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Evolutionary molecular structure determination using grid-enabled data mining

Mark L. Green, Russ Miller *

*Department of Computer Science and Engineering, Center for Computational Research,
State University of New York, Buffalo, NY 14260, USA*

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Abstract

A new computational framework is developed for the evolutionary determination of molecular crystal structures using the *Shake-and-Bake* methodology. Genetic algorithms are performed on the *SnB* results of known structures in order to optimize critical parameters of the *SnB* computer program. The determination of efficient *SnB* input parameters can significantly reduce the time required to solve unknown molecular structures. Further, the grid-enabled data mining approach that we introduce exploits computational cycles that would otherwise go unused.

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1. Introduction

The ACDC-Grid [1–5] is a proof-of-concept grid that has been implemented in Western New York. The driving application provides a cost-effective solution to the problem of determining molecular structures from X-ray crystallographic data

* Corresponding author.

E-mail addresses: mlgreen@ccr.buffalo.edu (M.L. Green), miller@buffalo.edu (R. Miller).

via the *Shake-and-Bake* direct methods procedure. *SnB* [6], a computer program based on the *Shake-and-Bake* method [7,8], is the program of choice for solving such structures in numerous laboratories [9–11]. This computationally-intensive procedure can exploit the grid's ability to present the user with a computational infrastructure that will allow for the processing of a large number of related molecular trial structures [12,13].

SnB has been used in a routine fashion to solve difficult atomic resolution structures, containing as many as 1000 unique non-Hydrogen atoms, which could not be solved by traditional reciprocal-space routines. Recently, the *Shake-and-Bake* research team has extended the application of *SnB* to solve heavy-atom and anomalous-scattering substructures of much larger proteins, provided that 3–4 Å diffraction data can be measured. In fact, while direct methods had been applied successfully to substructures containing on the order of a dozen selenium sites, *SnB* has been used to determine as many as 180 selenium sites. Such solutions have led to the determination of complete structures containing hundreds of thousands of atoms.

As shown in Fig. 1, X-ray data and the corresponding molecular structure are related by a Fourier transform. The X-ray data that is collected typically consists of positions and intensities. However, the corresponding phases are lost in the data collection process. Given positions, intensities, and phases, a Fourier transform can be used to generate the positions of the atoms in the molecule. Therefore, the solution to the problem of determining structures from X-ray data is referred to as *the phase problem*. That is, once the phases are determined, the positions of the atoms for the structure in question are easily derived.

The *Shake-and-Bake* procedure consists of generating structure invariants and coordinates for a (large) set of randomly generated “trial” structures. Each such trial structure is subjected to an automated cyclical procedure (refer to Fig. 2) between real space (where atoms live) and reciprocal space (where phases live). The *Shake-and-Bake* procedure includes (a) computing a Fourier Transform to determine phase values from the existing set of atoms, (b) determining a figure-of-merit [14] associated with these phases, (c) refining these phases locally against this figure-of-merit, (d) computing a Fourier Transform to produce an electron density map, and (e) employing a peak-picking routine to examine the map and find the maxima. These peaks (maxima) are then considered to be atoms, and the cyclical process is repeated for a user-determined number of cycles.

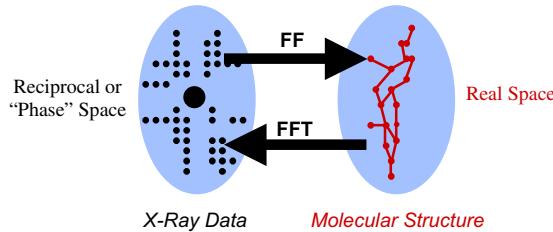


Fig. 1. X-ray data and corresponding molecular structure.

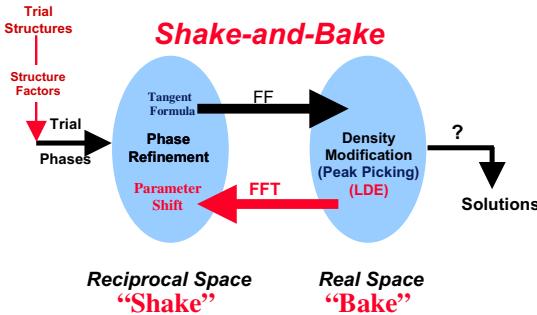


Fig. 2. *Shake-and-Bake* cyclic peak-picking procedure.

