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Preprint

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*Presented at the 2nd International Workshop on Data Reduction for
Big Scientific Data (DRBSD-2) at SC17
November 12-17 2017
Denver, Colorado*

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Conference Paper
NREL/CP-2C00-70265
November 2017

Contract No. DE-AC36-08GO28308

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Contextual Compression of Large-Scale Wind Turbine Array Simulations

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Abstract—Data sizes are becoming a critical issue particularly for HPC applications. We have developed a user-driven lossy wavelet-based storage model to facilitate the analysis and visualization of large-scale wind turbine array simulations. The model stores data as heterogeneous blocks of wavelet coefficients, providing high-fidelity access to user-defined data regions believed the most salient, while providing lower-fidelity access to less salient regions on a block-by-block basis. In practice, by retaining the wavelet coefficients as a function of feature saliency, we have seen data reductions in excess of 94%, while retaining lossless information in the turbine-wake regions most critical to analysis and providing enough (low-fidelity) contextual information in the upper atmosphere to track incoming coherent turbulent structures. Our contextual wavelet compression approach has allowed us to deliver interactive visual analysis while providing the user control over where data loss, and thus reduction in accuracy, in the analysis occurs. We argue this reduced but contextualized representation is a valid approach and encourages contextual data management.

1. Introduction

There is a data analysis dilemma growing in the field of computational science: our ability to generate numerical data from scientific computations is outpacing our ability to store, move, and analyze those data. In large high performance compute (HPC) systems, I/O access, including bandwidth, memory, and storage capacity have not scaled with microprocessor performance. The issue is only expected to worsen across the computational science community with architectural changes expected at the exascale. Generally, as this data analysis disparity grows, some form of data reduction will become necessary, even before post-processing [1].

The study of the interactions between turbine wakes and the atmospheric boundary layer in wind farm simulations lead to our development of a multi-resolution approach to data compression. Specifically, analysis of these datasets requires the detailed examination of turbine wakes, however the larger computational domain is only needed for contextual information. Thus, much of the data coming from a full-resolution simulation is not necessary. As a response, we developed a heterogeneous wavelet-based storage scheme to contextually compress wind farm model data based on feature saliency.

The data volume is decomposed into independent blocks of wavelet coefficients, which are fully retained in blocks

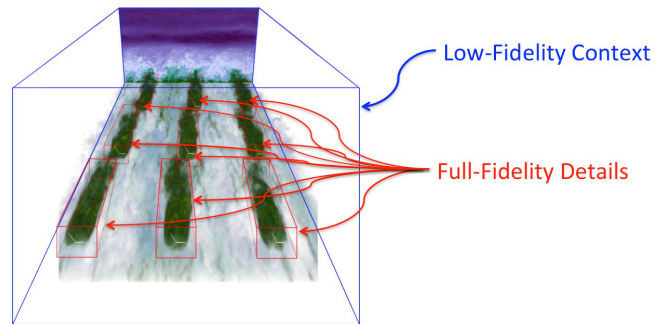


Figure 1. The study of the interactions between the atmospheric boundary layer and a wind-turbine array provide inherent opportunities for multi-resolution analysis. Detailed examinations of the turbine wakes are of analytical interest, while the larger computational domain is only needed for contextual information.

intersecting the turbine wakes, losslessly capturing their dynamics, while retaining only a subset of coefficients in the non-waked blocks, thereby providing a contextually compressed volume (see Figure 1). This approach has shown massive data reduction in excess of 94% for these models, improving storage cost and rendering times.

2. Wind Turbine Array Modeling

The U.S. Department of Energy’s 2008 report *20% Wind Energy by 2030* [2] envisioned that wind power could supply 20% of the U.S. electricity demand. However, significant advances in cost, performance, and reliability will be needed to achieve this vision. For example, large wind plants are consistently found to be sub-optimal in terms of performance and reliability. One of the culprits of this underperformance is hypothesized to be related to inadequate accounting for the inter-turbine effects through the propagation of turbine wakes [3]. Wakes form immediately downstream of the wind turbines with a lower mean velocity and an increased turbulence intensity. Downstream turbines waked by upstream turbines can experience vastly reduced power output, and abrupt, massive stressing of turbine components [4]. The dynamics of these wakes are generally not well understood, and involve complex interactions of wind speed, momentum, temperature, and moisture, resulting in complicated wake motion, such as 3D periodic undulation, meandering, and lateral growth.

