



HAL
open science

Refinable-precision in mesh compression for upscaling and upgridding in reservoir simulation with HexaShrink

Lauriane Bouard, Laurent Duval, Christophe Preux, Frédéric Payan, Marc Antonini

► To cite this version:

Lauriane Bouard, Laurent Duval, Christophe Preux, Frédéric Payan, Marc Antonini. Refinable-precision in mesh compression for upscaling and upgridding in reservoir simulation with HexaShrink. RING Meeting, Research for Integrative Numerical Geology, École Nationale Supérieure de Géologie de Nancy, GeoRessources, Sep 2019, Nancy, France. <hal-03138861>

HAL Id: hal-03138861

<https://hal.science/hal-03138861v1>

Submitted on 8 Jul 2025

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



HAL Authorization

Refinable-precision in mesh compression for upscaling and upgridding in reservoir simulation with HexaShrink

Lauriane Bouard^{1,3}, Laurent Duval², Christophe Preux², Frédéric Payan³, and Marc Antonini³

¹*IFP Energies nouvelles, Rond-point de l'échangeur de Solaize, 69360 Solaize, France*

²*IFP Energies nouvelles, 1-4 Avenue du Bois Préau, 92852 Rueil-Malmaison, France*

³*Université Côte d'Azur (UCA), CNRS, Laboratoire I3S, 06900 Sophia Antipolis, France*

September 2019

Abstract

A reservoir mesh in Corner Point Grid format may contain up to millions of cells. It accurately models geological fields, in order to obtain realistic (yet computationally expensive) flow simulations. To gain in computing time, upscaling methods have been proposed to decrease the number of cells. Such approaches generally end up with several models of different precision, built iteratively, in a trade-off between computing complexity and model simplification. However storage and transmission of the generated data remain a major challenge. In PEYROT *et al.* (2019), a multiresolution scheme for structured hexahedral volume meshes was developed, allowing efficient mesh visualization and storage. Our objective is now to evaluate whether this multiresolution framework is also suitable for flow simulations at different scales, obtained by partial decoding with a refinable precision of the compressed mesh structure. In this paper, promising results on a two-phase flow model are presented, suggesting significant speed improvements with consistent approximate simulation results.

Introduction

In the context of simulation, reservoir grids must be sufficiently realistic, yet simpler than reality. To meet these requirements, grids usually contain a large number of cells, and also integrate structural discontinuities (to describe faults or channels, for instance), leading to a complex and heterogeneous data structure. The *Pillar Grid* representation (also termed *Corner Point Grid*, cf. PONTING (1989)) permits to efficiently describe such data. It can be seen as an enhanced hexahedral mesh, dealing with spatial discontinuities, containing additional cell information such as continuous petrophysical properties (porosity/permeability), or cell activity, to characterize the spatial distribution of geological formations.

Because of the large size of the resulting meshes and the heterogeneity of their components (in terms of dimension, magnitude, number representation, precision and statistics), managing reservoir grids is often laborious, whatever it be for visualization, storage, or transmission. This is also the case in simulation, leading to long and inconvenient computation times, and growing energetic costs in high-performance computing (HPC) (GEVELER *et al.*, 2015).

Upscaling methods are often used to make simulations faster with better energy efficiency. It consists in simplifying meshes before simulation. Although efficient and widely used in geosciences to reduce computation times, this approach has drawbacks: upscaled meshes must either be stored as extra data (increasing the data volume in a domain where data tends to be larger), or regenerated before each simulation.

During a previous project, we developed HexaShrink, a solution for decomposing hexahedral volume meshes progressively (PEYROT *et al.*, 2019), by coherently blending different wavelet-like schemes. It provides a consistent and reversible multiscale representation of all mesh components (geometry, properties...). This representation can be seen as a hierarchy of embedded meshes at increasing levels of details. As a consequence, this multiscale representation has the same overall dimension than the input mesh.

Our current objective is to evaluate whether this multiresolution framework can be valuable also in the simulation field. Indeed, it would be positive if flow simulations performed at different (HexaShrink) scales could produce satisfactory results. Hence, it could be an alternative to upscaling

schemes for accelerating flow simulations, while being more compact, because of its hierarchy of embedded meshes.

The rest of this paper is organized as follows. Section 1 recalls principles behind HexaShrink lossless compression. Section 2 introduces the notion of refinable precision. Section 3 details the case study and simulation results.

1 HexaShrink, a comprehensive multiscale representation for meshes

HexaShrink (PEYROT *et al.*, 2019) is based on combined wavelet-like schemes (MALLAT, 1998). The core idea behind generic discrete wavelets consists in splitting original data into a dyadic representation (approximations and details). The approximation is considered as a coarser rendering of the original data, while the associated details are a sparser representation of singularities preserved to rebuild the original mesh from its approximation. The decomposed data (approximations+details) has the advantage to have the same dimension than the original one (Figure 1).

