1440	mult_dcop_03.mtx		
1441	Regular		
1442		GPU 64 COO min	5.140 max* 5.140 mean 5.140
1443		CSR min	10.340 max*10.390 mean 10.365
1444		H	min 9.689 max 9.689 mean 9.689
1445	Row-Premute		
1446		GPU 64 COO min	4.970 max 4.990 mean 4.980
1447		CSR min	9.420 max 9.430 mean 9.425
1448		H	min 10.739 max 10.739 mean 10.739
1449	Row-Gradient		
1450		GPU 64 COO min	5.080 max 5.090 mean 5.085
1451		CSR min	9.720 max 10.300 mean 10.010
1452		H	min 10.579 max 10.582 mean 10.580
1453	Column-Gradient		
1454		GPU 64 COO min	5.030 max 5.120 mean 5.075
1455		CSR min	9.330 max 9.770 mean 9.550
1456		H	min 10.835 max*10.838 mean 10.836
1457	Row-Column-Permute		
1458		GPU 64 COO min	5.000 max 5.010 mean 5.005
1459		CSR min	7.580 max 9.460 mean 8.520
1460		H	min 10.739 max 10.741 mean 10.740
1461	mult_dcop_03.mtx		
1462	Regular		
1463		GPU 64 COO min	5.140 max* 5.140 mean 5.140
1464		CSR min	10.340 max*10.390 mean 10.365
1465		H	min 9.689 max 9.689 mean 9.689
1466	Row-Premute		
1467		GPU 64 COO min	4.970 max 4.990 mean 4.980
1468		CSR min	9.420 max 9.430 mean 9.425
1469		H	min 10.739 max 10.739 mean 10.739
1470	Row-Gradient		
1471		GPU 64 COO min	5.080 max 5.090 mean 5.085
1472		CSR min	9.720 max 10.300 mean 10.010
1473		H	min 10.579 max 10.582 mean 10.580

1474	Column-Gradient					1548		CSR min	6.360	max	7.450	mean	6.711
1475		GPU 64	COO	min	5.030	max	5.120	mean	5.075				
1476					CSR min	9.330	max	9.770	mean	9.550			
1477		H			min	10.835	max*10.838	mean	10.836				
1478	Row-Column-Permute												
1479		GPU 64	COO	min	5.000	max	5.010	mean	5.005				
1480					CSR min	7.580	max	9.460	mean	8.520			
1481		H			min	10.739	max	10.741	mean	10.740			
1482	mult_dcop_03.mtx												
1483	Regular												
1484		GPU 64	COO	min	5.130	max*	5.220	mean	5.142				
1485					CSR min	7.250	max*	9.320	mean	7.722			
1486		H			min	9.689	max	9.689	mean	9.689			
1487	Row-Premute												
1488		GPU 64	COO	min	4.980	max	5.030	mean	4.999				
1489					CSR min	6.460	max	8.470	mean	6.950			
1490		H			min	10.738	max	10.742	mean	10.740			
1491	Row-Gradient												
1492		GPU 64	COO	min	5.070	max	5.140	mean	5.088				
1493					CSR min	6.780	max	8.700	mean	7.268			
1494		H			min	10.572	max	10.584	mean	10.580			
1495	Column-Gradient												
1496		GPU 64	COO	min	4.980	max	5.030	mean	5.010				
1497					CSR min	6.390	max	7.640	mean	6.982			
1498		H			min	10.825	max*10.845	mean	10.836				
1499	Row-Column-Permute												
1500		GPU 64	COO	min	4.990	max	5.010	mean	4.997				
1501					CSR min	6.300	max	7.160	mean	6.636			
1502		H			min	10.738	max	10.743	mean	10.740			
1503	mult_dcop_01.mtx												
1504	Regular												
1505		GPU 64	COO	min	5.120	max*	5.140	mean	5.134				
1506					CSR min	6.990	max*	9.230	mean	7.546			
1507		H			min	9.689	max	9.689	mean	9.689			