Computational models of large-scale wind farms are being used to better understand these phenomena. Currently, large-eddy simulations are being used to create atmospheric winds and compute the wind turbine flows [5], while flexible, revolving actuator lines model the structural and system dynamics of the turbines [6]. To capture relevant atmospheric boundary layer scales, and applicable turbine and wake dynamics, the simulation domain must represent at least a 3 km by 3 km by 1 km volume with a grid resolution of approximately 1 m and a temporal resolution of 1 Hz [7]. As a consequence, capturing just a few minutes of flow through these farms can result in hundreds of terabytes of data. As computational capabilities continue to improve, higher fidelity models of these wind farms are envisioned that capture more of the relevant scales, spanning blade-level turbulence to atmospheric flow at the mesoscale, potentially increasing the data demands by orders of magnitude.

Early versions of these models employed a uniform grid, facilitating the post-processing and visualization of these data but with significant storage penalties. These models have recently evolved to using a multi-resolution nested grid, with ~ 10 m resolution in the peripheral boundary layer and stepping down to ~ 1 m surrounding the array. The nested grid significantly improves simulation times and storage requirements, but comes at the cost of increased complexity and cost in visualization and analysis, as non-uniform grids of this magnitude (on order of a billions cells) are difficult to interrogate interactively. Specifically, volume rendering these large non-uniform grids becomes untenable without using leadership-class HPC resources [8], [9], [10].

3. Wavelet-Based Compression

The existence of high and low areas of interest in turbine simulations (see Figure 1) led us to the idea of acceptable data loss and to explore the use of multi-resolution wavelets for data compression. Multi-resolution wavelets allow the reconstruction of a data set at varying resolutions in much the same way as a MIP-mapping scheme. A wavelet transform decomposes a signal into a set of wavelet functions of different sizes and positions, and the result of the transform is a set of coefficients that describe how the wavelet functions need to be modified to reconstruct the original signal. Scaling the wavelets adapts them to different components of the signal and provides a multi-resolution view of that signal; the large scales provide an overview, while smaller scales fill in the details. The wavelet transform provides excellent energy compaction, i.e., it concentrates energy (information) into a small number of coefficients [11], and the multi-resolution structure of the coefficients provides the ability to reconstruct the data at varying resolutions [12]. Clyne et al. [13] demonstrated that a simple hierarchical access scheme based on the multi-resolution properties of wavelets can enable the interactive analysis of large terabyte-sized data sets.

When wavelet reconstruction leads to an approximation of the original signal, data loss occurs (referred to as lossy compression). Computational scientists have recently begun

to investigate the role of lossy compression when applied to scientific data [11], [14], [15], [16], [17], and many visualization and analysis operations have been shown to be relatively insensitive to this type of data coarsening [18], [19], [20]. However, lossy compression is not yet widely used in practice in the computational science community, as many scientists are hesitant to incur the loss of data that has been computed at great cost. The idea of lossless compression is certainly appealing; however, the randomness of lower order bits in scientific data has limited lossless compression rates to less than 2:1 [16], [21], [22], [23], [24], [25]. As a consequence, only with lossy techniques are we likely to achieve compression rates high enough to balance the coming disparity between computational and I/O subsystems. The novelty of the scheme we explored is that the level of compression can be specified at different levels throughout the data volume guided by domain knowledge, allowing the domain expert to choose which regions of the data they are willing to tolerate data loss. In contrast, lossy compression techniques reported in the literature attempt to minimize the information loss across the entirety of data largely without any domain knowledge of the data or analyses that will be subsequently applied.

3.1. Method

The VAPOR Data Collection (VDC) [26] provides a progressive access data model based on a wavelet transform's multi-resolution and energy compaction properties. Specifically, the model decomposes each time step of each variable into a set of wavelet coefficients. These coefficients are sorted based on their information content (i.e., magnitude) and stored in a hierarchical *level-of-detail* sub-setting scheme. The number of coefficients across all the levels is equivalent to the number of grid points in the original data. The reconstruction of a variable from the wavelet space using all of the coefficients losslessly restores that variable. However, the user can select a level-of-detail by using only a subset of these levels (i.e., those containing the largest magnitude coefficients) to reconstruct an approximation of the original data.