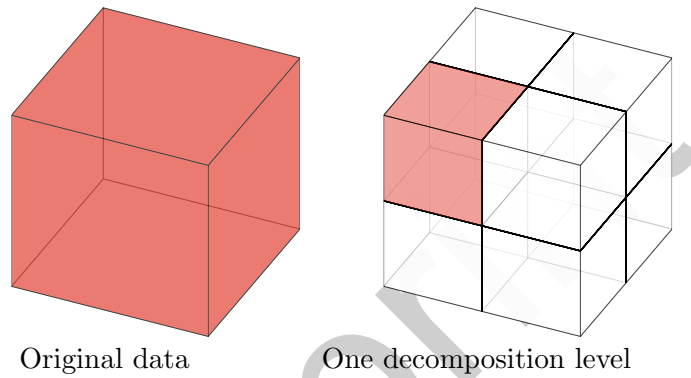


Figure 1: *Left: 3D decomposition of a volumetric data (red). Right: decomposed data, consisting of a data approximation (red) and 7 detail subbands (transparent).*

Moreover, wavelet decompositions can be iterated on approximations, leading to a hierarchy of embedded meshes at increasing levels of details, as illustrated in Figure 2 on a real reservoir mesh.

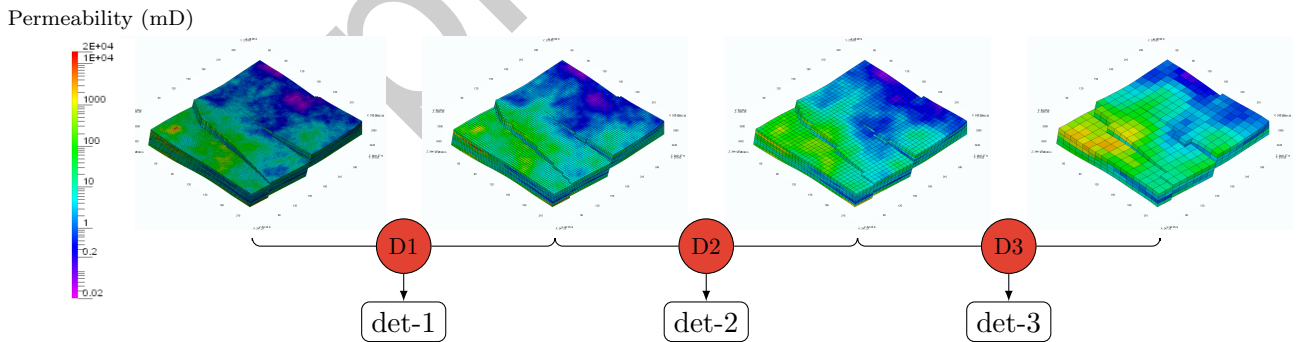


Figure 2: *Three wavelet iterations (D_n) on an hexahedral mesh (left) generates the coarser approximation (right), and associated details (det- n). Fault networks are preserved across resolutions, while the permeability (colors) is decomposed in an upscaling fashion.*

Upgridding structure geometry In *Pillar Grid* representations, the geometry of an hexahedral reservoir mesh is defined by two kinds of elements. First, pillars, that can be seen as nearly vertical curves, defined by the coordinates of their extremities. Then hexahedral cells are stacked, between pillars. The position and the shape of each cell is defined from the position of its 8 corners along

the pillars. In addition, each cell can have additional attributes, such as continuous petrophysical properties (porosity/permeability), rock type...

HexaShrink combines several wavelet-like schemes, to take into account the component-wise specificity of the reservoir mesh. For instance, to preserve some fault shapes at different resolutions, a morphological wavelet transform is applied, to detect which pillars must be kept at the lower resolution. Also, the position of cell corners along the pillars are decomposed by a linear 1D wavelet transform.

Upscaling properties In the same way the upgridded mesh is filled with the approximation of continuous properties obtained by 3D separable wavelets. The permeability is handled with the Cohen-Daubechies-Feauveau 9/7 wavelet, used in the JPEG2000 for image compression (ACHARYA & TSAI, 2005). The latter wavelet was also used in (PAZHOOHESH *et al.*, 2006; RASAEI & SAHIMI, 2008) for the purpose of locally upscaling the permeability.

Compression performance The compression performance of HexaShrink was firstly demonstrated in (PEYROT *et al.*, 2019). Wavelet-like schemes provide sets of details that are sparser. The efficiency of generic lossless encoders such as gzip, bzip2 or LZMA thus was foreseeable: we obtained compression gains between 3 and 13 depending on mesh complexity. Nevertheless, even if the decomposed mesh is globally easily compressible with generic lossless coders, we observed disparity according to the mesh components, and mesh specificity. Moreover, even satisfactory the compression performance remains low, when comparing with more powerful coders, in particular those exploiting the data correlation across resolutions.

