



GPU-Accelerated Batch-ACPF Solution for N-1 Static Security Analysis

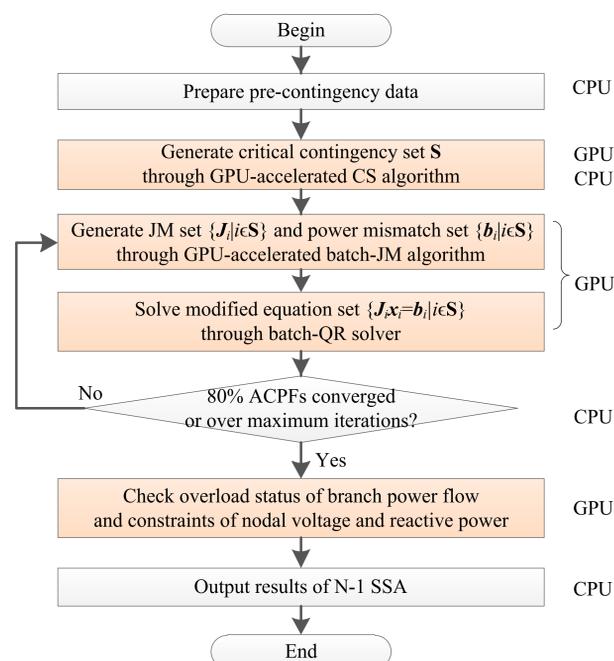
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Introduction

- The N-1 static security analysis (SSA) is used to ensure steady-state security of power system under the loss of any single element. For a system with N elements, **a strict N-1 SSA requires solving N alternating-current power flows (ACPF)**
- Several **sparse linear systems (SLS)** need to be calculated by Newton's method in each ACPF
- Even with the contingency screening (CS), the N-1 SSA is still a computational intensive task. For example, the East China power grid has **8,503 buses** and 12,475 expected contingencies. In a test platform with an Intel Xeon 2G Hz CPU, it takes about **2.4 minutes** to solve a SSA with only a CCS of **475 contingencies**, which cannot meet the speed requirement of on-line analysis.
- This poster presents a GPU-Accelerated **Batch-ACPF Solution** for N-1 Static Security Analysis, which is different from GPU-accelerated **sequential-ACPF solution** who uses GPU to accelerating ACPF one by one

Batch-ACPF Solution for SSA Overview



ANALYSIS OF GPU-ACCELERATED SEQUENTIAL-ACPF SOLUTION

When GPU technique is employed, one natural solution is utilizing it to accelerate ACPFs one by one, which is termed sequential-ACPF solution in this poster. More specifically, each contingency in the CCS is chosen one after another to carry out GPU-based ACPF analysis. The potential bottlenecks with this solution include:

- For a mainstream HPC-purposed GPU such as NVIDIA Tesla K20 or K40, a one-million-order SLS is considered as a small-to-medium-scale computation problem. **In contrast, the power system JM is typically less than 0.1 million order and so solving this ACPF is only a small-scale calculation problem.** Moreover, the numerical factorization process for JM is excessively sequential, so it does not create enough parallelism to saturate the numerous cores in HPC-purposed GPU.
- Even if an ACPF solving problem has enough parallelism to keep all GPU cores utilized, **random memory access resulted from sparse numerical factorization** will lead to massive uncoalesced memory access and therefore the high bandwidth of GPU cannot be fully utilized.

GPU-Accelerated Batch-QR Solver

A Choosing QR factorizing method

QR factorization is absolutely numerical stable even **without pivoting** and so it is more suitable for solving GPU-based batch-SLS.

B QR solver for a single SLS

Parallel sparse left-looking QR factorization Algorithm

for $i = 1 : n$ **do** // n is the number of levels in dependence graph T .

