Highly Scalable Quantum Transfer Matrix Simulations of Molecule-Based Nanomagnets on a Parallel IBM BlueGene/P Architecture

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Abstract: In this work we present a very efficient scaling of our two applications based on the quantum transfer matrix method which we exploited to simulate the thermodynamic properties of Cr9 and Mn6 molecules as examples of the uniform and non-uniform molecular nanomagnets. The test runs were conducted on the IBM BlueGene/P supercomputer JUGENE of the Tier-0 performance class installed in the Jülich Supercomputing Centre.

Key words: parallelization of processing, MPI, numerical simulations, magnetic rings, Heisenberg model

I. INTRODUCTION AND PHYSICAL BACKGROUND

A lot of research on molecular nanomagnets has been done in the last years [1]. Such intensive scientific interest was to a large extent stimulated by expected applications in molecular spintronics, information storage [2], quantum information processing [3-6] and other. Yet even if these applications seem to be a matter of a rather distant future, molecular magnets are already very interesting materials where quantum effects can be observed in bulk samples. Thus, they are a very good test ground for various microscopic theories and computation tools. The interest in spin assemblies stems from the fact that they set the low-size limit for magnetic nanoparticles. They can display such behavior as magnetic quantum tunneling [7] and quantum-size effects in the thermodynamic properties [8].

One of the interesting phenomena that interfere with the quantum nature of the molecules is magnetic frustration. It appears e.g. in antiferromagnetic odd-membered molecular rings based on transition metal ions [9-13]. To observe the frustration effects, new odd nine-numbered homometallic rings Cr9 have recently been synthesized. They are based on Cr3+ ions [14, 15] with spin $S = 3/2$ and their example is shown in Fig. 1. To simulate frustrated molecules it is impossible to use probabilistic methods like Monte Carlo.

An example of hetero-spin molecules with ferromagnetic couplings which we consider here [16, 17] is [Mn(hfac)$_2$-NITPh]$_6$ compound (hfac, hexafluoroacetyl acetone; NITPh, 2-phenyl-4,4,5,5-tetramethyl-4,5-dihydro-1H-imidazolyl-1-oxy -3-oxide) pictured in Fig. 2 referred to as Mn6 molecule. It contains twelve paramagnetic centers (six Mn$^{2+}$ ions with spin $S = 5/2$ and six organic radicals with non-paired $S = 1/2$ electrons) and belongs also to a class of nanocompounds actively investigated for their magnetic properties [18, 19].

The molecular magnetic rings are quantum objects modeled by the Heisenberg spin Hamiltonian. For a uniform
Fig. 1. The crystallographical structure of the Cr₉ molecule which consists of nine chromium spins $S = 3/2$ surrounded by organic radicals and is represented by the chemical formula $[\text{Pr}_2\text{NH}_2][\text{Cr}_9\text{F}_9(\text{O}_2\text{C}^\text{t}\text{Bu})_{17}\text{Cl}_2]$. 

ring composed of $N$ spins $S$, the dimension of the corresponding matrix representation of the Hamiltonian amounts to $(2S + 1)^N$. This implies that within the exact diagonalization (ED) method, a solution of a physical problem needs the memory size of the order of $(2S + 1)^{2N}$, whereas the computational complexity raises even more to $(2S + 1)^{3N}$. Such an exponential complexity imposes strong bounds on the physical systems which can be considered within ED so that there are many methods devised to overcome the ED constraints. Among them the quantum transfer-matrix method (QTM) deserves special attention [20, 21] due to its high accuracy and direct addressing the partition function which is a key quantity needed to calculate the free energy and its derivatives, in particular the magnetic susceptibility, specific heat or magnetization. These quantities are measured experimentally and need theoretical interpretation. We note that the convergence of the QTM results depends on temperature and is deteriorated approaching the limit $T = 0$ and then the ED technique is more convenient. [15, 22, 23]