Such decompositions should however deal in the simulation field with high numerical dynamic data, coded on single (32 bit) or double (64 bit) floating-point format. Our objective in this work consists in demonstrating the potential of multiscale methods associated with evolved progressive coders such as refinable-precision zerotrees (presented in the next section) in reservoir simulation. A two-phase flow simulation is then applied on various versions of the compressed data to study the required multiscale resolution and numerical precision.

2 Zerotrees: refinable-precision for multiscale decompositions

The HexaShrink methodology — described above — yields a multiscale representation of the various data structures present in hexahedral meshes. As illustrated in Figure 2, observations at different scales of the same property (here, permeability) exhibit evident visual correlations. The latter can be employed to improve efficiency in data representations, with the help of refinable binary precision.

This can be illustrated, first in one dimension, with Figure 3. The original data sequence (Fig. 3-top-left) symbolizes what may happen around a mesh discontinuity (either in geometry or in property): an upward slope separated — by a jump (14 vs 5) — from a downward variation. Such data may typically be coded with 4 bit for each value, from the Most Significant Bit (MSB) to the Least Significant one (LSB), plus a sign bit. Except for the MSB₀ with index 3, binary digits do not exhibit clear organization. For the sake of simplicity, we hereafter describe a reversible, multiscale decomposition, termed S+P transform, for sequential/prediction, *cf.* SAID & PEARLMAN (1993). It can be considered as a non-linear avatar of the Haar wavelet (HAAR, 1910; JACQUES *et al.*, 2011), allowing integer-to-integer mappings. If $a_l[k]$ denotes a sequence of approximation coefficients at a given level l , the S+P transform yields two half-length subsequences:

$$a_{l+1}[k] = \left\lfloor \frac{a_l[2k] + a_l[2k + 1]}{2} \right\rfloor, \quad (1)$$

$$d_{l+1}[k] = a_l[2k] - a_l[2k + 1]. \quad (2)$$

with $d_l[k]$ denoting detail coefficients at level l . Iterated over two levels, the outcome is represented on Figure 3-right. Red bars separate wavelet scales. The multiscale data (which can exactly recover the original data) is globally smaller in amplitude (despite the jump), as the transform captures data regularity at different scales. Reading the associated binary table, we observe rows of zeros on the most significant bits. It is possible to rearrange, and transmit, the multiscale data from most to least

significant bits, with rows of zeros encoded by a specific binary symbol, leading to sensitive lossless compression improvements.

Original data	2 3 4 5 14 13 12 11	Multiscale data	3 12 -2 2 -1 -1 1 1
Sign	1 1 1 1 1 1 1 1	Sign	1 1 0 1 0 0 1 1
Most Significant Bit (MSB _O)	3 0 0 0 0 1 1 1 1	Most Significant Bit (MSB _M)	3 0 1 0 0 0 0 0 0
	2 0 0 1 1 1 1 1 0		2 0 1 0 0 0 0 0 0
	1 1 1 0 0 1 0 0 1		1 1 0 1 1 0 0 0 0
Least Significant Bit	0 0 1 0 1 0 1 0 1	Least Significant Bit	0 1 0 0 0 1 1 1 1

Figure 3: Original 1D data stream, with binary composition (left) versus the two-level multiscale representation (right).

This methodology can be further deployed in two dimensions (and above in d dimensions), using dependencies between sets of values at different levels. Since approximations shrink by a factor of two in each dimension (see Eq. 1), 2^d blocks of values at level l relate to one value at level $l + 1$. This can be modeled as binary trees, as depicted in Figure 4.

When data is represented in multiscale fashion, parsed from most to least significant bits, trees with a significant quantity of 0 digits are observed. They are called zerotrees (ZT). They have been popularized for image compression, early with the Embedded Zerotree Wavelet (SHAPIRO, 1993), later in combination with the S+P transform with Set Partitioning In Hierarchical Trees or SPIHT, from SAID & PEARLMAN (1996).

Aside pure compression gains, we are interested in the ZT potential to contribute to simulation efficiency using 3D ZT extensions (CHRISTOPHE *et al.*, 2008). Recently, works have been devoted to finding alternatives to floating-point (MULLER *et al.*, 2018) representation (LINDSTROM *et al.*, 2018; CAPPELLO *et al.*, 2019). ZT-type bit ordering permits to decrease the grid resolution in a dyadic fashion, and to refine the precision by power-to-two factors. Its combination with multiscale approximations is illustrated in Figure 5. Starting with properties values coded on 5 bit (top-left image), grids are represented at three different resolutions, keeping the n most significant bits in the multiscale resolution ($nMSB_M$).

The transfer of only the necessary precision in values, and the reduction of the grid size (as a proxy to upscaling), may benefit simulation. This study evaluates the impacts of this compression strategy on the volume permeability property and the simulation results obtained with it.