1508	Row-Premute												
1509		GPU 64	COO	min	4.990	max	5.020	mean	5.004				
1510					CSR min	6.370	max	7.220	mean	6.771			
1511		H			min	10.738	max	10.743	mean	10.740			
1512	Row-Gradient												
1513		GPU 64	COO	min	5.060	max	5.100	mean	5.082				
1514					CSR min	6.730	max	7.720	mean	7.317			
1515		H			min	10.574	max	10.585	mean	10.580			
1516	Column-Gradient												
1517		GPU 64	COO	min	4.980	max	5.100	mean	5.012				
1518					CSR min	6.580	max	7.510	mean	7.054			
1519		H			min	10.828	max*10.842	mean	10.835				
1520	Row-Column-Permute												
1521		GPU 64	COO	min	4.970	max	5.000	mean	4.986				
1522					CSR min	6.390	max	7.050	mean	6.677			
1523		H			min	10.738	max	10.742	mean	10.740			
1524	mult_dcop_02.mtx												
1525	Regular												
1526		GPU 64	COO	min	5.120	max	5.140	mean	5.133				
1527					CSR min	6.950	max	7.590	mean	7.336			
1528		H			min	9.689	max	9.689	mean	9.689			
1529	Row-Premute												
1530		GPU 64	COO	min	4.970	max	4.990	mean	4.984				
1531					CSR min	6.440	max	7.110	mean	6.719			
1532		H			min	10.738	max	10.742	mean	10.740			
1533	Row-Gradient												
1534		GPU 64	COO	min	5.070	max*	5.150	mean	5.086				
1535					CSR min	6.650	max*	7.930	mean	7.304			
1536		H			min	10.574	max	10.587	mean	10.580			
1537	Column-Gradient												
1538		GPU 64	COO	min	4.980	max	5.040	mean	5.012				
1539					CSR min	6.520	max	7.650	mean	7.139			
1540		H			min	10.829	max*10.846	mean	10.836				
1541	Row-Column-Permute												
1542		GPU 64	COO	min	4.970	max	5.050	mean	4.983				
1543					CSR min	6.440	max	7.380	mean	6.779			
1544		H			min	10.738	max	10.743	mean	10.740			
1545	lp_fit2d.mtx												
1546	Regular												
1547		GPU 64	COO	min	3.960	max	3.960	mean	3.960				
1548													
1549													
1550	Row-Premute												
1551		GPU 64	COO	min	3.950	max*	3.980	mean	3.953				
1552					CSR min	6.330	max	7.400	mean	6.661			
1553		H			min	11.098	max	11.104	mean	11.101			
1554	Row-Gradient												
1555		GPU 64	COO	min	3.960	max	3.980	mean	3.961				
1556					CSR min	6.270	max*10.770	mean	7.017				
1557		H			min	11.109	max	11.109	mean	11.109			
1558	Column-Gradient												
1559		GPU 64	COO	min	3.940	max	3.960	mean	3.950				
1560					CSR min	6.270	max	7.370	mean	6.696			
1561		H			min	11.329	max*11.334	mean	11.331				
1562	Row-Column-Permute												
1563		GPU 64	COO	min	3.950	max	3.960	mean	3.952				
1564					CSR min	6.180	max	7.420	mean	6.641			
1565		H			min	11.098	max	11.105	mean	11.101			
1566	bloweya.mtx												
1567	Regular												
1568		GPU 64	COO	min	0.000	max	0.000	mean	0.000				
1569					CSR min	0.000	max	0.000	mean	0.000			
1570		H			min	7.205	max	7.205	mean	7.205			
1571	Row-Premute												
1572		GPU 64	COO	min	4.020	max	4.030	mean	4.023				
