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Efficient statistical mapping of energy surfaces of nanoclusters and molecules

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8 Abstract

9 A statistical technique to efficiently map out the energy surfaces of nanoclusters and molecules is described. Global
10 energy minimizations are performed to reach of the catchment basins of the lowest energy stationary points. Saddle
11 points are located by using a large value of the iterative energy change as the stopping criterion of a final local re-
12 laxation. Minima are derived from saddle points by simply tightening the stopping criterion and continuing the re-
13 laxation. A statistical approximation to the widths of the paths in phase space between saddle points and minima is
14 obtained. Application is made to argon clusters of 7 and 38 atoms.

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17 1. Introduction

18 Understanding the dynamical behavior of small
19 clusters of atoms and molecules in nonzero tem-
20 perature environments is indispensable to their
21 eventual utility in nano-chemical, nano-electronic,
22 and nano-optic applications [1,2]. Equilibrium
23 molecular dynamics is normally employed to
24 model the thermodynamical behavior of an en-
25 semble of such systems by employing the ergodic
26 hypothesis. However, a time averaged, or even an
27 ensemble description is not very useful for pre-
28 dicting the time local dynamical behavior of a
29 single nanocluster or molecule. Such behavior can

only be obtained by knowing the initial state and
by detailing the local free energy surface of the
system in the neighborhood of that state. Fur-
thermore, molecular dynamics cannot readily
identify particular reaction paths, these can only
be delineated by directly mapping the topography
of the energy surface.

Even if the interest is in the average behavior
of an ensemble in thermodynamic equilibrium,
calculation of the forces in molecular dynamics is
computationally expensive, and it can be expected
that a typical trajectory, even for small clusters,
will only visit a small fraction of the allowed
phase space, making a poor approximation to
ergodicity. The need for statistically based meth-
ods to characterize the potential energy surface
for large systems has been previously emphasized
[3,4].

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48 Periodic quenching along molecular dynamic
49 traces to find minima, and eigenvector following to
50 find associated saddle points, has been the tech-
51 nique of choice to statistically map out potential
52 energy surfaces [5–8]. This technique samples effi-
53 ciently the potential energy minima and some of
54 the lowest energy connecting saddle points, there-
55 by allowing construction of ‘disconnectivity
56 graphs’ [9–11] which characterize the global nature
57 of the energy surface. However, this method does
58 not provide a very detailed map of the lowest en-
59 ergy topography, since, for reasons of computa-
60 tional economy, normally only the path
61 determined by the smallest positive eigenvalue of
62 the Hessian, evaluated at the minimum, is ex-
63 plored. All other paths available from one given
64 minimum to another are usually ignored. The re-
65 sulting map is thus only a skeleton of the real
66 multi-dimensional topography, defining the path
67 of likely least activation energy. Even in excep-
68 tional cases where all of the saddle points are ob-
69 tained [12], information needed for describing the
70 dynamics or thermodynamics is still lacking since
71 no measure is obtained of the widths of the paths
72 in phase space, or, in other words, of the most
73 important part of the entropic contribution to the
74 free energy.

75 Another proposed technique, also employing
76 molecular dynamics, is to raise the total energy
77 starting from a given minimum until the potential
78 energy drops below this minimum. Quenching
79 finds the second minimum, and the saddle point
80 connecting the two is then obtained by quenching
81 from the point of maximum potential energy on
82 the molecular dynamic trace using a large cutoff
83 value for the kinetic energy [13]. As with the ei-
84 genvector following approach, this method ob-
85 tains a path which may be the most probable
86 reaction path in phase space, but little information
87 is provided on the possible range of paths and their
88 probabilities and thus on the spectrum of allowed
89 dynamical behavior.