3 Simulation results

Input data To experiment our multiresolution framework (HexaShrink+Zerotree) in a simulation context, we modeled the mesh shown in Figure 6 with the following features:

- Model size: $220 \times 220 \times 30 \text{ m}^3$,
- Cell size: $1.70 \times 1.70 \times 0.95 \text{ m}^3$,
- Mesh dimension: $128 \times 128 \times 32$ cells,
- Petrophysical properties: porosity and permeability are inspired by the Tarbert formation from SPE10 (CHRISTIE & BLUNT, 2001), commonly used with upscaling.

The reservoir is localized at a depth of 3400 m, and contains three faults whose surfaces are not aligned with the grid. Two wells are located on the grid diagonal to represent a quarter of five-spot models: distant from 300 m, the injector well sets on the lower corner while the producer sets on the higher one. The injector well pressure is constant at 300 bars, while the producer rate is constant at 300 m^3 per day.

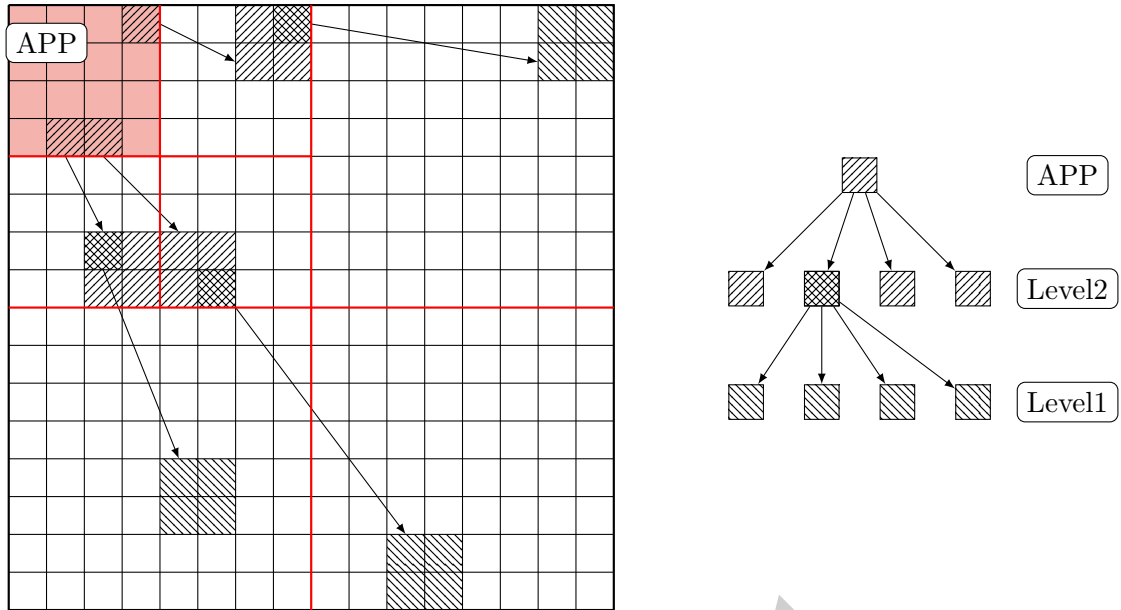


Figure 4: *Embedded zerotree concept illustration.*

Resolution	Mesh dimension	Number of cells
0	$128 \times 128 \times 32$	524288
-1	$64 \times 64 \times 16$	65536
-2	$32 \times 32 \times 8$	8192
-3	$16 \times 16 \times 4$	1024

Table 1: *Features of approximated mesh resolutions generated with HexaShrink.*

Methodology Firstly, we apply HexaShrink to obtain several resolutions of the initial mesh. The resulting grid dimension at each resolution is given by Table 1.

As expected, the dimension is divided by two in each direction according to the previous resolution, and thus the cell number is well divided by 8 at each resolution. Five levels of decomposition could be performed, but we only keep the first three resolutions, the last two resolutions being too coarse to get reasonable flow simulation results. On Figure 2, we can observe the coherency of the fault network whatever the resolution, as well as of the global distribution of the continuous properties. Then, we make two experimentations:

- Exp1: a two-phase flow simulation is performed independently on the **different resolutions**. It amounts to performing the same simulation on downscaled meshes as described in the first column of Figure 5, to analyze the influence of resolution. By comparing the results obtained at lower resolutions with those at full resolution, we will know if it is possible to get similar results, with significant reduction of computation times.
- Exp2: the same two-phase flow simulation is performed on the full resolution encoded beforehand with the zerotree coder, and then decoded partially at **different refinable precision**. It amounts to performing the same simulation along rows of Figure 5. The objective is to evaluate the precision required (in the multiscale domain) during simulation, or if we can reach similar performances with a limited number of significant bits. More precisely, we performed the same simulation on the full resolution reconstructed with respectively 15, 9, 7 and 5 MSB_Z . Table 2 indicates the corresponding binary size for each configuration, in bits and in percentage with respect to the original data stream size.

In both experimentations, simulations are performed according to well parameters, and we particularly focus on the resulting watercut curves obtained at the producer.

