Accelerating Simulation for High-Fidelity PV Inverter System Reliability Assessment with High-Performance Computing

Preprint

Liwei Wang,[1] Ramanathan Thiagarajan,[2]
Shuangshuang Jin,[1] and Zheyu Zhang[1]

1 Clemson University
2 National Renewable Energy Laboratory

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National Renewable Energy Laboratory
15013 Denver West Parkway
Golden, CO 80401
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Accelerating Simulation for High-Fidelity PV Inverter System Reliability Assessment with High-Performance Computing

Liwei Wang[1], Ramanathan Thiagarajan[2], Shuangshuang Jin[1], and Zheyu Zhang[1]

[1]Clemson University, North Charleston, SC, 29405, USA

[2]National Renewable Energy Laboratory, Golden, CO, 80401, USA

***Abstract*—The overall cost of photovoltaic (PV) systems has shown a downward trend during the last decade; however, PV inverter failures account for the highest cost of operation and maintenance. To address this, reliability tools with powerful computation and better accuracy are required for the lifetime prediction and degradation evaluation of PV inverters. This paper proposes an event-driven parallel computing-based simulator. The proposed simulator applies high-performance computing techniques and other accessory optimization techniques—including cluster merging, adaptive model updates, and steady-state identification—to make reliability assessments for PV inverters under given input mission profiles and operating conditions with high efficiency and high fidelity. The main idea of the simulator and its workflow are introduced. Then, a demo PV inverter system simulator is implemented, and the speedup of the total simulations of the switching model reaches 123.03 times.**

Keywords—PV System, Reliability Assessment, Power Electronics, High-performance Computing

I. Introduction

The U.S. Department of Energy estimates the photovoltaic (PV) penetration in the U.S. power market to be upward of 18% by 2050, with a $1/watt price point. As the price of PV modules decreases, the price of inverters becomes more important. Inverters now constitute 8%–12% of the total PV lifetime cost [1]. One key price driver of the inverter components is inverter reliability. PV modules are offered up to 30-year warranties. In contrast, typical warranties on inverters last only 5–10 years. Even with the most optimistic view of inverter lifetime, it will be essential to replace or repair an inverter multiple times during the lifetime of a PV module [2]. Further, field data from PV power plant operators demonstrate that power electronics converters contribute the most to operation-and-maintenance events, which are responsible for between 43% and 70% of the service calls [3]. This leads to increased maintenance costs, lost energy production, and, finally, higher levelized cost of energy. Consequently, it is critical to have a generic tool from a third party for PV inverter reliability assessment.

Various tools have been developed to provide reliability assessments for power electronics systems. References [4], [5], [6], [7] introduced physics-to-failure-based analysis tools that the designer could use to predict the corresponding reliability interactively with the design change. But even if these tools can provide decent assessment results, they have some limitations, such as lacking a comprehensive investigation of system-level and/or component-level degradation and not considering long-term actual mission profiles. The Design for Reliability and Robustness (DfR2) tool [8] was proposed as a complete assessment tool for power electronics components and systems. DfR2 integrates advanced reliability models, such as the electrical model and thermal model that consider statistical distribution for lifetime assessment, which enable the thorough investigation of significant factors associated with component degradation.

The current state of the art presents a trend: The accuracy requirements for reliability assessment tools are increasing because more factors are considered in the analytical model and more data are collected in the long-term mission profiles for the data analysis. It would be time-consuming to perform massive computations with high precision in complex evaluation models in a conventional way. High-performance computing (HPC) employing distributed and/or parallel computing mechanisms holds the promise to achieving the expected high computational efficiency. HPC systems are designed for aggregating large-scale computational resources to solve massive scientific problems. By leveraging the techniques spanning hardware, software, network, and security, HPC systems could provide well-optimized performance for scientific computations by efficiently using high-performance processors. With the rapid development of multiprocessor architectures and the emergence of new ideas such as heterogeneous architectures and cloud computing, HPC has incredible potential to provide great quantities of computational power. Even though HPC has been widely used in power systems simulations, power electronics simulations find very few applications in the current state-of-art.

This work proposes an event-driven parallel computing-based simulator to distribute the computational tasks to multiple machines to accelerate the computational speed. The cases with the same operating conditions are regarded as one event. All diverse events are then simulated in parallel. Adaptive model updates are also performed to guarantee the accuracy of the model. As a result, the computational efficiency of the simulations is significantly improved without sacrificing fidelity. The design and main workflow are introduced in

Section II; the performance and corresponding analysis are demonstrated in Section III; and Section IV gives a summary and conclusion.

