## MUMPS Solver Examples with mumps4py

March 09, 2025

### $_{\scriptscriptstyle 4}$ 1 Introduction

- 5 This report describes seven Python scripts demonstrating the MUMPS solver via the mumps4py
- 6 interface. Each example highlights different functionalities, such as centralized and dis-
- <sup>7</sup> tributed matrix assembly, sparse RHS solving, and elemental matrix formats. The scripts
- 8 use MPI for parallelism and NumPy for numerical operations. Full Python code with added
- 9 comments is included for clarity.

# 2 Example 1: Centralized COO Matrix with Dense RHS

This example solves a linear system Ax = b using a centralized sparse matrix in COO format with a dense RHS.

#### $_{\scriptscriptstyle 14}$ 2.1 Matrix Data

- irn (0-based): [0, 1, 2, 3]
- jcn (0-based): [0,1,2,3]
- a: [1.0, 2.0, 3.0, 4.0]

#### $_{18}$ 2.2 Code

```
21
   #!/usr/bin/env python3
    # -*- coding: utf-8 -*-
22
23
   Created on Thu Feb 27 14:08:37 2025
24
25
    @author: kissami
26
27
   import numpy as np
28
   from mpi4py import MPI
   from scipy.sparse import coo_matrix
   from mumps4py.mumps_solver import MumpsSolver
31
   # Get MPI rank and size for parallel execution
```

```
rank =MPI.COMM_WORLD.Get_rank()
   size =MPI.COMM_WORLD.Get_size()
35
36
37
   # Set system type to double precision
   system ="double"
38
   dtype =np.float32 if system =="single" else np.float64
   if system in ["complex64", "complex128"]:
40
    dtype =np.complex64 if system =="complex64" else np.complex128
41
42
    # Initialize MUMPS solver with double precision and no verbose output
43
44
    solver =MumpsSolver(verbose=False, system=system)
45
    # Define a 4x4 diagonal matrix in COO format
46
   A = coo_matrix(([1.0, 2.0, 3.0, 4.0], ([0, 1, 2, 3], [0, 1, 2, 3])), shape=(4, 4))
47
48
49
   # Set the centralized COO matrix in the solver
   solver.set_coo_centralized(A)
50
51
   # Define the right-hand side vector
52
53
   rhs =np.array([1.0, 2.0, 3.0, 4.0])
   solver.set_rhs_centralized(rhs)
55
   # Perform analysis phase (symbolic factorization)
56
   solver.analvze()
57
  # Perform numerical factorization
   solver.factorize()
60
   # Solve the system, overwriting rhs with the solution
   solver.solve()
61
62
   # Print the solution on all ranks
   print("Solution is:", rhs)
```

$$A = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 2 & 0 & 0 \\ 0 & 0 & 3 & 0 \\ 0 & 0 & 0 & 4 \end{bmatrix}, \quad b = \begin{bmatrix} 1 \\ 2 \\ 3 \\ 4 \end{bmatrix}$$

Expected solution: x = [1, 1, 1, 1].

# 3 Example 2: Distributed COO Matrix with Dense RHS

This example uses a distributed COO matrix with a dense RHS.

### 70 3.1 Matrix Data

- irn (0-based): [0,1,3,4,1,0,4,2,1,2,0,2]
- jcn (0-based): [1, 2, 2, 4, 0, 0, 1, 3, 4, 1, 2, 2]
- a: [3.0, -3.0, 2.0, 1.0, 3.0, 2.0, 4.0, 2.0, 6.0, -1.0, 4.0, 1.0]