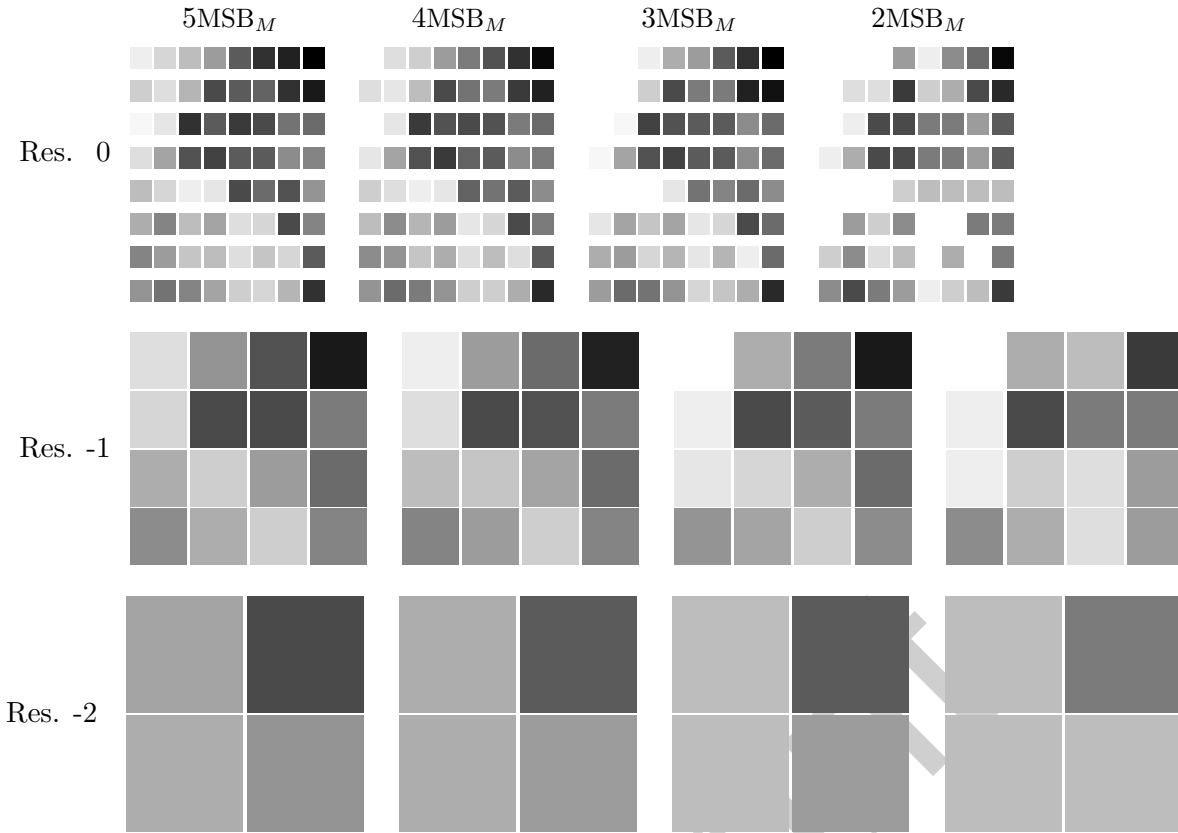


Figure 5: 2D data at three different resolutions (Haar wavelet) and refined numerical precision: from the original with 8×8 values in 0–31 with 5MSB_M (top-left) to a two-fold coarser resolution coded with 2MSB_M (bottom-right).

Results The watercut curves computed on the different resolutions during the first experimentation are compared on Figure 7. Taking resolution 0 as reference, resolution -1 provides comparable results, while containing eight times less cells. From resolution -2 we observe a delay of 20 days on the watercut curve. Such a difference could be explained because of the changing place of the well, located on the center of a cell. With 8^3 times less cells than the reference, resolution -3 provides poor results, because of a too coarse grid. Considering computing speed, simulation is almost instantaneous at resolution -2, while the simulation made on the initial resolution lasted a few hours on the supercomputer ENER220 (using 16 cores, IFPEN, Solaize). Despite a gap between resolution 0 and lower resolutions, the results are encouraging and demonstrate that HexaShrink, although locally perfectible, could be used in place of an upscaling/upgridding function in a context of simulation.

Figure 8 presents watercut curves obtained during the second experiment, in function of the number of significant bits used. The curve named 31MSB_Z is considered as the reference, as it is obtained by considering the initial mesh, with the permeability properties losslessly coded/decoded with zerotree parsing. Decreasing the number of significant bits from 31 to 7 MSB_Z , we observe that there is no difference in the simulation results: the watercut curves perfectly overlap. This is very satisfactory, as the data quantity is significantly reduced using ever less significant bits: until less than 1% of the binary stream generated by the zerotree coder is finally sufficient for this simulation. A bias becomes only perceptible at 5MSB_Z or less. Although attractive in a context of storage or transmission, note that a strong reduction in term of significant bits may be inappropriate in a context of visualization, as illustrated Figure 9. Nevertheless, we observe that the effect is not perceptible until 15 MSB_Z , corresponding to around 27% of the fully coded data (see Table 2), which remains very satisfactory.