II. Design for High-Speed, High-Fidelity Simulator

The Tool for Reliability Assessment of Critical Electronics in PV (TRACE-PV) is proposed for predicting the lifetime of PV inverters based on the physics-to-failure mechanisms. Compared to the state of the art [9], the TRACE-PV tool builds the degradation model considering all components with high failure rates and evaluates the reliability from different aspects, such as system configuration and grid disturbance. The summary diagram for TRACE-PV is shown in Figure 1.

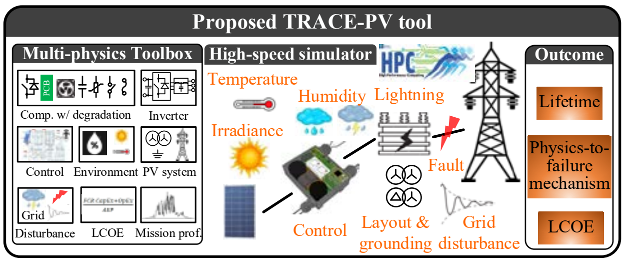

Fig. 1. Summary diagram of TRACE-PV

Figure 2 shows the overall workflow of the HPC simulator. The mission profile and the circuit design are inputs for the simulator. The first step of the simulator is to perform the cluster merging, which is used to preprocess the mission profile data to reduce the number of computations that need to occur. Then the simulator runs the simulation model for each set of data from the mission profile and determines stressors over time. The stressors are used as inputs for the degradation model to predict the lifetime and degradation status. A condition check for detecting whether a critical degradation happens follows. The model parameters are adaptively updated if a check is triggered. The simulator needs to undertake a complex computational workload and adaptively update the model according to the current operating conditions to reach high efficiency and high fidelity. To achieve these goals, several strategies are applied.

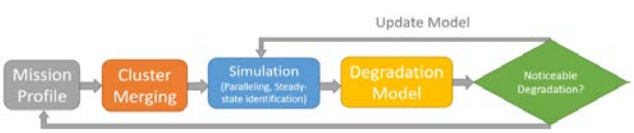

Fig. 2. Overall workflow of the simulator

A. Cluster merging

Mission profiles include environmental information, such as temperature, solar irradiance, and relative humidity; and operational condition information, including power (kW and kVA), voltage, and power factor. Each record in the mission profile indicates the operation condition and the external environmental factors that may affect the runnability of PV inverters during each time segment. This time-series information demonstrates the variance of PV inverters' operation conditions as the time change. Traditionally, sequentially performing simulations for the accumulated history record causes a long simulation time; however, it is observed that extensive records in the mission profile have high similarity. The weather information regularly changes following climate change and other natural factors over some time. The operation information barely changes in the adjacent time period. And the obvious change in the operating condition is usually caused by unexpected incidents or the occurrence of long accumulated degradation.

Therefore, merging similar records could eliminate redundant records and reduce the computational load. The similarity between each record in the mission profile needs to be evaluated. For each data field, only the two records whose difference between them is below a predefined threshold are regarded as similar records. Considering the efficiency of locating the data and the economy of storage, a lookup table is created to store the unique record, and each record will be transferred to a hash value calculated by the hash function. For each record, if it does not have a similar record existing in the lookup table, this record will be stored in the lookup table and will be treated as a new cluster. Otherwise, this record is merged into the existing cluster. The index of this record will be logged in the lookup table for the convenience of further locating it. The reduced number of records and the reduction rate corresponding to the difference threshold in the mission profile after the cluster merge is shown in Table 1. Considering the trade-off between simulation accuracy and reduction rate, the difference threshold is selected as 1%.

TABLE I. Reduction Rate for different thresholds

Difference Threshold (%)	*Number of categories in 2016–2019 (348,000 records in total)*	*Reduction Rate (%)*
50%	*43212*	*12.73%*
30%	*60242*	*17.63%*
10%	*105412*	*30.61%*
5%	*129236*	*37.45%*
1%	*142501*	*41.26%*
0.5%	*142651*	*41.31%*
0.1%	*142765*	*41.34%*

B. Parallel computing

For each mission profile record, one simulation gives out with corresponding stressors. A long-term mission profile will be used to calculate stressors over time. To further reduce the computational time of the simulation, parallel computing techniques are used. Task-level parallelism is applied to partition the large-scale computational workload. As a result of the heavy data dependency within the PV system model simulation, each model simulation is treated as a task. A task takes one mission profile record as the input and gives the over-time stressor as the output. Multiple computer processors are aggregated to execute the computational tasks in parallel. As a benefit from the least data dependency among tasks, each task is independently assigned to a processor. Figure 3 depicts the working pattern of this approach compared to sequential computing. Before the simulation for each case starts, the simulator checks whether the stressors of the corresponding record have been calculated. The simulation for the current case can be skipped if the results from similar inputs already exist in the lookup table without triggering the critical degradation condition. If the simulation model parameter update is triggered by critical degradation, the stressors need to be recalculated, and the corresponding information needs to be updated in the lookup table. Then multiple cases simultaneously simulate round by round, showing a big savings in the overall computational time compared to sequential computing.