### $_{74}$ 3.2 Code

```
<del>7</del>5
    #!/usr/bin/env python3
77
78
    # -*- coding: utf-8 -*-
79
    import numpy as np
    from mpi4py import MPI
80
   from mumps4py.mumps_solver import MumpsSolver
81
82
83
    # MPI setup
    rank =MPI.COMM_WORLD.Get_rank()
84
    size =MPI.COMM_WORLD.Get_size()
85
86
87
    # Set double precision
    system ="double"
88
    dtype =np.float32 if system =="single" else np.float64
89
    if system in ["complex64", "complex128"]:
90
    dtype =np.complex64 if system =="complex64" else np.complex128
91
92
93
    # Initialize solver
    solver =MumpsSolver(verbose=False, system=system)
94
95
96
    # Define matrix size on rank 0 only
97
    if rank ==0:
98
        n = 5
    else:
99
        n = None
100
101
    # Define COO matrix data (0-based indices)
102
    irn =np.array([0,1,3,4,1,0,4,2,1,2,0,2], dtype=np.int32)
103
    jcn =np.array([1,2,2,4,0,0,1,3,4,1,2,2], dtype=np.int32)
104
    a = np.array([3.0,-3.0,2.0,1.0,3.0,2.0,4.0,2.0,6.0,-1.0,4.0,1.0], dtype=dtype)
    b = np.array([[20.0,24.0,9.0,6.0,13.0],[20.0,24.0,9.0,6.0,13.0]], dtype=dtype)
106
107
    # Split matrix entries across MPI processes
108
    indices =np.arange(len(irn))
109
    split_indices =np.array_split(indices, size)
    local_indices =split_indices[rank]
111
112
    # Extract local portions of the matrix
113
    local_irn =irn[local_indices]
114
115
    local_jcn =jcn[local_indices]
116
    local_a =a[local_indices]
117
    # Set distributed matrix (convert to 1-based indices for MUMPS)
118
    solver.set_rcd_distributed(local_irn+1, local_jcn+1, local_a, n)
119
    solver.set_icntl(18,3) # Enable distributed assembly
120
121
    # Analyze and factorize the matrix
122
   solver.analyze()
123
    solver.factorize()
125
126
    # Set RHS on rank 0 only
127
    if MPI.COMM_WORLD.Get_rank() ==0:
128 solver.set_rhs_centralized(b)
130 # Solve the system
131 solver.solve()
132
    if rank ==0:
print("Solution 3", b)
```

$$A = \begin{bmatrix} 2 & 3 & 4 & 0 & 0 \\ 3 & -1 & -3 & 0 & 6 \\ 0 & 0 & 1 & 2 & 0 \\ 0 & 0 & 2 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

## Example 3: Distributed COO Matrix with Distributed Solution

This example extends Example 2 with a distributed solution.

### 38 4.1 Matrix Data

- irn: [0, 1, 3, 4, 1, 0, 4, 2, 1, 2, 0, 2]
  - jcn: [1, 2, 2, 4, 0, 0, 1, 3, 4, 1, 2, 2]
    - a: [3.0, -3.0, 2.0, 1.0, 3.0, 2.0, 4.0, 2.0, 6.0, -1.0, 4.0, 1.0]