90 2. Statistical characterization of the energy surface

91 In this Letter, we present an efficient technique
92 for mapping out in detail the topography of the

lowest energy regions of the potential energy sur- 93
face. This is achieved through a statistical sam- 94
pling of the probability of passing from saddle 95
point to saddle point, or from saddle point to 96
minimum by enumerating the trajectories taken by 97
a fast conjugate gradient local relaxation, once an 98
effective global search has put the system within 99
reach of the lowest energy saddle points and 100
minima. Saddle points are located by using a large 101
value of the relative energy change per iteration, 102
 $|\Delta V/V|$, as the convergence criterion of the local 103
relaxation. Minima are obtained from saddle 104
points by simply tightening the criterion for con- 105
vergence and continuing the relaxation. Saddle 106
points can be obtained from saddle points by 107
tightening the convergence criterion and relaxing it 108
once again if the potential energy has decreased by 109
more than a few percent. The relative volume in 110
phase space of the attraction basin associated to a 111
particular minimum or saddle point at the site of a 112
saddle point can thus be statistically estimated and 113
probabilities for reaction paths assigned. No cal- 114
culation of the forces in the global relaxation, nor 115
of the Hessian in the local search, is required. With 116
moderate computational resources, the low-energy 117
regions of systems of up to approximately 100 118
atoms can be routinely mapped out (with some- 119
what lower efficiency for short range potentials 120
since these give a more complex energy surface 121
[14]). 122

As a demonstration of this technique, we pres- 123
ent the topography mapping of the potential en- 124
ergy surface of argon clusters of 7 and 38 atoms, 125
modeled with a Lennard–Jones (LJ) potential of 126
form 127

$$V = \sum_{i < j} 4\epsilon \left[\left(\frac{\sigma}{r_{ij}} \right)^{12} - \left(\frac{\sigma}{r_{ij}} \right)^6 \right], \quad (1)$$

with $\sigma = 3.4 \text{ \AA}$ and $\epsilon = 1.671 \times 10^{-14} \text{ erg}$ [7]. The 129
potential energy surface of this system has been 130
studied through the conventional technique of 131
molecular dynamics and eigenvector following 132
[7,11–13,15–18]. It is known that, within the LJ 133
model, Ar_7 has four minima and at least 838 134
saddle points [12]. The low-energy minima and 135
their connections through the lowest energy saddle 136
points for Ar_7 have been enumerated by Wales and 137

138 Berry [7] through the eigenvector following meth-
139 od, providing a convenient check of our proposed
140 technique. Ar_{38} has a much more complicated
141 potential energy surface topography due to the
142 larger number of degrees of freedom. The global
143 minimum is known to be a truncated octahedron
144 fcc structure but an icosahedral structure is almost
145 degenerate in energy and has a much larger
146 catchment basin accessible from higher energy
147 [15]. Ar_{38} is presented here as a demonstration of
148 the efficiency of the proposed technique and of the
149 detail in the topography map which can be ob-
150 tained.

151 Our technique employs a hybrid algorithm
152 consisting of a global, 'symbiotic' variant [19] of
153 the genetic algorithm [20], followed by a local
154 conjugate gradient relaxation [21]. The conjugate
155 gradient relaxation (analogous to fast quenching
156 in the molecular dynamics scheme) is initiated if,
157 after a fixed number of generations of the global
158 genetic optimization, the lowest energy obtained
159 for the system has not changed [19]. Since the in-
160 terest is normally in the lowest energy minima and
161 saddle points, those with significant representation
162 at 300 K for example, for large systems the search
163 algorithm can be tuned to find only these sta-
164 tionary points by prolonging the global part of the

165 search. However, for the case of Ar_7 where the
166 system is relatively small, and to demonstrate the
167 completeness of our approach, we tune the algo-
168 rithm to find also higher energy stationary points.

169 The distribution in energy of stationary points,
170 and the number of times each was found in 860 000
171 distinct runs of the global algorithm for Ar_7 is
172 plotted in Fig. 1. In section (a) of the figure, the
173 convergence criterion, $\lambda \equiv |\Delta V/V|$, for stopping
174 the conjugate gradient refinement was set very
175 tight, $\lambda = 10^{-12}$ per iteration, meaning, as ex-
176 plained below, that the stationary points repre-
177 sented in large numbers in Fig. 1a are minima. For
178 example, explicit calculation of the Hessian reveals
179 that of the 55 points plotted in Fig. 1a only the
180 four lowest energy points are minima (as found in
181 [7]), the other 51 points corresponding to saddle
182 points, inflexion points, or partial cluster minima
183 with less than 7 atoms (for example, the spike at
184 -0.207×10^{-12} erg corresponds to the octahedral
185 global minimum of Ar_6 plus 1 atom at a large
186 distance).