The procedure has a philosophy of “run until solved” in that one trial structure after another is subjected to the cyclical procedure until the figure-of-merit determines that one of these initially random trial structures has morphed into the correct structure. In practice, the random trial structures are generated on the fly, either sequentially or in parallel, as is appropriate for the computing platform that is being used.

The running time of *SnB* varies widely as a function of the size of the structure, the quality of the data, the space group, and choices of critical input parameters, including the size of the Fourier grid, the number of reflections, the number and type of invariants, the number of cycles of the procedure used per trial structure, and critical real-space and reciprocal space refinement methods, to name a few. Therefore, the running time of the procedure can range from seconds or minutes on a PC to weeks or months on a supercomputer. Trial structures are continually and simultaneously processed, with the final figure-of-merit values of all structures stored in a file. The user can review a dynamic histogram during the processing of the trials in order to determine whether or not a solution is likely present in the set of completed trial structures.

2. Genetic algorithms

Genetic Algorithms (GAs) were developed by Holland [15] and are based on natural selection and population genetics. Traditional optimization methods focus on developing a solution from a single trial, whereas genetic algorithms operate with a *population* of candidate solutions.

We propose to use a GA to determine an efficient set of *SnB* input parameters in an effort to reduce the time-to-solution for determining a molecular crystal structure from X-ray diffraction data. We use a population of candidate *SnB* input parameters. Each member of the population is represented as a string in the population and a fitness function is used to assign a fitness (quality) value for each member. The members in the population obtain their fitness values by executing the *SnB*

program with the input parameter values represented by their strings. Using “survival-of-the-fittest” selection, strings from the *old* population are used to create a *new* population based on their fitness values. The member strings selected can recombine using crossover and/or mutation operators. A crossover operator creates a new member by exchanging substrings between two candidate members, whereas a mutation operator randomly modifies a piece of an existing candidate. This procedure of combining and randomly perturbing member strings has, in many cases, been shown to produce stronger (i.e., more fit) populations as a function of time (i.e., number of generations).

Sugal [16] (sequential execution) and PGAPack [17,18] (parallel and sequential execution) genetic algorithm libraries were used in our work. The Sugal library provided a sequential GA and has additional capabilities, including a restart function that proved to be very important when determining fitness values for large molecular structures. The PGAPack library provided a parallel master/slave MPICH/MPI implementation that proved very efficient on distributed- and shared-memory ACDC-Grid compute platforms. Other key features include C and Fortran interfaces, binary-, integer-, real-, and character-valued native data types, object-oriented design, and multiple choices for GA operators and parameters. In addition, PGAPack is quite extensible. The PGAPack library was extended to include restart functionality and is currently the only library used for the ACDC-Grid production work.

3. *SnB* input parameters

The *SnB* computer program has approximately 100 input parameters, though not all parameters can be optimized. For the purpose of this study, 17 parameters were identified for participation in the optimization procedure. The *SnB* parameter names and brief descriptions follow.

1. NUM_REF: number of reflections used for invariant generation and phase determination.
2. RESO_MAX: minimum data resolution.
3. E_SIG_CUT: $E/\Sigma(E) > \text{Cut}$.
4. NUM_INV: number of three-phase invariants to generate and utilize during the *Shake-and-Bake* procedure.
5. NUM_CYCLE: number of *Shake-and-Bake* cycles performed on every trial structure.
6. PH_REFINE_METHOD: fast parameter shift, slow parameter shift, tangent formula method.
7. PS_INIT_SHIFT: parameter shift angle in degrees.
8. PS_NUM_SHIFT: maximum number of angular shift steps.
9. PS_NUM_ITER: maximum number of parameter shift passes through phase list.
10. TAN_NUM_ITER: maximum number of passes through phase list when PH_REFINE_METHOD is set to tangent formula method.