1573					CSR min	6.070	max	6.750	mean	6.340			
1574		H			min	11.025	max	11.031	mean	11.028			
1575	Row-Gradient												
1576		GPU 64	COO	min	4.090	max*	4.160	mean	4.111				
1577					CSR min	5.980	max*	7.370	mean	6.678			
1578		H			min	10.295	max	10.304	mean	10.300			
1579	Column-Gradient												
1580		GPU 64	COO	min	3.980	max	4.010	mean	3.995				
1581					CSR min	5.880	max	6.780	mean	6.295			
1582		H			min	10.881	max*10.887	mean	10.883				
1583	Row-Column-Permute												
1584		GPU 64	COO	min	4.020	max	4.030	mean	4.023				
1585					CSR min	5.970	max	6.420	mean	6.183			
1586		H			min	11.025	max	11.033	mean	11.028			
1587	lp_osa_07.mtx												
1588	Regular												
1589		GPU 64	COO	min	4.260	max*	4.270	mean	4.261				
1590					CSR min	6.440	max	7.640	mean	6.863			
1591		H			min	8.412	max	8.412	mean	8.412			
1592	Row-Premute												
1593		GPU 64	COO	min	4.200	max	4.200	mean	4.200				
1594					CSR min	6.020	max	7.030	mean	6.418			
1595		H			min	9.255	max	9.257	mean	9.256			
1596	Row-Gradient												
1597		GPU 64	COO	min	4.210	max	4.240	mean	4.226				
1598					CSR min	6.070	max*10.050	mean	6.498				
1599		H			min	8.607	max	8.678	mean	8.671			
1600	Column-Gradient												
1601		GPU 64	COO	min	4.170	max	4.190	mean	4.180				
1602					CSR min	5.610	max	7.300	mean	5.988			
1603		H			min	9.534	max*	9.601	mean	9.585			
1604	Row-Column-Permute												
1605		GPU 64	COO	min	4.190	max	4.190	mean	4.190				
1606					CSR min	6.070	max	7.000	mean	6.386			
1607		H			min	9.255	max	9.257	mean	9.256			
1608	ex19.mtx												
1609	Regular												
1610		GPU 64	COO	min	6.140	max*	6.180	mean	6.159				
1611					CSR min	12.780	max*14.400	mean	13.328				
1612		H			min	8.228	max	8.228	mean	8.228			
1613	Row-P												

1622		GPU 64 COO min 5.760 max 5.840 mean 5.813	1696		H min 7.380 max 7.380 mean 7.380
1623		CSR min 9.710 max 14.220 mean 10.376	1697	Row-Premute	
1624		H min 11.873 max*11.882 mean 11.878	1698		GPU 64 COO min 4.130 max 4.170 mean 4.134
1625	Row-Column-Permute		1699		CSR min 6.180 max* 9.200 mean 6.796
1626		GPU 64 COO min 5.810 max 5.860 mean 5.838	1700		H min 10.041 max 10.046 mean 10.044
1627		CSR min 9.920 max 10.820 mean 10.240	1701	Row-Gradient	
1628		H min 11.836 max 11.841 mean 11.838	1702		GPU 64 COO min 4.150 max* 4.220 mean 4.163
1629	brainpc2.mtx		1703		CSR min 6.410 max 7.500 mean 6.816
1630	Regular		1704		H min 9.682 max 9.706 mean 9.693
1631		GPU 64 COO min 0.000 max 0.000 mean 0.000	1705	Column-Gradient	
1632		CSR min 0.000 max 0.000 mean 0.000	1706		GPU 64 COO min 4.080 max 4.110 mean 4.096
1633		H min 7.478 max 7.478 mean 7.478	1707		CSR min 6.020 max 7.220 mean 6.309
1634	Row-Premute		1708		H min 10.597 max*10.658 mean 10.631
1635		GPU 64 COO min 4.760 max 4.790 mean 4.773	1709	Row-Column-Permute	