To summarize, these experimentations highlight the disparity between the human perception and the simulation needs. In a visual purpose, using 27% of the encoded data can be satisfactory, whereas

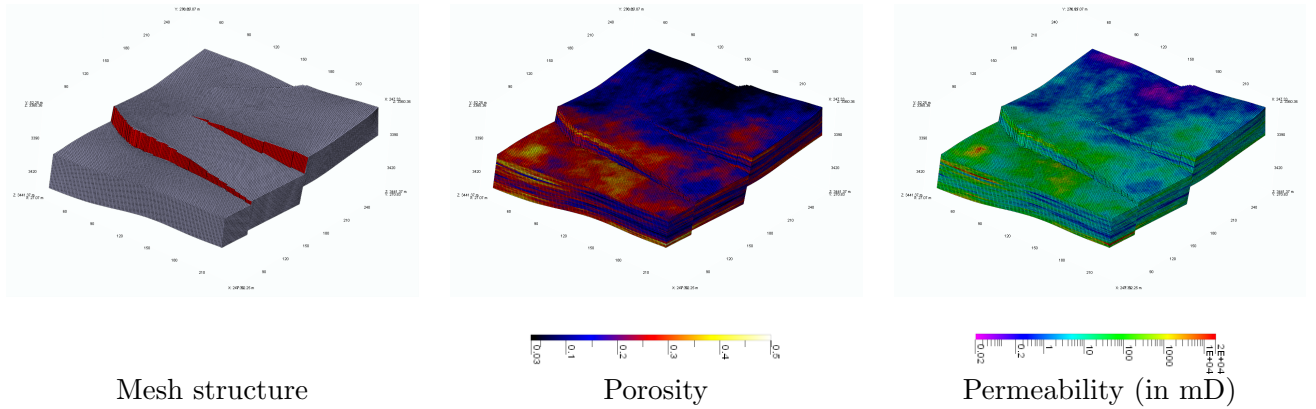


Figure 6: *Tested mesh. Left: geometry information, with the faults colored in red. Middle and right: petrophysical properties with porosity and permeability, respectively.*

MSB _Z used	Size (in bits)	Zerotree stream percentage
31	12 000 000	100 %
15	3 100 000	27 %
9	64 000	0.55 %
7	12 000	0.10 %
5	2600	0.022 %

Table 2: *Different MSB_Z used to reconstruct the permeability during the second experimentation, with the corresponding amount of bits decoded by the zerotree, and the percentage with respect to the full binary stream size.*

much less can be used to get good simulation results, and thus to ease data management and to fasten simulations at the same time.

4 Conclusions

A two-phase flow simulation has been successfully run on various approximations of a reservoir mesh generated from the embedded structure provided by HexaShrink, in an upscaling/upgridding purpose.

During our first experimentation, the well parameters, resulting of the watercut, are consistent across the resolutions. It means that simulation computation times could be reduced by using lower resolutions, while obtaining similar results. Thanks to the use of the supercomputer of IFPEN, computation times are already competitive on the initial resolution: it becomes really attractive on the lower resolutions provided by HexaShrink. Yet, some details as the wells location still needs to be improved. The second experimentation showed the influence of the data precision on a simulation result, by combining a zerotree coder to HexaShrink.

Prioritizing information on either the resolution of meshes or data numerical precision is important in simulation. Working on the permeability property, and keeping only significant bits, less than 1 % of the original data can meet simulation requirements, while a fourth of the lossless data size suffices for visualization purposes. Simulation engineering thus requires novel quality metrics, to account for both computational accuracy and visual mesh perception.

Acknowledgments

We are thankful to Corinne Mailhes (University of Toulouse), Emmanuel Christophe (Google), Christophe Latry and Carole Thiebaut (CNES) for discussions and code. We also acknowledge the ENER220 IFPEN supercomputing resource (220 Tflops) inaugurated in August 2018.