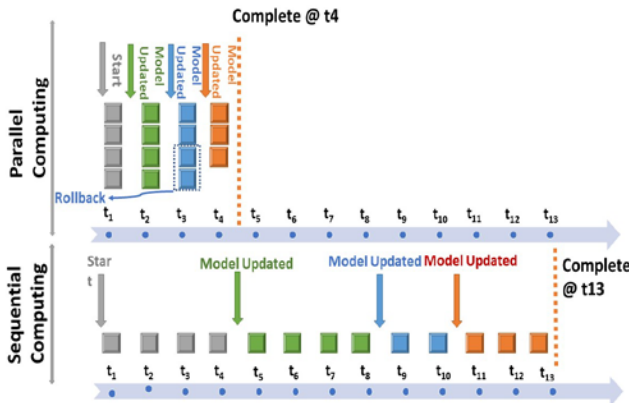

Fig. 3. Timeline comparison of parallel computing with four processors and sequential computing

C. *Adaptive model update*

As time goes by, the durability of the components degrades. Even if under the same environmental and operating conditions, the components might endure heavier pressure. With the accumulated stressors, the components will experience critical degradation at some point. This change in component parameters is reflected in the voltage and power. To accommodate this change, the simulator sets a condition check to detect whether noticeable degradation happens. Once the change in the operating condition reaches a predefined threshold, the parameters of the simulator will be updated so that it can properly evaluate the current degradation condition of the components. To address the issue that some processors are likely running the outdated simulation model while a certain processor might have triggered the noticeable degradation check, the model implements a rollback function to keep itself updated.

As shown in the parallel computing part of Figure 3, four processors are fully used to simultaneously run four simulation cases at each moment. At each round, only one simulation runs on each processor. When these four processors finish one round of simulations, the simulation results will be checked to see whether noticeable degradation happens. Each simulation result triggering the check will be abandoned, and the corresponding cases will be rolled back to execute the simulation again with the updated model. To minimize the number of simulation results that need to be discarded, a log for the time-series simulation result is recorded in the lookup table. When a check is triggered, only the first case requiring an update needs to be discarded, instead of all the simulation results being abandoned in a row. When the predefined threshold is triggered, the value threshold will be updated according to the degradation condition variance compared to the previous level.

D. *Steady-state identification*

In addition to the mentioned HPC techniques, another optimization method is applied. For each simulation case, which is limited by the data gap between two consecutive time steps, the simulation will keep running to feed the interval before the next mission profile point arrives; however, the stressors remain the same once the simulation steady state is reached. The simulator is thus designed to perform a steady-state detection by tracking the change in the stressors with the longest time constant (e.g., temperature information originating from the thermal model of the inverters) to save simulation time without affecting accuracy. Figure 4 shows the temperature variance curve of the thermal model of the inverters. The temperature is used as an indicator to demonstrate the operation condition of the inverter. It assumes that the system reaches steady state when the consecutive three temperature differences at the neighboring two time stamps are the same (1% error tolerance). Based on the calculation of the temperature difference, the data point at 110 seconds is detected as a steady-state point, and the simulation will be terminated at this data point. According to the shown curve, we believe the calculated steady-state point can indicate the steady-state status of the system.