11. MIN_MAP_RESO: Fourier grid map resolution.
12. NUM_PEAKS_TO OMIT: number of peaks to omit.
13. INTERPOLATE: a Boolean value that specifies whether or not to *interpolate* the density map.
14. C1: cycle 1 start.
15. C2: cycle 2 end.
16. P1: number of peaks to pick.
17. P2: number of heavy atom peaks to pick.

Eight known molecular structures were initially used to evaluate the genetic algorithm evolutionary molecular structure determination framework performance. These structures are 96016c [19], 96064c [20], crambin [21], Gramicidin A [22], Isoleucinomycin [23], pr435 [24], Triclinic Lysozyme [25], and Triclinic Vancomycin [26].

In order to efficiently utilize the computational resources of the ACDC-Grid, an accurate estimate must be made in terms of the resource requirements for *SnB* jobs that are necessary for the GA optimization. This includes runs with varying parameter sets over the complete set of eight known structures from our initial database.

This was accomplished as follows. First, a small number of jobs were run in order to determine the required running time for each of the necessary jobs. Typically, this consisted of running a single trial for each of the jobs in order to predict the time required for the required number of trials for the job under consideration.

Approximately 25,000 population members were evaluated for the eight known molecular structures and stored in a MySQL [27] database table (evo_results). PhpMyAdmin [28] is a tool written in PHP for administration and use of MySQL over the web. The phpMyAdmin interface was used to display the evo_results database table, as shown in Fig. 3.

Field	Type	Attributes	Null	Default	Extra	Action
DB_LOC	varchar(255)		No		Change Drop Primary Index Unique Fulltext	
PREPV_OUT	varchar(255)		No		Change Drop Primary Index Unique Fulltext	
ATOMSIZE	int(11)		No	0	Change Drop Primary Index Unique Fulltext	
NUM_REF	int(11)		No	0	Change Drop Primary Index Unique Fulltext	
PS_NUM_SHIFT	float		No	0	Change Drop Primary Index Unique Fulltext	
PS_INT_SHIFT	float		No	0	Change Drop Primary Index Unique Fulltext	
NUM_PEAKS_TO OMIT	int(11)		No	0	Change Drop Primary Index Unique Fulltext	
INTERPOLATE	tinyint(1)		No	0	Change Drop Primary Index Unique Fulltext	
C1	int(11)		No	0	Change Drop Primary Index Unique Fulltext	
C2	int(11)		No	0	Change Drop Primary Index Unique Fulltext	
P1	int(11)		No	0	Change Drop Primary Index Unique Fulltext	
P2	int(11)		No	0	Change Drop Primary Index Unique Fulltext	
NUM_TRIAL	int(11)		No	0	Change Drop Primary Index Unique Fulltext	
FUNC_VALUE	float		No	0	Change Drop Primary Index Unique Fulltext	
AVG_RMNN	float		No	0	Change Drop Primary Index Unique Fulltext	
RMN_CUTOFF	float		No	0	Change Drop Primary Index Unique Fulltext	
RUNTIME	float		No	0	Change Drop Primary Index Unique Fulltext	
ID	bigint(20)	UNSIGNED	No	auto_increment	Change Drop Primary Index Unique Fulltext	

Fig. 3. MySQL database table for *SnB* trial results.

Fig. 4. Standard scores for Pearson product–moment correlation coefficient calculations.

From these trial results, the mean (\bar{X}^j) and standard deviations (s^j) were calculated for each input parameter j and used to determine the standard scores (z_i^j) for each trial i ,

$$z_i^j = \frac{X_i^j - \bar{X}^j}{s^j},$$

for all i and j where the trial parameter value for trial i and parameter j is X_i^j . Fig. 4 shows the standard scores of the parameters under consideration.

The Pearson product–moment correlation coefficients (r_k^j) are calculated for input parameter j and molecular structure k by

$$r_k^j = \frac{\sum z_k^j z_k^{\text{runtime}}}{N - 1},$$

for all j and k , where N denotes the degrees of freedom and z_k^{runtime} represents the standard score of the GA trial run time. Refer to Fig. 5.