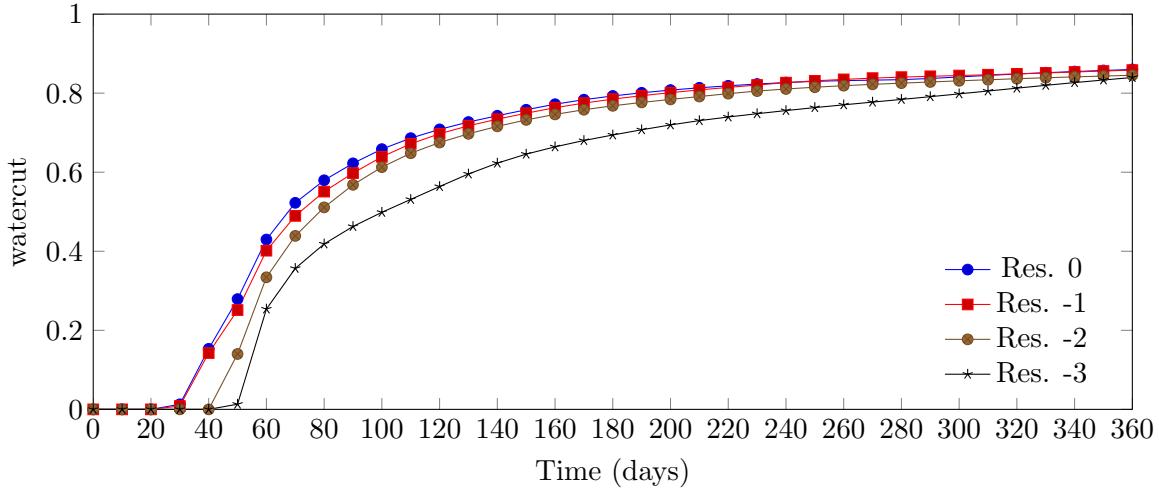


Figure 7: Comparison of the watercut curves generated at the producer well of the reservoir, at different resolutions obtained with HexaShrink.

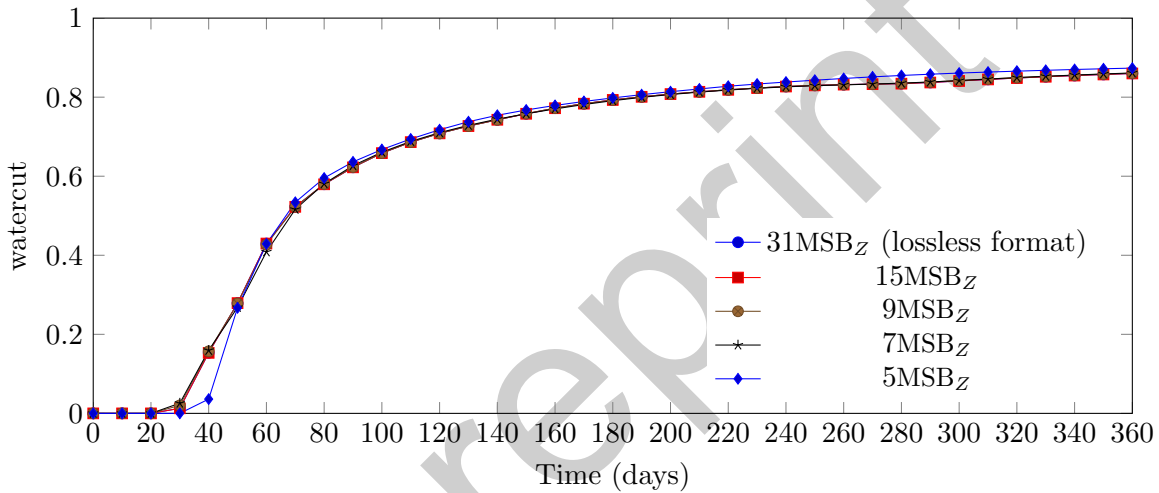


Figure 8: Comparison of the watercut curves generated at the producer well of the reservoir at the full resolution, by using different MSB_Z for the decoded permeability properties.

References

- T. ACHARYA & P.-S. TSAI [2005]. *JPEG2000 Standard for Image Compression. Concepts, Algorithms and VLSI Architectures*. Wiley-Interscience.
- F. CAPPELLO, S. DI, S. LI, X. LIANG, A. M. GOK, D. TAO, C. H. YOON, X.-C. WU, Y. ALEXEEV & F. T. CHONG [2019]. Use cases of lossy compression for floating-point data in scientific data sets. *Int J High Perform Comput Appl*. doi:10.1177/1094342019853336.
- M. CHRISTIE & M. BLUNT [2001]. Tenth SPE comparative solution project: A comparison of upscaling techniques. In: *SPE Reservoir Simulation Symposium*. Society of Petroleum Engineers. doi:10.2118/66599-ms.
- E. CHRISTOPHE, C. MAILHES & P. DUHAMEL [2008]. Hyperspectral image compression: Adapting SPIHT and EZW to anisotropic 3-D wavelet coding. *IEEE Trans Image Process*, **17**(12):2334–2346. doi:10.1109/tip.2008.2005824.
- M. GEVELER, M. KÖHLER, D. RIBBROCK, J. SAAK, G. TRUSCHKWITZ, P. BENNER & S. TUREK [2015]. Future data centers for energy-efficient large scale numerical simulations. In: *7th KoMSO Challenge Workshop*.
- A. HAAR [1910]. Zur Theorie der orthogonalen Funktionen Systeme. *Math Annalen*, **69**:331–371.
- L. JACQUES, L. DUVAL, C. CHAUX & G. PEYRÉ [2011]. A panorama on multiscale geometric represen-