#### 4.2 Code

```
143
145
     #!/usr/bin/env python3
    # -*- coding: utf-8 -*-
146
147
148
    Created on Thu Feb 27 14:23:15 2025
149
150
     @author: kissami
151
    from mumps4py.mumps_solver import MumpsSolver
153
    import numpy as np
154
     from mpi4py import MPI
155
    # MPI initialization
156
    comm =MPI.COMM_WORLD
    rank =comm.Get_rank()
158
     size =comm.Get_size()
160
    # Set double precision
161
    system ="double"
    dtype =np.float32 if system =="single" else np.float64
163
     if system in ["complex64", "complex128"]:
164
    dtype =np.complex64 if system =="complex64" else np.complex128
165
166
167
    # Initialize solver
    solver =MumpsSolver(verbose=False, system=system)
168
    # Define matrix size
170
171
    # Define COO matrix (1-based indices for MUMPS)
172
173
    irn = np.array([0,1,3,4,1,0,4,2,1,2,0,2], dtype=np.int32) +1
     jcn =np.array([1,2,2,4,0,0,1,3,4,1,2,2], dtype=np.int32) +1
    a = np.array([3.0,-3.0,2.0,1.0,3.0,2.0,4.0,2.0,6.0,-1.0,4.0,1.0], dtype=dtype)
175
    b = np.array([20.0,24.0,9.0,6.0,13.0], dtype=dtype)
177
    # Distribute matrix entries across processes
178
179
    indices =np.arange(len(irn))
    split_indices =np.array_split(indices, size)
180
    local_indices =split_indices[rank]
182
     # Local matrix portions
183
    local_irn =irn[local_indices]
184
    local_jcn =jcn[local_indices]
185
    local_a =a[local_indices]
187
    # Configure solver for distributed assembly and solution
    solver.set_icntl(18, 3) # Distributed matrix input
```

```
solver.set_rcd_distributed(local_irn, local_jcn, local_a, n)
191
    solver.set_icntl(21, 1) # Distributed solution output
192
193
    # Analyze and factorize
    solver.analyze()
194
    solver.factorize()
196
    # Set RHS on rank 0
197
198
    if rank ==0:
    solver.set_rhs_centralized(b)
199
200
    # Enable and compute distributed solution
201
    solver.enable_distributed_solution(1)
202
203
    solver.solve()
204
205
    # Retrieve distributed solution
    shape =b.shape
206
207
    dtype =np.float64
    distributed_solution =solver.pointer_to_numpy(solver.struct.sol_loc, dtype, shape)
208
    print("Distributed solution :", distributed_solution)
210
    # Get solution indices
211
    isol_indices =solver.pointer_to_numpy(solver.struct.isol_loc, np.int32, b.shape)
212
    print("Solution indices :", isol_indices)
213
215
    # Reconstruct full solution
216
    final_solution =np.zeros(n, dtype=dtype)
217
    final_solution[isol_indices -1] =distributed_solution # Adjust for 0-based indexing
    print("Final solution :", final_solution)
```

## 5 Example 4: Elemental Matrix Format

This example uses an elemental matrix format for a complex-valued system.

### $_{22}$ 5.1 Matrix Data

```
eltptr (1-based): [1,4,7]
eltvar (1-based): [1,2,3,3,4,5]
a_elt: [-1,2,1,2,1,1,3,1,1,2,1,3,-1,2,2,3,-1,1]
```

### 5.2 Code

```
337
    #!/usr/bin/env python3
229
    # -*- coding: utf-8
231 import numpy as np
232
    from mpi4py import MPI
233
    from mumps4py.mumps_solver import MumpsSolver
234
235
    # MPI setup
    rank =MPI.COMM_WORLD.Get_rank()
236
237
    size =MPI.COMM_WORLD.Get_size()
238
239 # Set complex128 precision
240 system ="complex128"
    dtype =np.float32 if system =="single" else np.float64
241
    if system in ["complex64", "complex128"]:
```

```
dtype =np.complex64 if system =="complex64" else np.complex128
244
245
    # Initialize solver
246
    solver =MumpsSolver(verbose=False, system=system)
247
    # Define matrix parameters
    n = 5 # Matrix order
249
    nelt =2 # Number of elements
250
251
    # Elemental matrix data (1-based)
252
    eltptr =np.array([1, 4, 7], dtype=np.int32) # Element pointers
253
    eltvar =np.array([1, 2, 3, 3, 4, 5], dtype=np.int32) # Variable indices
254
    a_elt =np.array([-1, 2, 1, 2, 1, 1, 3, 1, 1, 2, 1, 3, -1, 2, 2, 3, -1, 1], dtype=dtype) # Values
255
    bb =np.array([1, 20, 3, 4, 5], dtype=dtype) # RHS
256
    rhs =bb.copy() # Copy for verification
257
258
    # Configure solver for elemental format
259
260
    solver.set_icntl(5, 1) # Use elemental matrix format
    solver.set_icntl(18, 0) # Centralized assembly
261
262
263
    # Set matrix and RHS
    solver.set_elemental_matrix(eltptr, eltvar, a_elt, n, nelt)
264
    solver.set_rhs_centralized(bb)
265
266
    # Solve the system
267
268
    solver.analyze()
269
    solver.factorize()
270
    solver.solve()
271
    # Print solution on rank 0
273 if rank ==0:
    print("Solution:", bb)
274
275
    # Define A for verification (not in original code)
276
277 A = np.array([[-1, 2, 3, 0, 0], [2, 1, 1, 0, 0], [1, 1, 3, -1, 3], [0, 0, 1, 2, -1], [0, 0, 3, 2, 1]], dtype=dtype)
    print("Check solution:", A.dot(bb) -rhs)
```