187 The novelty of the approach presented here is
188 that the ratio of finding saddles to finding minima
189 may be increased by increasing the value of the
190 convergence criterion λ . Section (b) of Fig. 1
191 corresponds to the results of the runs with the

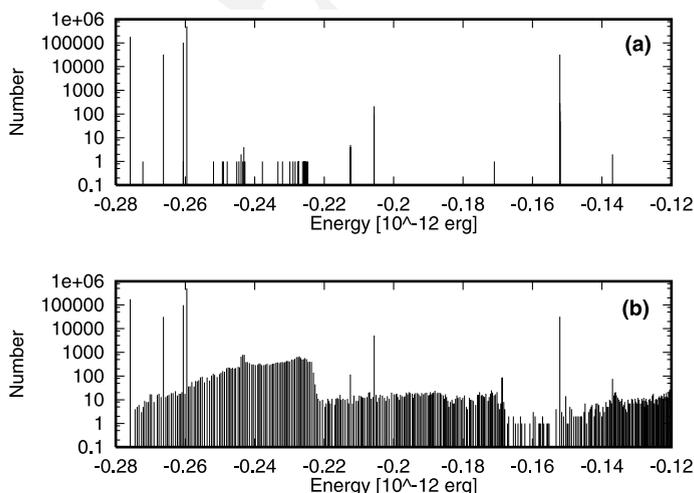


Fig. 1. (a) Energy distribution of the stationary points found for Ar_7 in 860 000 runs of the algorithm using a tight convergence criteria of $\lambda = 10^{-12}$. (b) The same but for $\lambda = 10^{-8}$, showing that the algorithm converges more often on points which are not minima (many of which are saddle points). The number of times the point was found is plotted with logarithmic scale on the y-axis.

192 same initial conditions but with the convergence
193 criterion set loose at $\lambda = 10^{-8}$. The algorithm now
194 converges with greater probability on stationary
195 points which are not minima. Explicit calculation
196 of the Hessian of 80 points chosen at random from
197 the distribution shows that roughly 64% of these
198 are saddle points, 11% are inflexion like points or
199 shallow valleys, while the rest correspond to min-
200 ima of less than 7 atoms, saddles of minima of less
201 than 7 atoms, and minima of 7 atoms. The in-
202 creased probability of converging on a saddle
203 point when using a larger value of λ is due to the
204 fact that the implementation of the conjugate
205 gradient minimization is necessarily discrete.
206 Therefore, unless the discrete displacement in
207 configuration space is in the direction of the ei-
208 genvector corresponding to an eigenvalue of the
209 Hessian which is negative, i.e., on the concave
210 downward part of the saddle, a larger value of λ
211 leads to a higher probability that the algorithm
212 will converge if the search is in the immediate
213 neighborhood of the saddle point. This probability
214 is related to the number of positive eigenvalues of
215 the Hessian at the saddle point and to the inverse
216 of the magnitudes of these. The convergence
217 probability will be greater for conjugate gradient
218 minimizations than for steepest decent methods
219 which tend to follow directly the eigenvectors
220 corresponding to large negative eigenvalues.

221 Making the convergence criteria too large leads
222 to preferential convergence on neither a minimum
223 nor a saddle point, but somewhere else, for ex-
224 ample, at some point in the basin of a shallow
225 valley or at an inflexion like point. Although such
226 topographical features clearly play an important
227 role in the dynamics, the immediate interest of this
228 Letter is to locate either saddle points or minima.
229 The optimal is thus to converge on as many true
230 low-energy saddle points as possible while at the
231 same time avoid converging elsewhere. A value of
232 $\lambda = 10^{-8}$ was empirically determined for the LJ
233 potential, and for the cluster sizes presented here,
234 to provide the best compromise in this sense. This
235 rather tight stopping criteria eliminates the possi-
236 bility of stopping on all slopes which are not al-
237 most zero on the potential energy surface. To
238 eliminate inflexion like points from the sample, we
239 require that the stationary point connects directly

240 at least two distinct minima. Finally, we require
241 that the stationary point–minima connections are
242 found at least three or more times for Ar_7 , and at
243 least two or more times for Ar_{38} where the statis-
244 tics are less. Since each run of the algorithm is
245 from a different initial configuration, it is im-
246 probable that the algorithm will converge at the
247 same point in energy within a shallow valley in
248 distinct runs. However, the probability of con-
249 verging at the same point will be much higher if the
250 algorithm is lead to that point by the curvature of
251 the potential energy surface, as in the case of true
252 saddle points. These three saddle point selection
253 criteria eliminate, to a great extent, spurious,
254 shallow valley and inflexion like points.