1636		CSR min 6.930 max 7.780 mean 7.310	1710		GPU 64 COO min 4.120 max 4.140 mean 4.130
1637		H min 9.810 max 9.813 mean 9.811	1711		CSR min 6.210 max 7.200 mean 6.609
1638	Row-Gradient		1712		H min 10.041 max 10.046 mean 10.044
1639		GPU 64 COO min 4.820 max* 4.840 mean 4.831	1713	TSOPF_FS_b9_c6.mtx	
1640		CSR min 7.220 max 8.290 mean 7.583	1714	Regular	
1641		H min 9.721 max 9.725 mean 9.723	1715		GPU 64 COO min 0.000 max 0.000 mean 0.000
1642	Column-Gradient		1716		CSR min 0.000 max 0.000 mean 0.000
1643		GPU 64 COO min 4.760 max 4.820 mean 4.779	1717		H min 7.380 max 7.380 mean 7.380
1644		CSR min 6.870 max* 8.300 mean 7.393	1718	Row-Premute	
1645		H min 10.368 max*10.373 mean 10.370	1719		GPU 64 COO min 4.120 max 4.140 mean 4.129
1646	Row-Column-Permute		1720		CSR min 6.170 max 7.160 mean 6.664
1647		GPU 64 COO min 4.750 max 4.780 mean 4.765	1721		H min 10.041 max 10.045 mean 10.043
1648		CSR min 6.940 max 7.580 mean 7.298	1722	Row-Gradient	
1649		H min 9.809 max 9.814 mean 9.811	1723		GPU 64 COO min 4.150 max* 4.180 mean 4.162
1650	shermanACb.mtx		1724		CSR min 6.420 max 7.360 mean 6.723
1651	Regular		1725		H min 9.682 max 9.706 mean 9.693
1652		GPU 64 COO min 4.090 max* 4.130 mean 4.112	1726	Column-Gradient	
1653		CSR min 6.320 max* 7.200 mean 6.779	1727		GPU 64 COO min 4.080 max 4.120 mean 4.096
1654		H min 8.600 max 8.600 mean 8.600	1728		CSR min 5.880 max 7.090 mean 6.403
1655	Row-Premute		1729		H min 10.611 max*10.660 mean 10.637
1656		GPU 64 COO min 4.020 max 4.050 mean 4.036	1730	Row-Column-Permute	
1657		CSR min 5.670 max 6.460 mean 6.014	1731		GPU 64 COO min 4.130 max 4.140 mean 4.130
1658		H min 10.376 max 10.382 mean 10.379	1732		CSR min 6.330 max* 7.390 mean 6.695
1659	Row-Gradient		1733		H min 10.042 max 10.047 mean 10.044
1660		GPU 64 COO min 4.050 max 4.100 mean 4.074	1734	OPF_6000.mtx	
1661		CSR min 5.580 max 6.420 mean 5.996	1735	Regular	
1662		H min 9.918 max 9.924 mean 9.921	1736		GPU 64 COO min 7.270 max* 7.370 mean 7.293
1663	Column-Gradient		1737		CSR min 12.890 max*14.500 mean 13.566
1664		GPU 64 COO min 4.010 max 4.080 mean 4.033	1738		H min 8.799 max 8.799 mean 8.799
1665		CSR min 0.000 max 6.320 mean 5.527	1739	Row-Premute	
1666		H min 10.543 max*10.595 mean 10.589	1740		GPU 64 COO min 6.640 max 6.720 mean 6.678
1667	Row-Column-Permute		1741		CSR min 9.680 max 11.600 mean 10.040
1668		GPU 64 COO min 4.020 max 4.050 mean 4.036	1742		H min 11.873 max 11.877 mean 11.875
1669		CSR min 5.670 max 6.510 mean 6.092	1743	Row-Gradient	
1670		H min 10.377 max 10.381 mean 10.379	1744		GPU 64 COO min 7.090 max 7.140 mean 7.122
1671	cvxqp3.mtx		1745		CSR min 11.250 max 13.030 mean 12.142
1672	Regular		1746		H min 11.110 max 11.117 mean 11.114
1673		GPU 64 COO min 3.500 max* 3.540 mean 3.501	1747	Column-Gradient	