The model stores each level of detail as a set of blocks by decomposing the data volume into independent blocks before the forward transform. Decomposing the data into blocks improves the performance of the both the forward and inverse wavelet transformations, and facilitates the extraction of regions of interest by limiting the amount of data that needs to be traversed compared to a single large volume. Larger block dimensions allow deeper levels of detail at the expense of increased computational and storage access costs [26].

The VDC is a lossless storage format, allowing scientists to reconstruct the full-fidelity data by accessing all the wavelet coefficients across all levels of detail. We introduce an extension to this scheme by removing entire levels of detail on a block-by-block basis, achieving a block-level compression. This allows a domain expert to classify regions of the data as a function of how salient that data will be

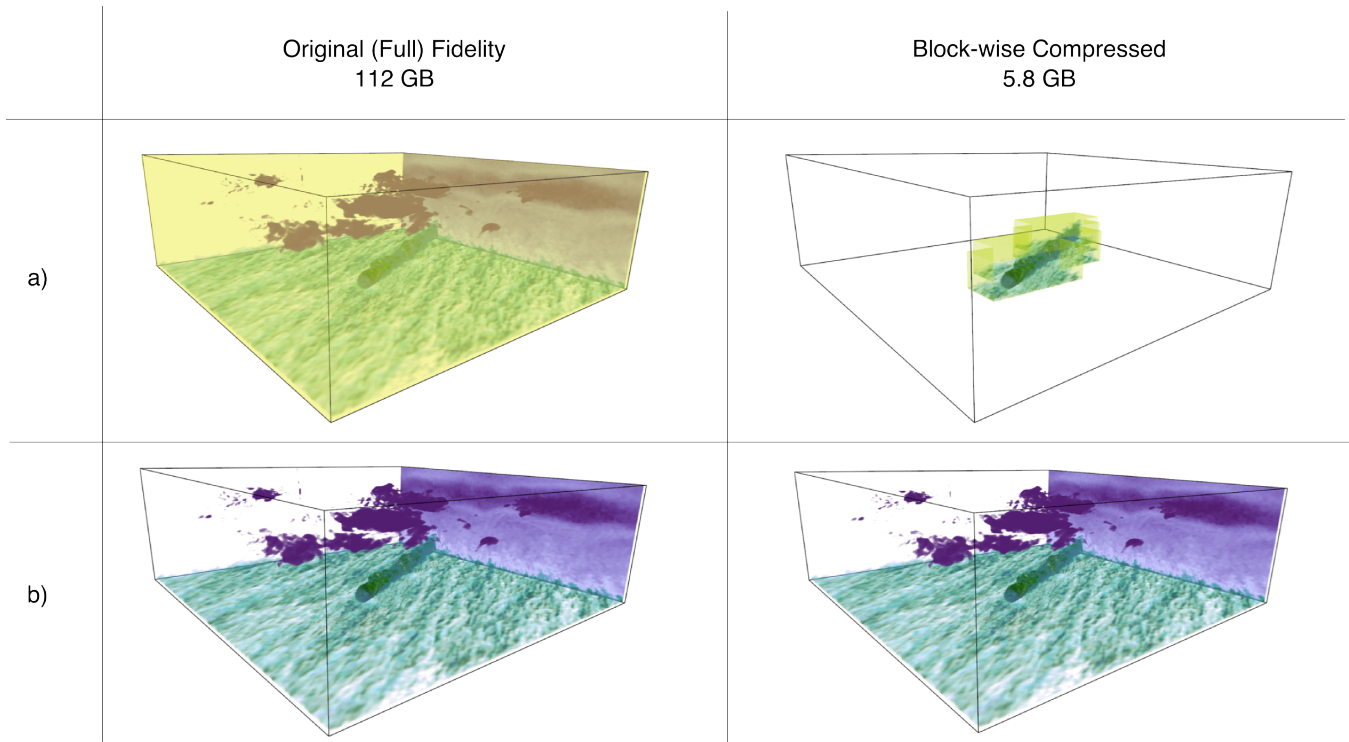


Figure 2. A comparison of renderings between the original full-fidelity velocity data (112 GB/timestep) and the block-level compressed data (5.8 GB/timestep). a) the yellow shading illustrates the regions that are losslessly preserved at the original fidelity. b) volume renderings of the two respective storage schemes.

to the *a posteriori* analysis of the data. That classification can be designed based on simple spatial regions of interest or on more complicated feature identification algorithms. Our extension stores blocks that overlap regions with high analytical importance with a complete set of coefficients across all levels of detail, while storing only a subset of the levels in blocks that contain only regions of lesser importance.