While there are still unfinished columns **do in parallel**

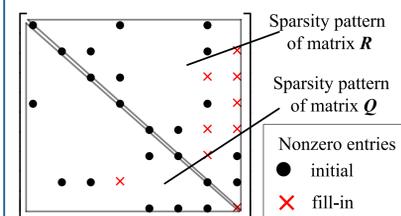
Factorize column according to T ;

Generate Householder vector;

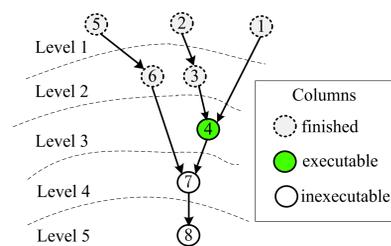
Modify right side vector;

end while

end for

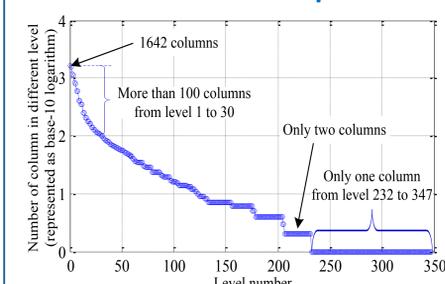


Sparsity pattern with fill-ins



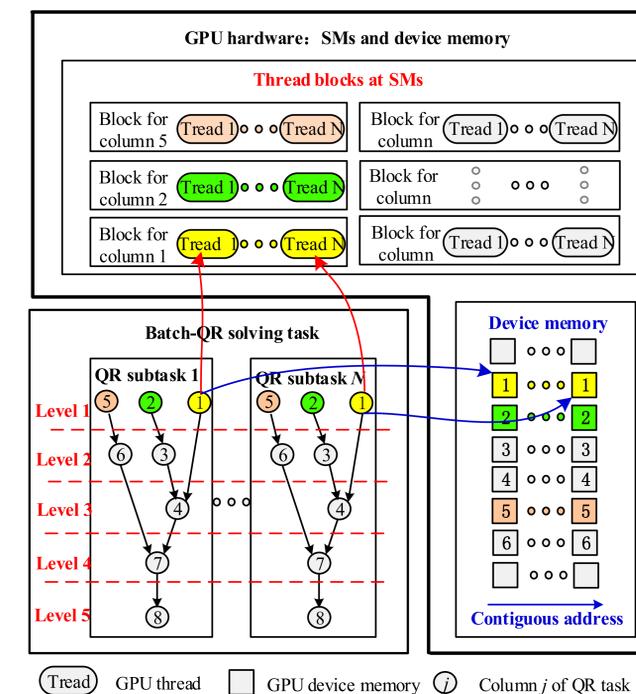
Dependence graph between different columns.

Level information of dependence graph on an 8503-bus case



The **parallelism** of Algorithm performs worse and worse with the execution of QR factorizing and the **random memory access** caused by sparse QR factorization is very difficult to optimize

C Batch-QR solver for massive number of SLSs



The poster presents a novel batch-QR solving method which can solve a set of linear systems $A_i x_i = b_i$ ($i=1, 2, \dots, N$) simultaneously where each nonsingular A_i must have the same sparsity pattern, x_i and b_i are dense vectors.

And as any contingency influences at most four elements of pre-contingency bus admittance matrix Y_0 , the sparsity pattern of any post-contingency admittance matrix Y_i can be designed as same as Y_0 . Similarly, the sparsity pattern of any post-contingency JM J_i can be designed as same as pre-contingency JM J_0 .

In this way, Batch-ACPF will be launched successfully, and the Batch-QR Solver overcome the shortcomings of Single QR solving.

Performance

Performance Analysis of Batch-ACPF Solution on 8503-bus system

Contingency set size	CPU	GPU-accelerated			
	Sequential ACPF Time (s)	Sequential ACPF Time (s)	Speedup	Batch ACPF Time (s)	Speedup
141	47.2	37.8	1.25×	1.99	23.7×
266	85.8	67.9	1.26×	2.13	40.2×
457	144.8	114.0	1.27×	2.51	57.6×
623	196.1	153.9	1.27×	3.02	64.9×

When the number of critical contingencies $S_{cs}=457$, the average computation time per ACPF is reduced from 309ms to only 4.43 ms and up to 69.7 times speedup is achieved in comparison to MATPOWER-based CPU counterpart.

The proposed GPU-accelerated batch-ACPF solution is very promising and can be widely used in **other power system applications** which deal with massive number of homogeneous subtasks, such as **Monte-Carlo simulation and probabilistic power flow**.