1674		CSR min 11.860 max*13.100 mean 12.694	1748		GPU 64 COO min 6.590 max 6.710 mean 6.644
1675		H min 8.646 max 8.646 mean 8.646	1749		CSR min 9.400 max 13.140 mean 9.991
1676	Row-Premute		1750		H min 12.040 max*12.046 mean 12.043
1677		GPU 64 COO min 3.360 max 3.370 mean 3.365	1751	Row-Column-Permute	
1678		CSR min 6.210 max 7.610 mean 6.631	1752		GPU 64 COO min 6.640 max 6.710 mean 6.679
1679		H min 11.027 max 11.032 mean 11.030	1753		CSR min 9.690 max 10.740 mean 10.050
1680	Row-Gradient		1754		H min 11.874 max 11.877 mean 11.875
1681		GPU 64 COO min 3.370 max 3.380 mean 3.376	1755	OPF_3754.mtx	
1682		CSR min 6.170 max 7.070 mean 6.499	1756	Regular	
1683		H min 11.059 max 11.068 mean 11.064	1757		GPU 64 COO min 4.430 max* 4.450 mean 4.443
1684	Column-Gradient		1758		CSR min 9.710 max*13.000 mean 11.377
1685		GPU 64 COO min 3.350 max 3.390 mean 3.371	1759		H min 8.393 max 8.393 mean 8.393
1686		CSR min 6.150 max 7.180 mean 6.531	1760	Row-Premute	
1687		H min 11.125 max*11.133 mean 11.130	1761		GPU 64 COO min 4.230 max 4.250 mean 4.240
1688	Row-Column-Permute		1762		CSR min 7.430 max 8.750 mean 7.986
1689		GPU 64 COO min 3.350 max 3.380 mean 3.364	1763		H min 11.266 max 11.272 mean 11.269
1690		CSR min 6.040 max 7.440 mean 6.603	1764	Row-Gradient	
1691		H min 11.028 max 11.033 mean 11.030	1765		GPU 64 COO min 4.370 max 4.420 mean 4.382
1692	case9.mtx		1766		CSR min 8.160 max 9.470 mean 8.682
1693	Regular		1767		H min 10.462 max 10.473 mean 10.468
1694		GPU 64 COO min 0.000 max 0.000 mean 0.000	1768	Column-Gradient	
1695		CSR min 0.000 max 0.000 mean 0.000	1769		GPU 64 COO min 4.210 max 4.240 mean 4.227

1770		CSR min 7.160 max 8.080 mean 7.595	1844	Row-Premute	
1771		H min 11.394 max*11.401 mean 11.398	1845		GPU 64 COO min 10.340 max 10.430 mean 10.362
1772	Row-Column-Permute		1846		CSR min 12.880 max 13.340 mean 13.057
1773		GPU 64 COO min 4.230 max 4.250 mean 4.243	1847		H min 10.777 max 10.778 mean 10.777
1774		CSR min 7.230 max 8.940 mean 8.056	1848	Row-Gradient	
1775		H min 11.264 max 11.271 mean 11.269	1849		GPU 64 COO min 10.650 max*10.740 mean 10.688
1776	c-47.mtx		1850		CSR min 12.310 max 13.670 mean 12.562
1777	Regular		1851		H min 11.247 max 11.300 mean 11.281
1778		GPU 64 COO min 5.320 max* 5.340 mean 5.329	1852	Column-Gradient	
1779		CSR min 8.890 max* 9.590 mean 9.249	1853		GPU 64 COO min 10.340 max 10.440 mean 10.398
1780		H min 8.364 max 8.364 mean 8.364	1854		CSR min 9.480 max 10.110 mean 9.782
1781	Row-Premute		1855		H min 12.023 max*12.069 mean 12.047
1782		GPU 64 COO min 5.240 max 5.250 mean 5.241	1856	Row-Column-Permute	
1783		CSR min 7.790 max 8.890 mean 8.214	1857		GPU 64 COO min 10.330 max 10.380 mean 10.356
1784		H min 10.059 max 10.063 mean 10.061	1858		CSR min 12.840 max 13.530 mean 13.119