255 The algorithm is thus first run with $\lambda = 10^{-8}$,
256 and, after recording the energy at which the al-
257 gorithm converges (with significant probability on
258 a saddle point), changing the value of λ to 10^{-12}
259 and continuing the optimization. This convergence
260 criterion is almost always sufficient to allow the
261 discrete search to leave the saddle point. If the
262 potential energy then drops by more than 2%, λ is
263 again changed to 10^{-8} , allowing for the possibility
264 of convergence on a second, lower energy saddle
265 point. The process is repeated until the conjugate
266 gradient code converges finally, with $\lambda = 10^{-12}$, on
267 what must be a local minimum. Since the algo-
268 rithm is efficient and can be run hundreds of
269 thousands, or millions, of times, each starting from
270 a distinct random initial configuration of the at-
271 oms, statistics are accumulated concerning the
272 widths of paths in phase space leading from sad-
273 dles to minima, or saddle points to saddle points.
274 The same saddle point may be found on the route
275 to various different minima. The reconstructed
276 energy surface thus consists of not only the inter-
277 connections between saddle points and between
278 saddle points and minima, but also probabilities
279 associated to these reaction paths. To the extent to
280 which the conjugate gradient relaxation is similar
281 to the relaxation approach taken by Nature, the
282 calculated probabilities provide an approximation
283 to the real attraction basin widths in phase space.
284 It is noted that here we are moving over a surface
285 defined by an empirical potential fitted to experi-
286 mental data rather than by a quantum first prin-
287 ciples calculation incorporating all relevant

288 degrees of freedom. However, notwithstanding
289 the much larger CPU costs involved in the latter,
290 the method is applicable to both approaches.

291 The detail in the potential energy surface for
292 Ar₇ can be surmised from Fig. 2 which plots the
293 minima, saddle points, and their interconnections
294 (saddle point to saddle point connections are not
295 shown). The connection of a saddle point to a
296 minimum is drawn only if the point was found to
297 connect at least two minima and only if the the
298 connection was found three or more times. Min-
299 ima were considered to be the same if their ener-
300 gies were within 0.00001×10^{-12} erg and saddle
301 points were considered to be the same if their en-
302 ergies were within $.0003 \times 10^{-12}$ erg. In Fig. 2, the
303 horizontal and vertical positions of the minima

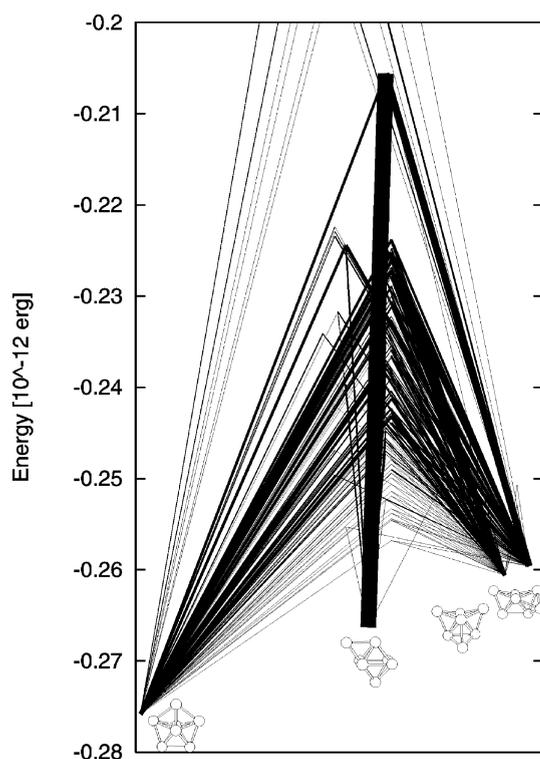


Fig. 2. Plot of saddle points and connections to minima for Ar₇. The saddle points were obtained with a convergence criterion $\lambda = 10^{-8}$ while the minima were obtained with $\lambda = 10^{-12}$. Only saddle points which connect at least two minima, and only connections obtained at least three times are plotted. The thickness of the connecting lines is proportional to the number of times the connection was found.