The input parameters that have the largest absolute magnitude Pearson product–moment correlation coefficient with respect to the observed trial run times are selected and used to form a predictive run time function that is fit using a linear least squares routine

$$X_i^{\text{runtime}} = \sum a_j r_k^j \bar{X}^j,$$

where the observed X_i^{runtime} trial run time is fit to a selected sub-set of input parameter values j , \bar{X}^j denotes the input parameter value, r_k^j denotes the respective molecular structure k Pearson product–moment correlation coefficient, and a_j denotes the linear least square fit coefficients for each j input parameter. We use this function within the grid-enabled data-mining infrastructure to estimate the maximum number of SnB GA generations and the maximum size of the population that would run on a given computational resource within the specified time frame.

FIELD	ATOMSIZE	NUM_REF	RESO_MAX	E_SHC_CUT	NUM_INV	NUM_CYCLE	PH_REFINE_METHOD
Edit Delete	16c	0	0.019756	0.11805	-0.093701	0.053894	0.260354
Edit Delete	64c	0	0.018131	0.039265	-0.024268	0.106109	0.511443
Edit Delete	crombie	0	0.349576	0.334959	0.219192	0.349662	0.465749
Edit Delete	gramma	0	0.072786	0.020802	-0.239952	-0.196477	0.106406
Edit Delete	iled	0	-0.086154	0.038256	0.0714716	0.0251388	0.145795
Edit Delete	px435	0	0.348786	-0.11001	-0.240061	0.213774	0.573443

Fig. 5. Pearson product–moment correlation coefficient database table.

The ACDC-Grid infrastructure automatically updates the correlation coefficients based on the availability of new trial data appearing in the *SnB* trial result table. Thus, run time estimates for any given structure continually evolve throughout the GA optimization process.

For example, if there are 50 processors available for 150 minutes on ACDC-Grid compute platform “A”, we are interested in determining the maximum number of GA generations and the size of the population that can run on “A” and complete within 150 min. Based on this information, the data mining algorithms can make intelligent choices of not only which structures to evaluate, but they can completely define the *SnB* GA job that should be executed. This type of run time prediction is an essential component of our system for providing a level of quality of service. Further, in our experience, this type of run time parameter-based prediction is almost always necessary when queue managed computational resources are employed.

4. Shake-and-Bake grid-enabled data mining

The *SnB* grid-enabled data mining application utilizes the ACDC-Grid infrastructure and web portal, as shown in Fig. 6.

A typical *SnB* job uses the Grid Portal to supply the molecular structures parameter sets to optimize, the data file metadata, the grid-enabled *SnB* mode of operation (dedicated or back fill), and the *SnB* termination criteria. This information can be provided via the point and click web portal interface or by specifying a batch script, as shown in Fig. 7.

The database job script can accept command line arguments and can be activated or de-activated at any time by adjusting the database job grid portal parameters. A fully configurable time interval is used by the grid portal to execute some or all of the configured database jobs (normally this time interval is set to 10 min).

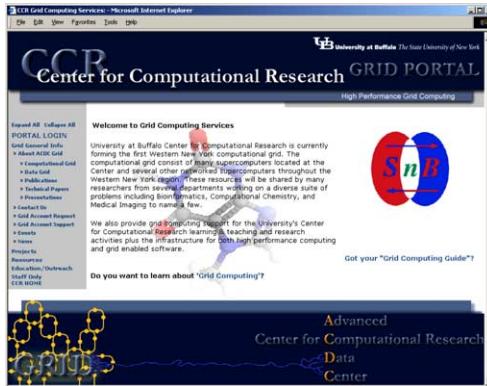


Fig. 6. The ACDC-Grid web portal user interface.