1785	Row-Gradient		1859		H min 10.776 max 10.778 mean 10.777
1786		GPU 64 COO min 5.230 max 5.260 mean 5.242	1860	aft01.mtx	
1787		CSR min 7.080 max 8.050 mean 7.673	1861	Regular	
1788		H min 10.206 max 10.226 mean 10.218	1862		GPU 64 COO min 3.680 max* 3.690 mean 3.688
1789	Column-Gradient		1863		CSR min 13.860 max*14.830 mean 14.560
1790		GPU 64 COO min 5.080 max 5.120 mean 5.105	1864		H min 7.811 max 7.811 mean 7.811
1791		CSR min 5.780 max 6.970 mean 6.359	1865	Row-Premute	
1792		H min 11.205 max*11.233 mean 11.222	1866		GPU 64 COO min 3.510 max 3.530 mean 3.513
1793	Row-Column-Permute		1867		CSR min 6.420 max 10.520 mean 7.265
1794		GPU 64 COO min 5.220 max 5.250 mean 5.227	1868		H min 11.161 max*11.170 mean 11.165
1795		CSR min 7.860 max 8.710 mean 8.247	1869	Row-Gradient	
1796		H min 10.059 max 10.064 mean 10.061	1870		GPU 64 COO min 3.630 max 3.670 mean 3.643
1797	mhd4800a.mtx		1871		CSR min 10.760 max 13.510 mean 12.199
1798	Regular		1872		H min 10.248 max 10.265 mean 10.258
1799		GPU 64 COO min 3.090 max* 3.100 mean 3.098	1873	Column-Gradient	
1800		CSR min 11.570 max*12.290 mean 12.092	1874		GPU 64 COO min 3.510 max 3.520 mean 3.519
1801		H min 7.132 max 7.132 mean 7.132	1875		CSR min 6.490 max 11.230 mean 7.645
1802	Row-Premute		1876		H min 11.112 max 11.121 mean 11.117
1803		GPU 64 COO min 3.020 max 3.020 mean 3.020	1877	Row-Column-Permute	
1804		CSR min 5.560 max 7.270 mean 6.007	1878		GPU 64 COO min 3.510 max 3.540 mean 3.515
1805		H min 10.959 max*10.968 mean 10.963	1879		CSR min 6.510 max 11.650 mean 7.311
1806	Row-Gradient		1880		H min 11.161 max 11.168 mean 11.165
1807		GPU 64 COO min 3.080 max 3.100 mean 3.088	1881	TSOPF_RS_b39_c7.mtx	
1808		CSR min 10.250 max 12.150 mean 11.340	1882	Regular	
1809		H min 9.509 max 9.528 mean 9.520	1883		GPU 64 COO min 5.970 max* 6.010 mean 5.988
1810	Column-Gradient		1884		CSR min 12.470 max*21.120 mean 13.816
1811		GPU 64 COO min 3.020 max 3.050 mean 3.026	1885		H min 7.304 max 7.304 mean 7.304
1812		CSR min 5.530 max 10.580 mean 6.432	1886	Row-Premute	
1813		H min 10.933 max 10.946 mean 10.939	1887		GPU 64 COO min 5.840 max 5.870 mean 5.856
1814	Row-Column-Permute		1888		CSR min 10.780 max 15.810 mean 11.425
1815		GPU 64 COO min 3.020 max 3.020 mean 3.020	1889		H min 10.537 max 10.540 mean 10.539
1816		CSR min 5.510 max 6.830 mean 6.136	1890	Row-Gradient	
1817		H min 10.959 max 10.967 mean 10.963	1891		GPU 64 COO min 5.950 max 6.000 mean 5.975
1818	gen4.mtx		1892		CSR min 11.520 max 17.250 mean 12.799
1819	Regular		1893		H min 9.638 max 9.646 mean 9.641
1820		GPU 64 COO min 3.300 max* 3.320 mean 3.308	1894	Column-Gradient	
1821		CSR min 5.250 max 6.340 mean 5.705	1895		GPU 64 COO min 5.790 max 5.860 mean 5.827
1822		H min 9.234 max 9.234 mean 9.234	1896		CSR min 10.500 max 14.080 mean 11.237