304 correspond to their actual energies. The vertical
305 positions of the saddle points correspond to their
306 actual energies while the horizontal positions were
307 taken to be at the center of the distribution in
308 energy of all the minima they connect. The width
309 of the connecting lines in the figure is drawn pro-
310 portional to the number of times the connection
311 was found, and represents an approximation to
312 phase space widths. In total, 305 saddle points
313 connecting directly two or more minima, and
314 found three or more times, are shown in the figure.
315 We did not find any points in Fig. 2 which were
316 not either saddle points, or minima of 6 atoms
317 with one atom at a large distance.

Note that the lowest energy saddles connect
318 isomer 1 with isomers 3 and 4, and not with isomer
319 2. The number of saddle points which connect
320 more than two minima is substantial, and these
321 connect isomer 1 with isomers 3 and 4. Note that
322 isomer 2, which is the capped octahedron, is fed
323 only substantially from the Ar₆ octahedron plus
324 one atom (energy -0.207×10^{-12}). Even though
325 such a point is not a traditional saddle point,
326 neither is it an inflexion point (since the potential
327 energy surface is asymptotically flat in the config-
328 uration coordinates of the single atom) nor a
329 shallow valley (since it connects in fact three dis-
330 tinct minima directly). Its delineation, however, is
331 important to the thermodynamics of the system.
332 For example, it predicts that the capped octahe-
333 dron will be stable with respect to thermal excita-
334 tion since the only reaction path of substantial
335 phase space volume consists of essential evapora-
336 tion of the capping atom (occurring at a rather
337 high total energy, or temperature).
338

339 For Ar₃₈, 100 000 runs of the algorithm were
340 performed. Here, in order to obtain good statistics
341 for the different paths leading to the very lowest
342 energy minima, the results of the global optimi-
343 zation are augmented by a factor of 10 by applying
344 light, stochastic perturbations, 'shakes', of the low-
345 energy configurations found. Local optimization,
346 with the conjugate gradient relaxation, then pro-
347 ceeds for each shake in the same manner as de-
348 scribed above. In Fig. 3 only those saddles which
349 connect at least two minima of low energy
350 ($< -2.83 \times 10^{-12}$ erg), and found two or more
351 times, are shown (4803 saddle to minima connec-

6

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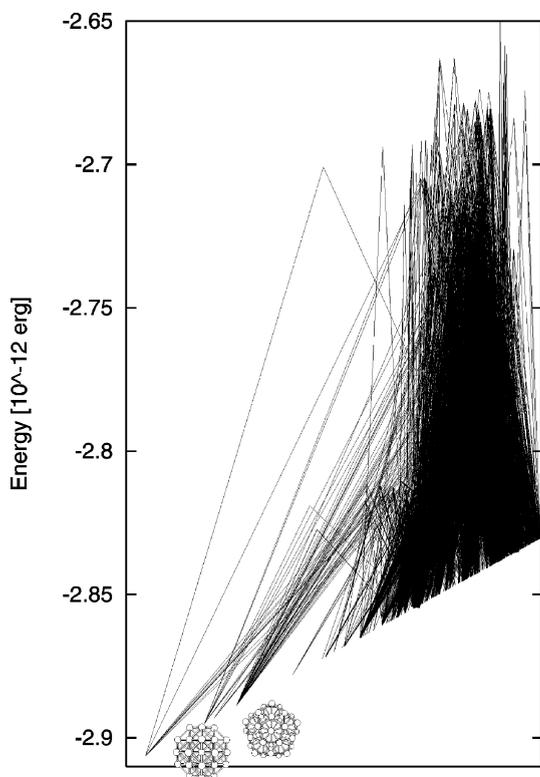


Fig. 3. The same as for Fig. 2 but for Ar_{38} . Only saddle points which connect at least two minima with energies below -2.83×10^{-12} erg, and which were obtained two or more times, are plotted.