$$A = \begin{bmatrix} -1 & 2 & 1 & 0 & 0 \\ 2 & 1 & 1 & 0 & 0 \\ 1 & 1 & 3 & -1 & 3 \\ 0 & 0 & 1 & 2 & -1 \\ 0 & 0 & 3 & 2 & 1 \end{bmatrix}$$

# 6 Example 5: Centralized COO Matrix with Manual Job Calls and Reused Factorization

This example uses manual MUMPS job calls to solve a  $5 \times 5$  system and illustrates that if the matrix structure (irn, jcn) and values (a) remain unchanged, the factorization step can be reused for multiple RHS vectors, avoiding redundant computation.

#### 6.1 Matrix Data

281

- irn: [0, 1, 3, 4, 1, 0, 4, 2, 1, 2, 0, 2]
- jcn: [1, 2, 2, 4, 0, 0, 1, 3, 4, 1, 2, 2]

• a: [3.0, -3.0, 2.0, 1.0, 3.0, 2.0, 4.0, 2.0, 6.0, -1.0, 4.0, 1.0]

### 6.2 Code

```
<del>2</del>90
    #!/usr/bin/env python3
292
    # -*- coding: utf-8 -*-
293
294
    import numpy as np
    from mpi4py import MPI
295
    from mumps4py.mumps_solver import MumpsSolver
297
    # MPI setup
299
    rank =MPI.COMM_WORLD.Get_rank()
    size =MPI.COMM_WORLD.Get_size()
301
    # Set double precision
302
    system ="double"
    dtype =np.float32 if system =="single" else np.float64
304
    if system in ["complex64", "complex128"]:
305
    dtype =np.complex64 if system =="complex64" else np.complex128
306
307
308 # Initialize solver
    solver =MumpsSolver(verbose=False, system=system)
309
310
    # Define matrix and two different RHS vectors
311
312 n = 5
    irn =np.array([0,1,3,4,1,0,4,2,1,2,0,2], dtype=np.int32)
314
    jcn =np.array([1,2,2,4,0,0,1,3,4,1,2,2], dtype=np.int32)
    a = np.array([3.0, -3.0, 2.0, 1.0, 3.0, 2.0, 4.0, 2.0, 6.0, -1.0, 4.0, 1.0], dtype=dtype)
    b1 =np.array([20.0, 24.0, 9.0, 6.0, 13.0], dtype=dtype) # First RHS
    b2 =np.array([1.0, 2.0, 3.0, 4.0, 5.0], dtype=dtype) # Second RHS
317
318
    n = len(b1) # Matrix size from RHS
319
320
    # Start timing
321
322
    ts = MPI.Wtime()
323
324
    # Set centralized matrix (1-based indices)
325
    solver.set_rcd_centralized(irn+1, jcn+1, a, n)
    solver._mumps_call(job=1) # Analysis phase (symbolic factorization)
326
328
    # Factorize once (numerical factorization)
    solver._mumps_call(job=2) # Factorization phase, done only once
330
    # Solve for first RHS
331
332 rhs1 =b1.copy() # Copy to preserve original
333
    solver.set_rhs_centralized(rhs1)
    solver._mumps_call(3) # Solve phase
334
    if rank ==0:
335
    print("Solution for b1:", rhs1)
336
337
    # Solve for second RHS reusing factorization
338
339
    rhs2 =b2.copy() # Copy to preserve original
    solver.set_rhs_centralized(rhs2)
341 solver._mumps_call(3) # Solve phase, no need to re-factorize
342 if rank ==0:
343 print("Solution for b2:", rhs2)
345 # Print total CPU time
346 if rank ==0:
   print("CPU time is ", MPI.Wtime() -ts)
```