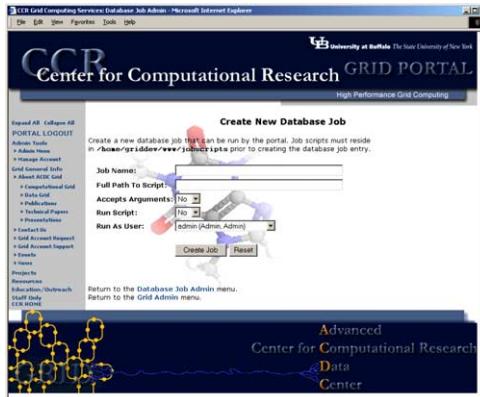


Fig. 7. The ACDC-Grid web portal database job interface.

The Grid Portal then assembles the required *SnB* application data and supporting files, execution scripts, database tables, and submits jobs for parameter optimization based on the current database statistics. ACDC-Grid job management automatically determines the appropriate execution times, number of trials, number of processors for each available resource, as well as logging and status of all concurrently executing resource jobs. In addition, it automatically incorporates the *SnB* trial results into the molecular structure database, and initiates post-processing of the updated database for subsequent job submissions. Fig. 8 shows the logical relationship for the *SnB* grid-enabled data mining routine described.

For example, starting September 8, 2003, a backfill data mining *SnB* job was activated at the Center for Computational Research using the ACDC-Grid computational and data grid resources. The ACDC-Grid historical job-monitoring infrastructure is used to obtain the jobs completed for the period of September 8, 2003 to January 10, 2004, as shown in Fig. 9.

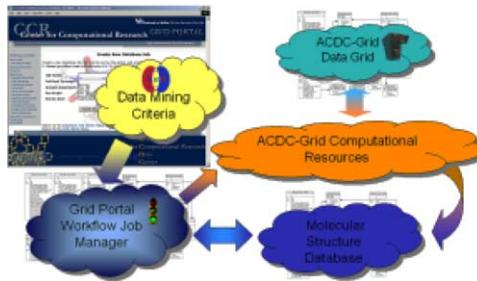


Fig. 8. ACDC-Grid grid-enabled data mining diagram.

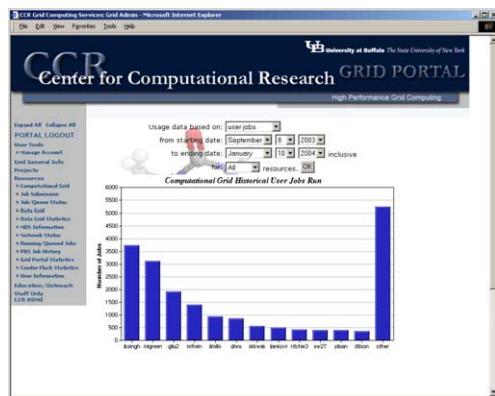


Fig. 9. ACDC-Grid job monitoring information for all resources and users.

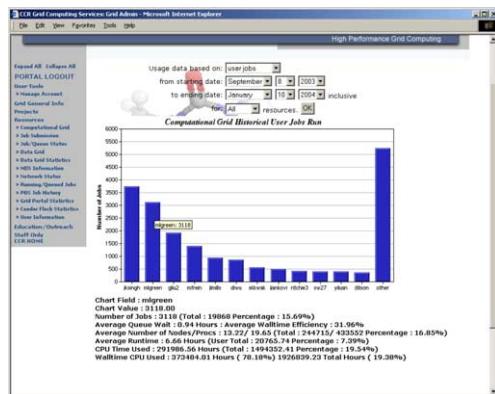


Fig. 10. ACDC-Grid job monitoring statistics for user mlgreen.

The activated data mining *SnB* job template is being run by user *mlgreen*. By hovering over the bar in the chart, as shown in Fig. 10, one can see *mlgreen*'s job statistics. Further, notice that 3118 jobs have been completed on the ACDC-Grid resources over this time period. The ACDC-Grid job monitoring also dynamically reports job statistics for the data mining jobs. The total number of jobs completed by all users on all resource is 19,868 where the data mining jobs represent 15.69% of the total. The average number of processes for a data-mining job was 19.65 and the total number of processors used over this period was 433,552, where the data mining jobs accounted for 16.85% of the total. The data mining jobs consumed 291,987 CPU hours, which was 19.54% of the total CPU hours consumed (1,494,352 CPU hours).