Within the QTM method, an exponential of the Hamiltonian which is called transfer matrix is addressed and can be found via the Suzuki-Trotter transformation [20, 21]. The transfer matrix has the same size as that in the ED method (i.e. $(2S + 1)^N$), but it is expressed in a basis of a simple product of the Ising states. Its structure is complicated and contains $m$-fold replicas of the initial Hamiltonian, but can be reduced into a product composed of $m$ sparse matrices which are easy to implement. Because the partition function is related to a trace of the transfer matrix, the QTM computational complexity is determined by the number of the diagonal elements $(2S + 1)^N$, the number of the basis vectors $(2S + 1)^N$ and size $m$ of the products of the sparse matrices and amounts to $m(2S + 1)^{2N}$. The complexity remains exponential but it is lower than that of the ED method due to the relation $m \ll (2S + 1)^N$. Moreover, the diagonal matrix elements are determined by the scalar products of the same basis vectors so that they can be calculated independently and the trace of the transfer matrix can be efficiently executed in the parallel computing architecture. We also note the small QTM memory size needed which is only of the order of $(2S + 1)^N$ and is easily accessible on supercomputing platforms.

The foregoing description refers to the QTM simulations of the non-uniform spin rings consisting of two types of species with the spin values $S_1$ and $S_2$. In this case it is enough to map $(2S + 1) \to (2S_1 + 1)(2S_2 + 1)$ and consider $N$ as a number of pairs of spins $S_1$ and $S_2$.

The computations needed to demonstrate the high scalability of our applications intended to simulate the homo- and hetero-spin molecular rings (referred to as 1 and 2, respectively) were performed on JSC JUGENE supercomputer.
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Fig. 2. A scheme of the Mn$_6$ molecule composed of six manganese ions carrying the spin $S = 5/2$ and six unpaired $S = 1/2$ electrons localized on the adjacent radicals.

during the BlueGene/P Extreme Scaling Workshop 2011 organized in Jülich. At that time it was the biggest supercomputer in the world in terms of the number of computing cores.

II. DESCRIPTION OF THE CODES AND ITS PARALLELIZATION

Our codes have been designed to calculate thermodynamic properties of spin rings and chains which can be modeled by an anisotropic quantum Heisenberg model. In particular we use these codes to simulate molecular nanomagnets belonging to the Cr$_8$ family [13-15, 24, 25].

However, in our research the ED-based codes have also been executed, depending on the circumstances as the appropriate sizes of the molecules or the type of physical properties pursued [15, 23].

In our QTM applications each diagonal element of the final transfer matrix is calculated separately and requires approximately the same number of arithmetic operations. The number of elements calculated by a give core was defined by the ratio of the total number of basis vectors and the number of cores involved. The communication was based on the MPI directives and took place only at the beginning and end of the processes running in each core. The only limiting factors to the efficiency are the uniform distribution of the work among the computing cores and the size of the matrix. This size should not be too small, to avoid an impact of the latencies not directly related to the parallel implementation. Our application 1 was tested imposing $N = 11$, whereas it was designed to solve the problem of $N = 9$ interacting spins $S = 3/2$ in the Cr$_9$ molecules.

The size of the computational problem is determined by the number $L$ of the diagonal matrix elements which is equal

<table>
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<th>$N_r$</th>
<th>$N_c$</th>
<th>$n_1$</th>
<th>$n_2$</th>
<th>$t_1 [s]$</th>
<th>$t_2 [s]$</th>
<th>$e_1 [%]$</th>
<th>$e_2 [%]$</th>
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<td>870</td>
<td>104</td>
<td>94.9</td>
<td>85.9</td>
</tr>
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</table>