### $_{9}$ 6.3 Explanation

The matrix A is defined once, and its factorization (job=2) is performed only once after analysis (job=1). Two different RHS vectors,  $b_1 = [20, 24, 9, 6, 13]$  and  $b_2 = [1, 2, 3, 4, 5]$ , are solved using the same factorization by calling only the solve phase (job=3) for each. This demonstrates that as long as irn, jcn, and a do not change, re-factorization is unnecessary, optimizing performance.

### <sup>355</sup> 7 Example 6: Updating Centralized Matrix Values

This example updates matrix values without re-analysis.

#### $_{57}$ 7.1 Matrix Data

```
• irn: [0, 1, 3, 4, 1, 0, 4, 2, 1, 2, 0, 2]
```

```
• jcn: [1, 2, 2, 4, 0, 0, 1, 3, 4, 1, 2, 2]
```

- Initial a: [3.0, -3.0, 2.0, 1.0, 3.0, 2.0, 4.0, 2.0, 6.0, -1.0, 4.0, 1.0]
  - Updated a: [6.0, -33.0, 2.0, 1.0, 33.0, 22.0, 41.0, 2.0, 66.0, -11.0, 4.0, 1.0]

### 7.2 Code

359

360

```
363
    #!/usr/bin/env python3
365
366
    # -*- coding: utf-8 -*-
367
    Created on Wed Mar 5 11:23:56 2025
368
369
370
    Qauthor: kissami
371
    from scipy.sparse import coo_matrix
372
    from mumps4py.mumps_solver import MumpsSolver
    import numpy as np
374
375
    from mpi4py import MPI
376
    # MPI setup
377
378
    rank =MPI.COMM_WORLD.Get_rank()
    size =MPI.COMM_WORLD.Get_size()
379
    # Set double precision
381
    system ="double"
382
    dtype =np.float32 if system =="single" else np.float64
    if system in ["complex64", "complex128"]:
384
    dtype =np.complex64 if system =="complex64" else np.complex128
385
386
    # Initialize solver
387
    solver =MumpsSolver(verbose=False, system=system)
388
389
390
    # Define initial matrix and RHS
391
    irn =np.array([0,1,3,4,1,0,4,2,1,2,0,2], dtype=np.int32)
392
   jcn =np.array([1,2,2,4,0,0,1,3,4,1,2,2], dtype=np.int32)
393
    a = np.array([3.0, -3.0, 2.0, 1.0, 3.0, 2.0, 4.0, 2.0, 6.0, -1.0, 4.0, 1.0], dtype=dtype)
394
395
    b = np.array([20.0, 24.0, 9.0, 6.0, 13.0], dtype=dtype)
396
```

```
# Set initial matrix (1-based)
398
    solver.set_rcd_centralized(irn+1, jcn+1, a, n)
399
     solver._mumps_call(job=1) # Analyze structure
400
    # Solve with initial values
401
    rhs =b.copy()
    solver._mumps_call(job=2) # Factorize
403
     solver.set_rhs_centralized(rhs)
404
405
    solver._mumps_call(3) # Solve
    print("Solution:", rhs)
406
407
408
    # Update matrix values
     a = np.array([6.0, -33.0, 2.0, 1.0, 33.0, 22.0, 41.0, 2.0, 66.0, -11.0, 4.0, 1.0], dtype=dtype)
409
410
    solver.set_data_centralized(a, n) # Update values only
411
412
    # Solve with updated values
    rhs =b.copy()
413
414
     solver._mumps_call(job=2) # Re-factorize
    solver.set_rhs_centralized(rhs)
415
    solver._mumps_call(3) # Re-solve
417
    print("Solution:", rhs)
418
419
    # Verify solution
    n = 5
420
    A = coo_matrix((a, (irn, jcn)), shape=(n, n))
421
    print("check the solution:", A.dot(rhs), b)
423
```