In our context, the domain scientists are interested the turbine wakes in wind farms identified as low-velocity flows originating from fixed turbine positions. Therefore, we denote wakes as regions-of-interest and the larger surrounding atmospheric regions as contextual information. Wavelet blocks that intersect wake regions retain the full complement of wavelet coefficients, while atmospheric blocks retain and store only a subset of the coefficients.

In addition, we can quantify the expected level of compression with this technique. A data set size is scaled by the linear expression $\beta_u + \beta_c/r_c$, where β_u is the percentage of space occupied by uncompressed blocks, β_c is the percentage of space occupied by compressed blocks ($\beta_c = 1 - \beta_u$), and r_c is the compression rate.

4. Results

We evaluate data from two turbine-array simulations: a small array study with two turbines and a large 48-turbine array model of the Lillgrund wind farm described by Churchfield, et al. [7].

The two-turbine data set has a computational domain of 3008 m by 3008 m by 1024 m and a grid resolution of 1 m. This represents 9.2 billion grid points or 112 GB to represent one time step of three component velocity at single floating-point precision. These data are decomposed into 35,344 blocks of 64^3 voxels. We classify these blocks into two sets: *contextual blocks* and *salient blocks*. Blocks are classified as salient if the low-velocity wake region intersects the blocks, while all non-wake-intersecting blocks are classified as contextual. The full set of levels of detail are retained for the salient blocks, while only the highest (most significant) level of detail is retained for the contextual blocks. Therefore, the salient blocks can be reconstructed at the full original fidelity of the simulation, while the contextual blocks can only be reconstructed at reduced fidelity at 512:1 compression. In our two-turbine test case, the wake regions intersect 1,715 blocks, classifying the remaining blocks as contextual. This reduces the data size from 112 GB per time step to less than 6 GB per time step a 94.8% savings in storage and data movement (see Figure 2).

The results from 48-turbine Lillgrund simulation are less dramatic with 48 wakes occupying a much larger proportion of the full domain. This simulation domain represents a 4 km by 4 km by 1 km volume with a coarser 1.7 m grid resolution. This represents 3 billion grid points or 38.7 GB to represent a single time step of three component velocity. The data was decomposed into 11,664 blocks of 64^3 voxels, and the blocks that intersect with turbine wakes are classified

as salient. The wakes of the 48 turbines intersect 1,078 of the blocks and are preserved in full-fidelity. Compressing the remaining contextual blocks at 512:1, reduces the data from 38.7 GB down to a manageable 3.69 GB to represent a single time step of three-component velocity – a 90.6% space savings.

For both of these data sets, there was no information loss in the regions immediately surrounding the turbine wakes. Therefore, no compression-induced error was propagated to the quantitative analysis. Error and uncertainty has been introduced to the contextual regions through the wavelet compression. Fine small-scale structure have been lost, but the large-scale formations are still intact and visible. Qualitatively, the compression effects are difficult to perceive with the large global perspective shown in Figure 2. Taking a detailed view of the compression boundary between a salient and a contextual block, the compression effects become more apparent (see Figure 3). The loss of the small-scale turbulent structure at 512:1 compression is visible; however, the compressed regions still provide clear context for the analysis in the wake regions. We can identify incoming flows and distinguish the low velocity and high velocity air, which provides the contextual information to better understand how structures in the atmospheric boundary layer may correlate to the wake behavior.