1823	Row-Premute		1897		H min 11.128 max*11.223 mean 11.209
1824		GPU 64 COO min 3.290 max 3.310 mean 3.299	1898	Row-Column-Permute	
1825		CSR min 5.190 max 7.420 mean 5.683	1899		GPU 64 COO min 5.850 max 5.870 mean 5.855
1826		H min 10.249 max 10.254 mean 10.252	1900		CSR min 10.790 max 15.250 mean 11.718
1827	Row-Gradient		1901		H min 10.537 max 10.541 mean 10.539
1828		GPU 64 COO min 3.300 max 3.310 mean 3.301	1902	mult_dcop_03.mtx	
1829		CSR min 5.370 max 6.310 mean 5.659	1903	Regular	
1830		H min 9.934 max 9.958 mean 9.948	1904		GPU 64 COO min 5.130 max* 5.220 mean 5.142
1831	Column-Gradient		1905		CSR min 7.250 max* 9.320 mean 7.722
1832		GPU 64 COO min 3.240 max 3.260 mean 3.249	1906		H min 9.689 max 9.689 mean 9.689
1833		CSR min 5.090 max* 8.660 mean 5.546	1907	Row-Premute	
1834		H min 10.853 max*10.873 mean 10.864	1908		GPU 64 COO min 4.980 max 5.030 mean 4.999
1835	Row-Column-Permute		1909		CSR min 6.460 max 8.470 mean 6.950
1836		GPU 64 COO min 3.290 max 3.320 mean 3.296	1910		H min 10.738 max 10.742 mean 10.740
1837		CSR min 5.190 max 7.550 mean 5.659	1911	Row-Gradient	
1838		H min 10.249 max 10.255 mean 10.252	1912		GPU 64 COO min 5.070 max 5.140 mean 5.088
1839	Maragal_6.mtx		1913		CSR min 6.780 max 8.700 mean 7.268
1840	Regular		1914		H min 10.572 max 10.584 mean 10.580
1841		GPU 64 COO min 10.580 max 10.620 mean 10.599	1915	Column-Gradient	
1842		CSR min 15.620 max*16.470 mean 15.832	1916		GPU 64 COO min 4.980 max 5.030 mean 5.010
1843		H min 9.930 max 9.930 mean 9.930	1917		CSR min 6.390 max 7.640 mean 6.982

```

1918           H           min 10.825 max*10.845 mean 10.836
1919 Row-Column-Permute
1920           GPU 64 COO min 4.990 max 5.010 mean 4.997
1921           CSR min 6.300 max 7.160 mean 6.636
1922           H           min 10.738 max 10.743 mean 10.740

```

REFERENCES

- [1] Hartwig Anzt, Terry Cojean, Chen Yen-Chen, Jack J. Dongarra, Goran Flegar, Pratik Nayak, Stanimire Tomov, Yuhsiang M. Tsai, and Weichung Wang. 2020. Load-balancing Sparse Matrix Vector Product Kernels on GPUs. *ACM Trans. Parallel Comput.* 7, 1 (2020), 2:1–2:26. <https://doi.org/10.1145/3380930>
- [2] Paolo D’Alberto, Chris Drome, and Ali Dasdan. 2012. Non-Parametric Methods Applied to the N-Sample Series Comparison. (2012). arXiv:stat.CO/1205.1880
- [3] Enver Kayaaslan, Cevdet Aykanat, and Bora Uçar. 2018. 1.5D Parallel Sparse Matrix-Vector Multiply. *SIAM J. Scientific Computing* 40, 1 (2018). <https://doi.org/10.1137/16M1105591>
- [4] Brian A. Page and Peter M. Kogge. 2018. Scalability of Hybrid Sparse Matrix Dense Vector (SpMV) Multiplication. In *2018 International Conference on High Performance Computing & Simulation, HPCS 2018, Orleans, France, July 16-20, 2018*. IEEE, 406–414. <https://doi.org/10.1109/HPCS.2018.00072>