A subsequent mouse click on the bar chart provides additional information characterizing in more detail the jobs completed by user *mlgreen*. Here, we see five computational resources that processed the 3118 data mining jobs. The statistics for the Joplin compute platform are shown in Fig. 11. Note that all statistics are based only on the jobs completed by the *mlgreen* user. There were 869 jobs processed by the Joplin compute platform representing 27.87% of the 3118 data mining jobs.

Clicking on the bar chart drills down into a full description of all jobs processed by the Joplin compute platform, as shown in Fig. 12. The information presented includes job ID, username, group name, queue name, node count, processes per node, queue wait time, wall time used, wall time requested, wall time efficiency, CPU time, physical memory used, virtual memory used, and job completion time/date.

The ACDC-Grid data mining backfill mode of operation only uses computational resources that are currently not scheduled for use by the native queue scheduler. These resources are commonly referred to as “backfill jobs,” as users can run jobs on the associated nodes without affecting the queued jobs. Many queues and schedulers give this information in terms of the number of nodes available and the time for which the nodes are available. The ACDC-Grid infrastructure monitors this infor-

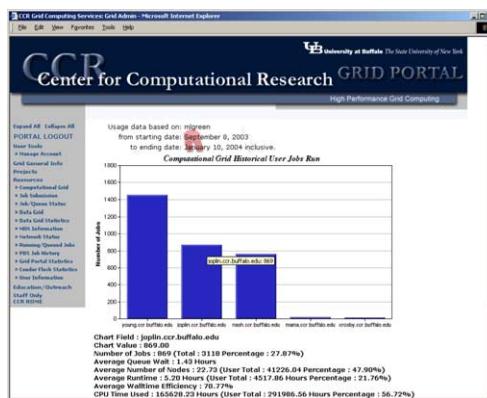


Fig. 11. ACDC-Grid job monitoring statistics for user *mlgreen*.

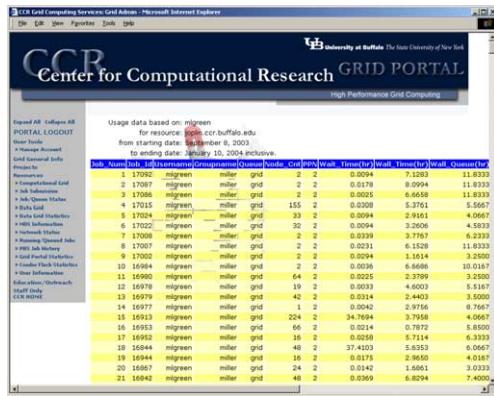


Fig. 12. ACDC-Grid job monitoring tabular accounting of completed job statistics.

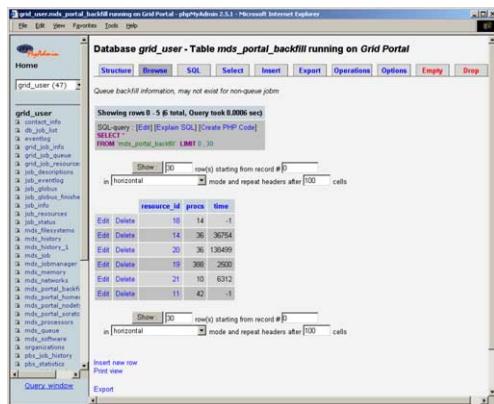


Fig. 13. ACDC-Grid backfill information for all resources.

mation for all of the computational resources and stores this information in a MySQL database table, as shown in Fig. 13.

Fig. 13 also shows the number of processors and wall time that are available for each resource. Note that a value of -1 for the available wall time represents an unlimited amount of time (no currently queued job require the use of these processors). The activated data mining template can obtain the number of processors and wall time available for a given compute platform and then check the status of the platform before determining the actual GA *SnB* data mining job parameters (see Figs. 14 and 15).

Using the Pearson product-moment fit function derived earlier, the new data mining job run time is estimated based on the current ACDC-Grid *SnB* molecular structure database information.