# 8 Example 7: Sparse RHS with Centralized COO Matrix

This example solves a system with a sparse RHS.

### 427 8.1 Matrix Data

- irn: [0,0,1,1,1,2,2,3,3]
- jcn: [0, 1, 0, 1, 2, 1, 2, 2, 3]
- a: [4.0, -1.0, -1.0, 4.0, -1.0, -1.0, 4.0, -1.0, 3.0]

### 8.2 Sparse RHS Data

- rhs values: [1.1, 2.2, 3.1, 4.1, 3.2]
- rhs\_row\_indices (1-based): [1, 3, 4, 2, 3]
- rhs col ptr (1-based): [1, 4, 6]

### 8.3 Code

```
      439

      438
      #!/usr/bin/env python3

      439
      # -*- coding: utf-8 -*-

      440
      """
```

```
441
    Created on Thu Feb 27 14:08:37 2025
442
443
    Qauthor: kissami
444
445 import numpy as np
446 from mpi4py import MPI
    from mumps4py.mumps_solver import MumpsSolver
447
448
449
    # MPI setup
450 rank =MPI.COMM_WORLD.Get_rank()
451
    size =MPI.COMM_WORLD.Get_size()
452
    # Set double precision
453
454 system ="double"
dtype =np.float32 if system =="single" else np.float64
456 if system in ["complex64", "complex128"]:
dtype =np.complex64 if system =="complex64" else np.complex128
458
459 # Initialize solver
460 solver =MumpsSolver(verbose=False, system=system)
461
462
    # Define 4x4 matrix
463 n = 4
464 nnz =9
irn =np.array([0, 0, 1, 1, 1, 2, 2, 3, 3], dtype=np.int32)
466 jcn =np.array([0, 1, 0, 1, 2, 1, 2, 2, 3], dtype=np.int32)
    a = np.array([4.0, -1.0, -1.0, 4.0, -1.0, 4.0, -1.0, 3.0], dtype=dtype)
467
468
   # Set centralized matrix (1-based)
469
470 solver.set_rcd_centralized(irn+1, jcn+1, a, n)
471
    solver.analyze()
    solver.factorize()
472
473
474 # Configure for sparse RHS
475 solver.set_icntl(20, 1) # Enable sparse RHS
476
    # Define sparse RHS parameters
477
478 nz_rhs =5 # Number of non-zeros
479 nrhs =2 # Number of RHS columns
480 rhs_values =np.array([1.1, 2.2, 3.1, 4.1, 3.2], dtype=dtype) # Non-zero values
481 rhs_row_indices =np.array([1, 3, 4, 2, 3], dtype=np.int32) # Row indices (1-based)
    rhs_col_ptr =np.array([1, 4, 6], dtype=np.int32) # Column pointers (1-based)
483
    # Initialize dense RHS storage on rank 0
484
485 if rank ==0:
486 rhs =np.zeros((2,4))
    solver.set_rhs_centralized(rhs)
487
488
   # Set sparse RHS
490 solver.set_rhs_sparse(rhs_values, rhs_row_indices, rhs_col_ptr, nrhs)
    solver.solve()
491
492
493 # Print solution
   print("Solution is :", rhs)
484
```

$$A = \begin{bmatrix} 4 & -1 & 0 & 0 \\ -1 & 4 & -1 & 0 \\ 0 & -1 & 4 & -1 \\ 0 & 0 & -1 & 3 \end{bmatrix}$$

## 9 Benchmarks: Python vs C

In this section, we compare the runtime of Python and C (through Cython wrapper) using MUMPS-5.3.5 (pt-scotch, without OpenMP) for various matrix sizes obtained from Finite Volume discretization using Manapy [?]. We attempt to determine if the Cython-based interface imposes any extra computational cost over the pure C implementation.