We evaluated the storage requirements (both data and metadata) and rendering times¹ for the 48-turbine data set, comparing a large uniform resolution data volume stored in the VDC format, a nested grid with coarse resolution in the atmosphere and finer resolution encapsulating the wakes, and our block-level compressed extension approximating the fidelity of the nested grid. For our block-level compression, we also evaluated rendering times for CPU-side wavelet reconstruction versus GPU-side reconstruction of nested textures. Results are provided in Table 1. Storing the data as an unstructured nested grid generally provides the worst metrics. The metadata requires nearly 40 GB of space, primarily to represent the grid, while a time step of three-component velocity, \vec{u} , requires 3.9 GB of space. We did not volume render these grids, as the state of the art would suggest there is no reasonable expectation of volume rendering these 3 billion unstructured cells interactively, except with the largest HPC resources [8], [9], [10]. Storing a uniform 1.7 m resolution across the entire domain in the VDC format requires 38.7 GB of storage for a time step of \vec{u} and 673 kB of storage for the VDC metadata with rendering times 0.5 frames per second. Storing mixed-fidelity blocks of wavelet coefficients in the VDC format reduces the \vec{u} data storage to 3.7 GB and only increases the metadata by 410 bytes to 674 kB. The CPU-side reconstruction of the mixed-fidelity blocks creates an artificially large data texture equivalent in size to the uniform case, and as expected, the rendering performance is identical at 0.5 frames per second. The GPU-side reconstruction of the mixed-fidelity blocks

1. All reported rendering times were measured on a Intel Xeon E5-2470 2.3GHz 8-core CPU with 384GB of RAM and NVIDIA Quadro 6000 with 6GB of RAM. Frame rate is reported once all data is memory resident.

into nested data textures of varying resolutions improves the rendering performance to near-interactive speeds with a 3-12 frames per second. Early ray termination makes the frame rate view-dependent and accounts for the large variance in measurements.

5. Conclusion & Future Work

We have presented a lossy wavelet-based compression technique that empowers the domain scientist to control the compression of data, preserving the most important areas of the data in full fidelity. Without the use of contextualized data compression, the interactive visualization and analysis of the wind turbine data would not have been possible. Using our technique, researchers were able to interactively volume render the flow through the turbine array to understand the turbine-to-turbine interactions, which is critical information in wind-plant siting and the design of more efficient and reliable wind turbines.

Keeping an eye towards the exascale systems of the future, we note that this scheme could be applied *in situ* (i.e., while the simulation is running), though this would require the domain scientist to classify regions or features of interest beforehand. How to best exploit the data locality of the simulation to perform that region of interest isolation in conjunction with the wavelet transform is an open research question, and a topic for future work.

The technique as presented is ideally suited to data with discrete regions of interest and non-interest that can be spatially isolated in wavelet blocks. The wind-energy simulations are exemplary examples with wake features intersecting a relatively small number of blocks. An opportunity for improvement of this work is the replacement of the block-level compression scheme with a function-based feature preservation capability. A user supplied function could be used to weight the wavelet coefficients based on different criteria. This approach would, for example, allow greater fidelity to be assigned to high-vorticity features, even when those features uniformly populate the wavelet blocks of the volume. More precisely, the approach would apply to features independent of their blocks, providing a compression ratio related directly to the volume of the features of interest rather than the volume of the blocks those features intersect.

In the current scheme, the set of compressed blocks are constant across both variable and time. Clearly there are opportunities to manipulate the compression from variable to variable and time step to time step, which could have interesting impacts on analyses and the I/O systems that support them, such as the promulgation of burst buffers within compute nodes.

Acknowledgments

The research was performed using computational resources sponsored by the Department of Energy's Office of Energy Efficiency and Renewable Energy and located at the National Renewable Energy Laboratory.