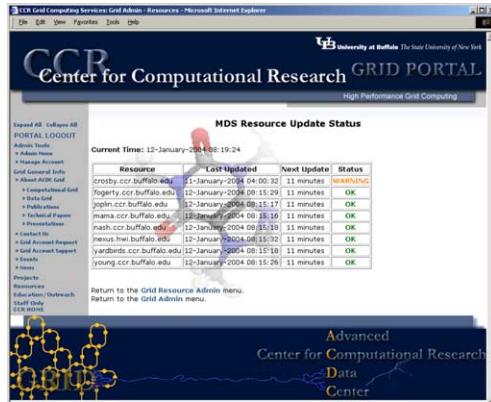


Fig. 14. ACDC-Grid computational resource status monitor.

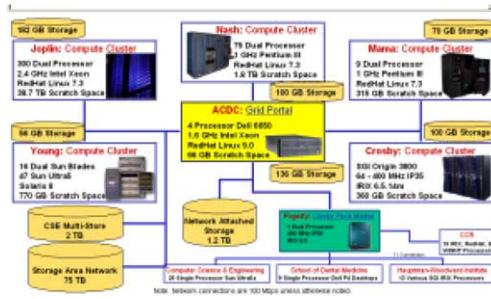


Fig. 15. ACDC-Grid data grid and computational grid integration.

Once the computational aspects of the data-mining job have been defined, the location of the required data files is determined by querying the ACDC-Grid Data Grid database. The ACDC-Grid Data Grid denotes a large network of distributed storage resources such as archival systems, Storage Area Networks, Network Attached Storage, and databases, which are linked logically creating global and persistent disk storage that can be accessed by all computational resources (refer to Fig. 15).

The data grid is designed to provide transparent management of data distributed across heterogeneous resources, such that the data is accessible via a uniform web interface and directly through a well-defined API. In addition, the data grid infrastructure enables the transparent migration of data between various resources while maintaining metadata information about each file and its location via a global database table. The system periodically migrates files between machines based on user patterns in order to achieve an efficient usage of resources.

The implementations of basic file management functions accessible via a platform-independent web interface provide the following features.

- User-friendly menus/interface.
- File Upload/Download to and from the Data Grid Portal.
- Simple web-based file editor.
- Efficient search utility.
- Logical display of files for a given user in three divisions (user/ group/ public).
 - Hierarchical.
 - List-based.
 - Three divisions: (user/ group/ public).
 - Sorting capability based on file metadata, i.e. filename, size, modification time, etc.
- Support multiple accesses to files in the data grid (file locking and synchronization primitives for version control).

Integrated security procedures allow authentication and authorization of users for data grid file access and enforce policies for data access and publishing. The gathering and display of statistical information on the data grid usage is automatically obtained through the data grid infrastructure. This information is particularly useful to administrators for optimizing the usage of resources. The data mining job template is then executed, leading to the migration and submission of the designed data-mining job and data files to the respective ACDC-Grid computational resource.

The activated data-mining template has two options of stopping criteria.

1. Continue submitting *SnB* data-mining application jobs until the optimal parameters have been found based on predetermined criteria.
2. Continue indefinitely (the data mining template is manually de-activated by the user when optimal parameters are found).

This illustrative example summarizes the evolutionary molecular structure determination optimization of the *Shake-and-Bake* method as instantiated in the *SnB* computer program.

5. Further remarks

The evolutionary strategy presented in this paper was used to substantially improve the performance of the *SnB* procedure. The GA procedure that we described improved the time-to-solution of *SnB* by up to a factor of two on a number of representative data sets.

Many scientific applications can take advantage of an evolutionary procedure in an effort to optimize its input parameters. We have identified several such applications and are currently generalizing the grid-enabled data mining procedure as a grid-enabling application template.

We are currently working on several related projects, including enhancing the ACDC-Grid infrastructure to include predictive scheduling, intelligent data

migration over several large data repositories, and lightweight hierarchical grid monitoring tools.

We plan to package and distribute much of this work in the near future.

Acknowledgments

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