Figures 1 and 3 show the performance of the 2D and 3D problems, respectively. The x-axis is the configuration (matrix size and number of processes), and the y-axis (log scale) is the execution time in seconds for analysis, factorization, and solution phases.

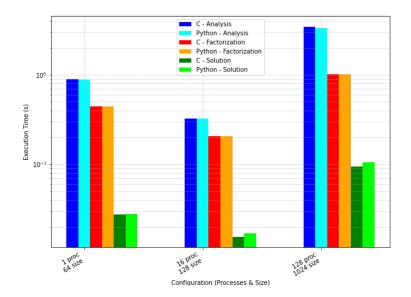


Figure 1: Timing (s) using MUMPS through C vs through Python for 2D matrices

Key Observations:

- All configurations tested have Python (through Cython) performing as well as C.
- There is no extra CPU cost of calling the Cython wrapper, i.e., the Python function calls are just as efficient as direct C function calls. This validates that Cython removes Python overhead by compiling Python code to C and providing almost native call speed in calling MUMPS.

Figures 2 and 4 illustrate the speedup achieved when using the Python-based MUMPS wrapper compared to the native C implementation for 2D and 3D matrices, respectively.

### 10 Conclusion

This report has demonstrated the use of MUMPS via the mumps4py interface for solving sparse linear systems in a parallel computing environment. Several examples were presented,

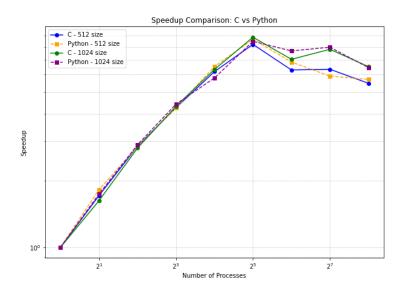


Figure 2: Speedup using MUMPS through C vs through Python for 2D matrices

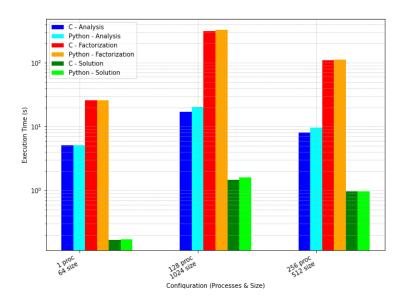


Figure 3: Timing (s) using MUMPS through C vs through Python for 3D matrices

covering different matrix assembly techniques (centralized and distributed), right-hand side (RHS) handling (dense and sparse), and factorization reuse to optimize performance.

The benchmarking results show that the Python-based MUMPS interface (via Cython) achieves performance comparable to the native C implementation, with negligible overhead. This validates the efficiency of the Python wrapper and confirms its suitability for high-performance computing (HPC) applications. The experiments also highlight the scalability of MUMPS and its ability to handle large sparse matrices efficiently.

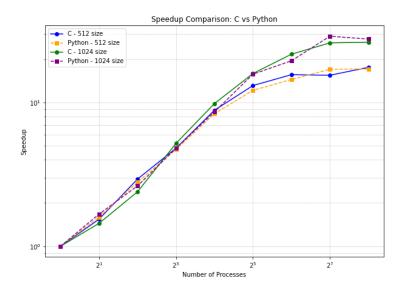


Figure 4: Speedup using MUMPS through C vs through Python for 3D matrices

Overall, mumps4py provides a convenient and flexible interface for leveraging MUMPS within Python, making it an excellent choice for researchers and engineers working on large-scale scientific computations. Future work could explore GPU acceleration and further optimizations for heterogeneous computing environments.