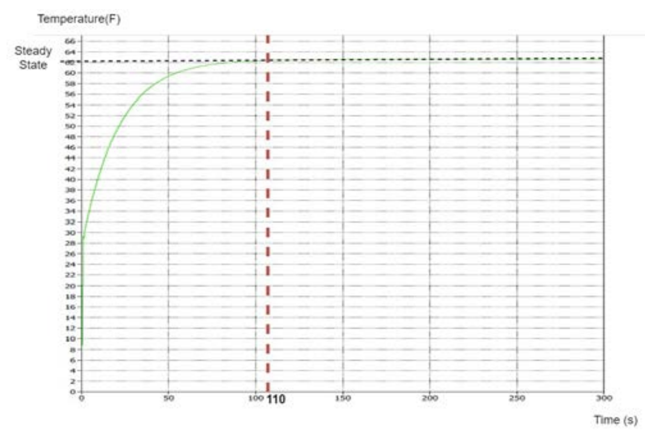

Fig. 4. Steady-state detection of the temperature of the thermal model

III. CASE STUDY AND PERFORMANCE ANALYSIS

To prove the effectiveness of the simulator, a demo simulator was designed for the PV inverters considering the PV system (e.g., PV panel, step-up transformer, and grid configuration). The demo is implemented based on MATLAB Simulink and Open MPI. The mission profiles contain historical environmental parameters that include temperature, relative humidity, solar irradiance from the National Renewable Energy Laboratory's National Solar Radiation Database (NSRDB) [10], and operational field conditions that include AC power, three-phase line-to-line voltages with a 5-minute resolution for an actual PV plant [11]. The demo model simulation is based on MATLAB Simulink, and each case of simulation is treated as an independent task, which runs on a single processor. With the help of the C++ MEX function [12], the model implemented by the MATLAB Simulink model can be called in the C++ program without consuming too much efficiency. MATLAB can accept inputs from the C++ code and return the simulation outputs to the C++ code. The parallel computing was implemented using the Open MPI on C++ [13]. Because running simulations of the data several years; long is time consuming, as a demo, 2016 cases are used as a preventative situation for 1 week. After performing the cluster merging, the number of cases was reduced to 963, 48% compared to the number before the cluster merging. In this case, steady-state detection was not used because the thermal model was not implemented in the demo model.

Figure 4 shows the speedup of the simulation after each optimization method. By applying the cluster merging, the number of cases that needs to be calculated has been reduced to 963, only 48% of the original number, and it achieves 2.09 times the speedup compared to the simulation time without any optimization. Then, with the use of parallel computing, the simulation time proportionally decreases when multiple processors are assigned. As the trend in the orange arrow shows, when 8 processors are used to do the simulation, the simulation performance is improved by 7.97 times. When 64 cores are assigned, the computational efficiency increases by 42.33 times compared to the sequential version. The simulation speed increases up to 58.77 times when 100 processors are used. The total simulation time will be reduced by 123 times with all the optimizations applied. Caused by` the native parallelism of the computation, the computational performance of the simulation is highly scalable with an increasing number of processors. The simulation performance can be further improved if more computing resources can be used. And it is noticeable that the increased rate of speed up after using more than 64 cores starts to decrease. Even if the data communications between each task is the least, the overhead consumption on the processors' schedule has more impact on the performance with more processors applied.

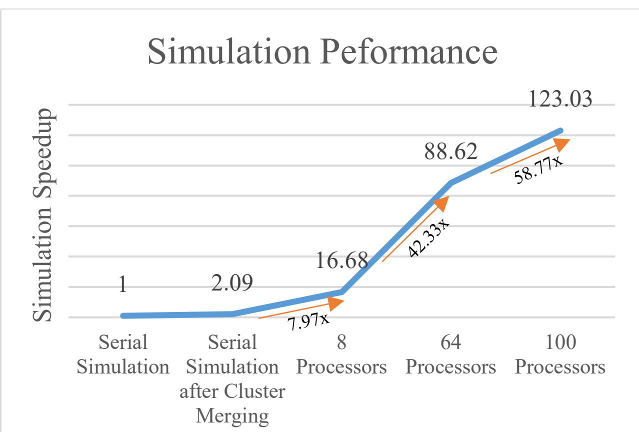

Fig. 5. Comparison of the simulation speedup contributed by each optimization method

IV. Conclusion and Future Work

With the high demand for accuracy and real-time capability of PV system degradation evaluation [8], future simulation tools are required to consider more parameters and more historical environmental and operation data. This paper proposes an event-driven HPC-based simulator to accelerate the PV system degradation assessment simulations of both the average model and the switch model. In addition to the parallel computing techniques, other optimization methods—such as cluster merging, model updates, and steady-state identification—are applied to reduce the computational workload and increase the computational efficiency as well as maintain the accuracy of the simulation results. **Our main contribution is designing a complete prototyping PV system degradation assessment simulator with high fidelity and high efficiency.** To better present the framework and validate the effectiveness, one PV system demo case study is implemented based on MATLAB Simulink and Open MPI on C++ according to our design. With all optimization methods applied, the computational efficiency of the simulation of the switch model reaches almost 123 times under the guaranteed fidelity compared to the traditional sequential simulator. Performance boosts are also promising with increased computing resources employed.

Though the decent performance gain has benefited from these optimization techniques, there is space for further improvements. Because the demo model is implemented in MATLAB Simulink and the simulator is implemented in C++, the initialization and transfer overhead caused by communication between C++ and MATLAB have a noticeable impact on the performance. To remove this overhead, a C++-based simulation model will be implemented in the future. More finely tuned partition strategies will be applied corresponding to the new implementation instead of treating the simulation model as a black box. Two-level parallelism can be applied: one for data-level parallelism within each model simulation and the other for simultaneously executing multiple simulation cases.

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