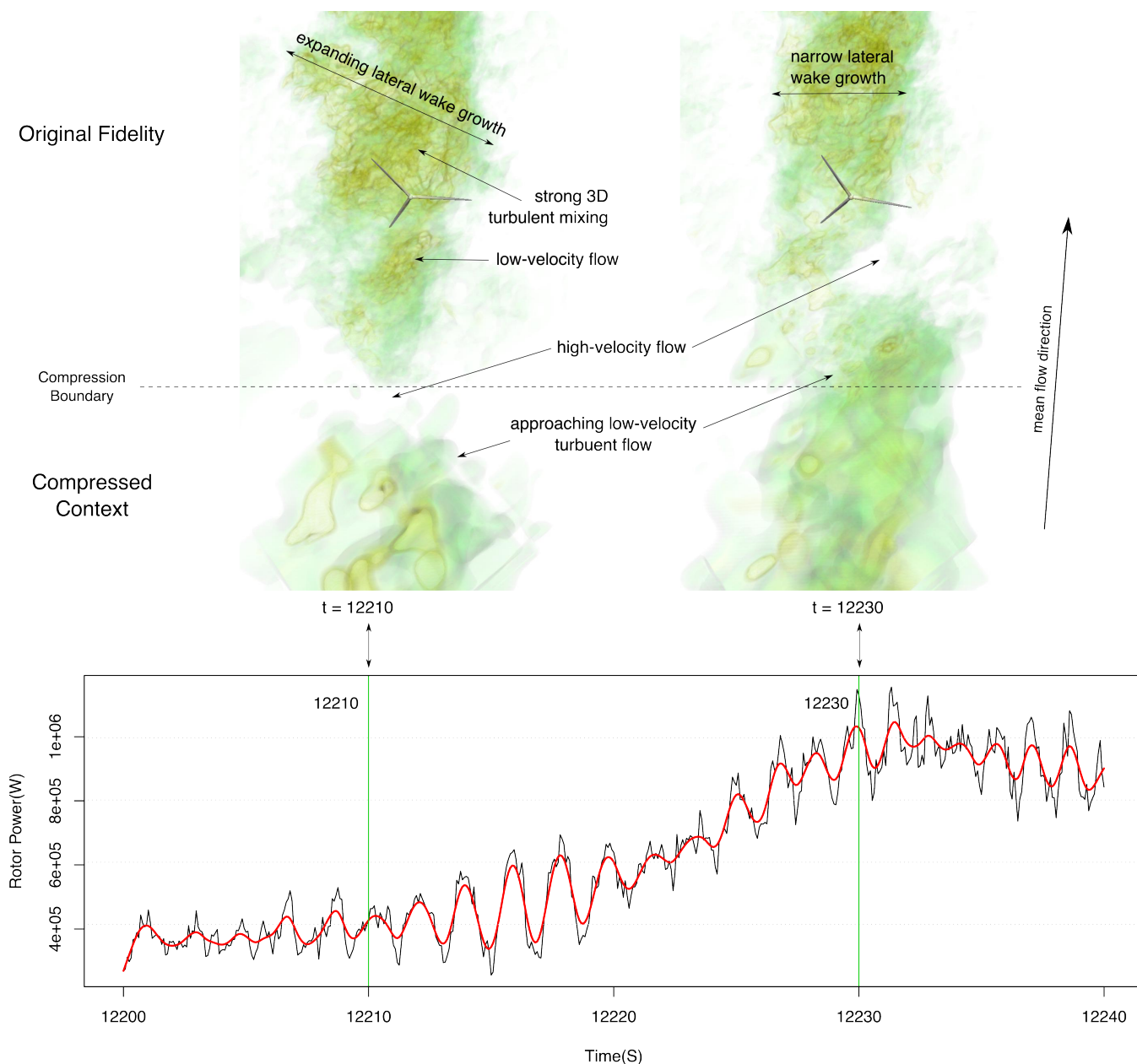


Figure 3. Illustration showing the time evolution of incoming flow at a compression boundary. In the upper portion of the figure, we show a volumetric rendering of the boundary, with the loss of small-scale structure at 512:1 compression visible; however, the compressed regions still provide clear context for the analysis in the wake regions. In the lower portion of the figure, we plot rotor power over time as derived from the simulation software, with a moving average in red. At time step 12210 (left), we see the turbine is in a low-velocity flow with expanding lateral wake growth, strong downstream turbulent mixing, and corresponding low power production. A high-velocity flow followed by a low-velocity structure can be identified upstream in the compressed area. At time step 12230 (right), that high-velocity flow has reached the turbine effecting the later wake growth, turbulent mixing, and power production.

TABLE 1. STORAGE AND RENDERING MEASUREMENTS FOR THE 48-TURBINE ARRAY SIMULATION TEST CASE.

	Unstructured Grid	Uniform Resolution VDC	Mixed Resolution VDC	Mixed Resolution VDC
Reconstruction	n/a	CPU	CPU	GPU
Frame Rate	*	0.5 fps	0.5 fps	3 fps to 12 fps
Render Time	*	2 s	2 s	0.08 s to 0.33 s
Time to Frame	hours	360 s	300 s	70 s
\bar{u} Volume Size	3.9 GB	38.7 GB	3.7 GB	3.7 GB
Metadata Size	39.9 GB	673 kB	674 kB	674 kB

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