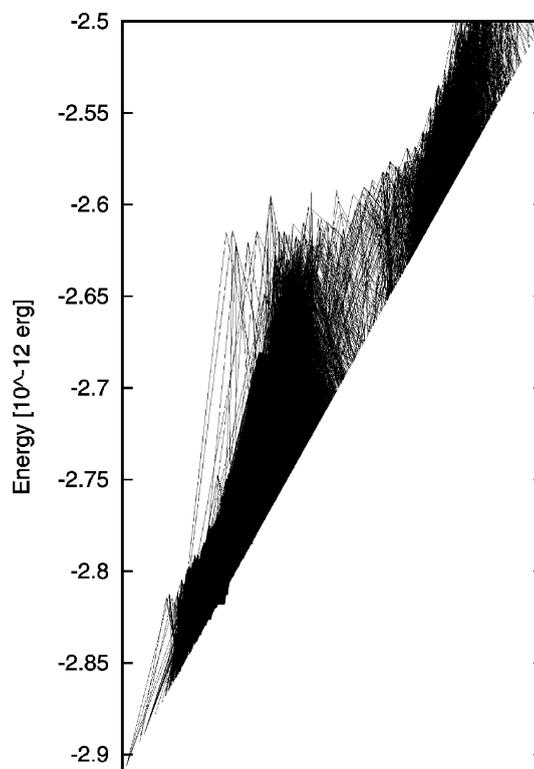


Fig. 4. Saddle point-minima connections found three or more times for Ar_{38} . The width of the lines is proportional to the number of times the connection was found.

352 tions in total). Note that information used in
353 plotting the figure is, for example, sufficient to
354 delineate the reaction paths between the global
355 minimum fcc and icosahedral isomers, and, addi-
356 tionally, to obtain an approximation of the phase
357 space widths of these paths. In Fig. 4, all of the
358 saddle to minima connections for Ar_{38} , found
359 more than three times, are shown. This figure in-
360 cludes more than 35,780 of the lowest energy
361 saddle to minima connections.

362 3. Discussion and conclusions

363 Energy surface maps such as the ones given in
364 Figs. 2-4 contain sufficient information to deter-
365 mine the dynamics and thermodynamics of these
366 finite systems at finite temperature. For example,

367 transition rates between isomers in equilibrium can
368 be estimated from the energies of the minima and
369 connecting saddle points, and a measure of the
370 phase space volume of the local potential wells and
371 saddle points [22]. The volume is usually obtained
372 through calculation of the 'curvature' of the po-
373 tential energy surface, obtained from the determi-
374 nant of the Hessian of the potential energy
375 function [22] evaluated at the minimum. Such a
376 description, however, is not very accurate since the
377 curvature at the site of the minimum is not the
378 curvature of the potential energy surface near the
379 saddle point. The statistical approach of enumer-
380 ating trajectories better approximates the phase
381 space volume of the actual path from a saddle to a
382 minimum. All reaction paths along with their re-
383 spective probability weights can be considered in
384 the calculation of the transition rate. Such phase
385 space volumes are also adequate for understanding

386 out of equilibrium processes such as relaxation or
387 nucleation, processes from high to low potential
388 energies. Explicit use of our topography maps to
389 predict the dynamics and thermodynamics of na-
390 noclusters will be the subject of a forthcoming
391 paper.

392 We have presented a very simple and efficient
393 technique for determining the low-energy topog-
394 raphy of the potential energy surface of molecules
395 and nanoclusters. The technique employs an effi-
396 cient global algorithm, combined with stochastic
397 perturbation, which reaches the lowest energy re-
398 gions of the potential energy surface, and an iter-
399 ative conjugate gradient local relaxation which can
400 be biased to converge in the neighborhood of a
401 saddle point by setting the convergence criterion
402 loose enough. The technique not only finds the
403 connections between saddle points and minima, or
404 between saddle points and saddle points, but also
405 approximates the phase space volumes of these
406 paths through statistical sampling.

407 The approach represents a considerable im-
408 provement over eigenvector following techniques
409 in the sense of being more efficient in the deter-
410 mination of the low-energy topography of the
411 energy surface, and of providing widths for the
412 paths in phase space. Most of the reaction paths
413 leading from one low-energy minimum to another
414 can be found and characterized, leading to an ac-
415 curate determination of the dynamical or ther-
416 modynamical behavior of clusters or molecules, in
417 or out of equilibrium.

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