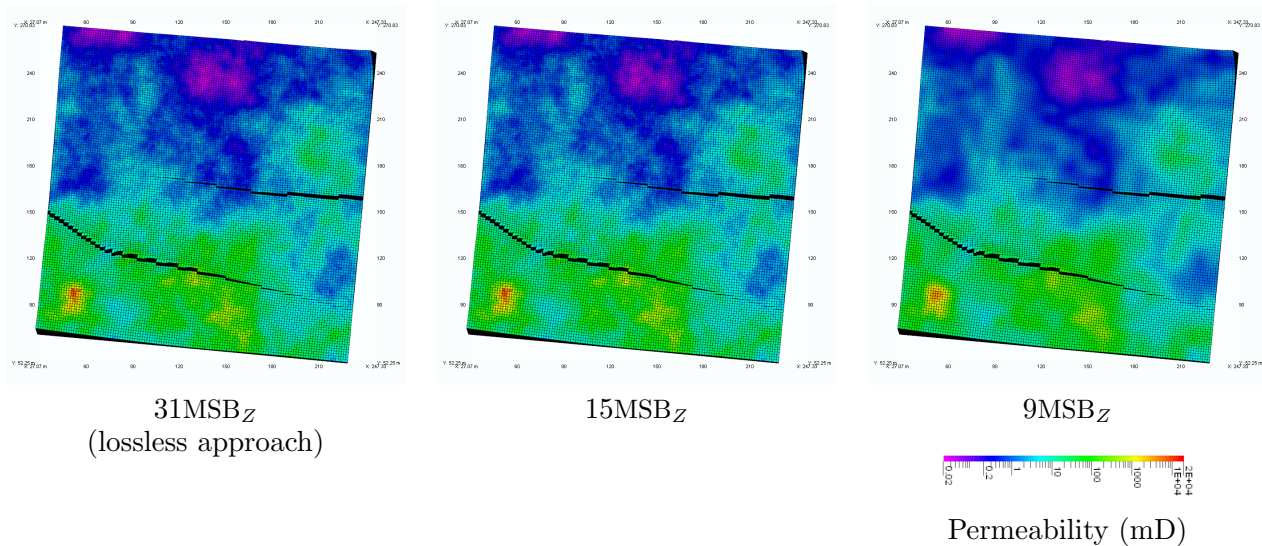


Figure 9: Permeability property visualization using different MSB_Z .

- tations, intertwining spatial, directional and frequency selectivity. *Signal Process*, **91**(12):2699–2730. doi:10.1016/j.sigpro.2011.04.025.
- P. LINDSTROM, S. LLOYD & J. HITTINGER [2018]. Universal coding of the reals: Alternatives to IEEE floating point. In: *Proc. Conference for Next Generation Arithmetic (CONGA)*. ACM Press. doi:10.1145/3190339.3190344.
- S. MALLAT [1998]. *A wavelet tour of signal processing*. Academic Press, San Diego, CA, USA, 2nd ed.
- J.-M. MULLER, N. BRUNIE, F. DE DINECHIN, C.-P. JEANNEROD, M. JOLDES, V. LEFÈVRE, G. MELQUIOND, N. REVOL & S. TORRES [2018]. *Handbook of Floating-Point Arithmetic*. Springer.
- E. PAZHOOHESH, H. HAMZEHPOUR & M. SAHIMI [2006]. Numerical simulation of ac conduction in three-dimensional heterogeneous materials. *Phys Rev B*, **73**(17). doi:10.1103/physrevb.73.174206.
- J.-L. PEYROT, L. DUVAL, F. PAYAN, L. BOUARD, L. CHIZAT, S. SCHNEIDER & M. ANTONINI [2019]. HexaShrink, an exact scalable framework for hexahedral meshes with attributes and discontinuities: multiresolution rendering and storage of geoscience models. *Computat Geosci*. doi:10.1007/s10596-019-9816-2.
- D. K. PONTING [1989]. Corner point geometry in reservoir simulation. In: *ECMOR I — 1st European Conference on the Mathematics of Oil Recovery*. doi:10.3997/2214-4609.201411305.
- M. RASAEI & M. SAHIMI [2008]. Upscaling and simulation of waterflooding in heterogeneous reservoirs using wavelet transformations: Application to the SPE-10 model. *Transp Porous Med*, **72**(3):311–338. doi:10.1007/s11242-007-9152-1.
- A. SAID & W. A. PEARLMAN [1993]. Reversible image compression via multiresolution representation and predictive coding. In: B. G. HASKELL & H.-M. HANG (Eds.), *Proc. SPIE Visual Communication Image Processing*. SPIE. doi:10.1117/12.157984.
- A. SAID & W. A. PEARLMAN [1996]. A new, fast, and efficient image codec based on set partitioning in hierarchical trees. *IEEE Trans Circuits Syst Video Technol*, **6**(3):243–250. doi:10.1109/76.499834.
- J. M. SHAPIRO [1993]. Embedded image coding using zerotrees of wavelet coefficients. *IEEE Trans Signal Process*, **41**:3445–3462. doi:10.1109/78.258085.