Tab. 1. The hardware characteristics and the data showing the scalability of applications 1 and 2. The notation of columns is the following: $N_r$ – number of racks, $N_c$ – number of cores, $n_i$ – the range of matrix elements assigned to a single core (the index $i = 1, 2$ and refers to a given application), $t_i$ – the total running time in seconds, $e_i$ – the corresponding efficiency.
to the size of the transfer matrix. Thus the applications 1 and 2 have dealt with the significant computational problems of the sizes $L = 4^{11} = 4194304$ and $L = 2^{26} = 2985984$, respectively. Of course such large matrices would not fit into memory limits for BlueGene/P systems. The memory footprint was reduced to the values of the order of $L$ by exploiting the sparseness of the matrices. In fact only a few vectors of size $L$ are needed to be remembered. Furthermore, using the same mechanisms the computational complexity for calculating a single element was also reduced from matrix-vector multiplications to vector-vector operations leading to the temporal complexity of the order of $L^2$ due to a small $m$ value adopted. The magnitude of the integer $m$ depends on the convergent rate. The slower convergence, the higher value of $m$ is needed. However, for the sake of testing the code parallelization, the size of $m$ is irrelevant.

### III. ANALYSIS OF CODE PERFORMANCE AND RESULTS

We have performed a number of successful large scale runs, proving an excellent scalability of both applications. We note that on JUGENE only full racks containing processors with $2^{12}$ cores could be assigned during execution. Application 1 was tested more thoroughly. Runs were performed from 8 racks up to the full number of 72 racks (see Table 1). In Table 1 we have assumed the following abbreviations: $N_r$ means the number of racks assigned during a given run; $N_c$ denotes the total number of cores engaged; $n_i$ shows the range of the number of elements processed by a single core in the case of the $i$th application, where $i = 1, 2$; $t_i$ describes the total processing time and $e_i$ yields the efficiency of a given parallelized code. Some fields in Table 1 are missing, as the application 2 was not granted so much computing time as the first one.

As one element of the matrix was calculated during a fixed amount of time, the more cores computed the whole numerical task, the smaller part of the task each slave core had to calculate on its own. Knowing that, it is possible to predict theoretical speed up and efficiency as a function of the number of computing racks or cores. This was done for Application 1 and is presented in Fig. 3. This application would maintain perfect linear scalability when the work distribution was optimal, i.e. the ratio of the total number of matrix elements $L$ and the number of cores $N_c$ was an integer.

The performance of application 1 is illustrated in Fig. 3. The full red straight lines in both panels illustrate the optimal theoretical speed up, whereas the black curves in the form of steps show the values obtained from the real computing runs. As expected, for the optimal distribution of slave processors, the ideal efficiency is accomplished. These cases are marked by the full red dots. In the insets we demonstrate predictions of the speedup and efficiency for a computer with as many as 1024 racks.

The corresponding predictions for application 2 are visualized in Fig. 4 by the blue curves. The only two experimental points available are denoted by the red symbols. That obtained from the 8-rack run fits the theoretical predictions quite well, but that from the full-machine run clearly deviates. Although at this size the efficiency should be around 92%, we got 86% only. The inspection of worklogs showed that in both cases the time required to compute one element did not vary much, so the total time should be very close to the predicted one. We believe that the loss of efficiency might be caused by some intrinsic problems with final MPI reduction operation performed on the whole machine, as this is the only place between the single-step and total run-time measurements which could affect the performance.
of application 2, unexpected reduction of efficiency emerged for the full 72-rack run which was attributed to some intrinsic MPI performance rather than to a failure of the parallelized code.

For the purpose of testing the scalability, we have considered a simplified model of the physical problem in order to shorten the calculations of a single matrix element. To this end the number \( m \) of replicas was kept very small. To obtain accurate real physical characteristics, the constraint on the \( m \) value should be relaxed and the applications should be invoked for a number of varying parameters so that the total running time would increase significantly.

As proper implementation of the QTM method is scalable over to the biggest machines currently available, this feature predisposes our tool for simulation of relatively large molecular magnetic complexes which are the subject of current experimental research.

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**References**


Michał Antkowiak received his MSc degree in computer science at the Umeå University, Sweden, in 2006. In the same year he received MSc degree in applied computer science at the Adam Mickiewicz University in Poznań, Poland. He defended his PhD in physics at the same university in 2013. His research interests include modelling of molecular nanomagnets and parallel processing.

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