# BCR Work-Precision Diagrams

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The following benchmark is of a 1122 ODEs with 24388 terms that describe a stiff chemical reaction network.

```
using ReactionNetworkImporters, OrdinaryDiffEq, DiffEqBiological,
      Sundials, Plots, DiffEqDevTools, ODEInterface, ODEInterfaceDiffEq,
      LSODA, TimerOutputs
gr()
prnbng = loadrxnetwork(BNGNetwork(), "BNGRepressilator",
joinpath(dirname(pathof(ReactionNetworkImporters)),"..","data","bcr","bcr.net"))
Parsing parameters...done
Adding parameters...done
Parsing species...done
Adding species...done
Parsing and adding reactions...done
Parsing groups...done
rn = deepcopy(prnbng.rn)
addodes!(rn; build_jac=false, build_symfuncs=false, build_paramjac=false)
tf = 100000.0
oprob = ODEProblem(rn, prnbng.u_0, (0.,tf), prnbng.p);
densejac_rn = deepcopy(prnbng.rn)
# zeroout_jac=true is needed to keep the generated expressions from being too big for
the compiler
addodes!(densejac_rn; build_jac=true, zeroout_jac = true, sparse_jac = false,
build_symfuncs=false, build_paramjac=false)
densejacprob = ODEProblem(densejac_rn, prnbng.u_0, (0.,tf), prnbng.p);
sparsejac_rn = deepcopy(prnbng.rn)
addodes!(sparsejac_rn; build_jac=true, sparse_jac = true, build_symfuncs=false,
build_paramjac=false)
sparsejacprob = ODEProblem(sparsejac_rn, prnbng.u_0, (0.,tf), prnbng.p);
Oshow numspecies(rn) # Number of ODEs
numspecies(rn) = 1122
Oshow numreactions(rn) # Apprx. number of terms in the ODE
numreactions(rn) = 24388
Oshow numparams (rn) # Number of Parameters
numparams(rn) = 128
128
```

## 0.1 Time ODE derivative function compilation

As compiling the ODE derivative functions has in the past taken longer than running a simulation, we first force compilation by evaluating these functions one time.

```
const to = TimerOutput()
u_0 = prnbng.u_0
u = copy(u_0);
du = similar(u);
p = prnbng.p
@timeit to "ODERHS Eval1" rn.f(du,u,p,0.)
@timeit to "ODERHS Eval2" rn.f(du,u,p,0.)
sparsejac_rn.f(du,u,p,0.)

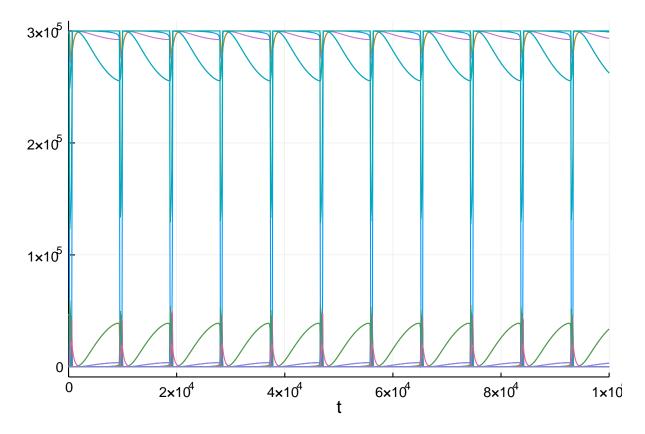
J = zeros(length(u),length(u))
@timeit to "DenseJac Eval1" densejac_rn.jac(J,u,p,0.)
@timeit to "DenseJac Eval2" densejac_rn.jac(J,u,p,0.)

Js = similar(sparsejac_rn.odefun.jac_prototype)
@timeit to "SparseJac Eval1" sparsejac_rn.jac(Js,u,p,0.)
@timeit to "SparseJac Eval2" sparsejac_rn.jac(Js,u,p,0.)
show(to)
```

		Time			Allocations		
Tot / % measured:		156s / 85.5%			17.1GiB / 80.6%		
Section	ncalls	time	%tot	avg	alloc	%tot	avg
DenseJac Eval1	1	64.6s	48.6%	64.6s	5.27GiB	38.3%	5.27GiB
SparseJac Eval1	1	46.0s	34.6%	46.0s	5.21GiB	37.8%	5.21GiB
ODERHS Eval1	1	22.4s	16.9%	22.4s	3.30GiB	23.9%	3.30GiB
DenseJac Eval2	1	$572 \mu  extsf{s}$	0.00%	$572 \mu  exttt{s}$	32.0B	0.00%	32.0B
SparseJac Eval2	1	50.7 $\mu$ s	0.00%	$50.7 \mu  exttt{s}$	32.0B	0.00%	32.0B
ODERHS Eval2	1	39.2 $\mu$ s	0.00%	$39.2 \mu  extsf{s}$	32.0B	0.00%	32.0B

## 0.2 Picture of the solution

```
sol = solve(oprob, CVODE_BDF(), saveat=tf/1000., reltol=1e-5, abstol=1e-5)
plot(sol,legend=false, fmt=:png)
```



For these benchmarks we will be using the timeseries error with these saving points since the final time point is not well-indicative of the solution behavior (capturing the oscillation is the key!).

### 0.3 Generate Test Solution

Dict(:alg=>CVODE\_BDF()),
#Dict(:alg=>rodas()),
#Dict(:alg=>radau()),

#Dict(:alg=>lsoda()),

#Dict(:alg=>Rodas4(autodiff=false)),
#Dict(:alg=>Rodas5(autodiff=false)),
Dict(:alg=>KenCarp4(autodiff=false)),
#Dict(:alg=>RadauIIA5(autodiff=false)),

```
@time sol = solve(oprob,CVODE_BDF(),abstol=1/10^12,reltol=1/10^12)
598.747572 seconds (5.55 M allocations: 2.225 GiB, 0.28% gc time)
test_sol = TestSolution(sol)
retcode: Success
Interpolation: 3rd order Hermite
t: nothing
u: nothing

0.4 Setups
abstols = 1.0 ./ 10.0 .^ (5:8)
reltols = 1.0 ./ 10.0 .^ (5:8);
setups = [
    #Dict(:alg=>Rosenbrock23(autodiff=false)),
    Dict(:alg=>TRBDF2(autodiff=false)),
```

3-element Array{Dict{Symbol,V} where V,1}:

Dict(:alg => OrdinaryDiffEq.TRBDF2{0,false,DiffEqBase.DefaultLinSolve,DiffEqBase.NLNewton{Rational{Int64},Rational{Int64}},DataType}(DiffEqBase.DefaultLinSolve(nothing, nothing), DiffEqBase.NLNewton{Rational{Int64},Rational{Int64}},Rational{Int64},Rational{Int64}}(1//100, 10, 1//5, 1//5), Val{:forward}, true, :linear, :PI))

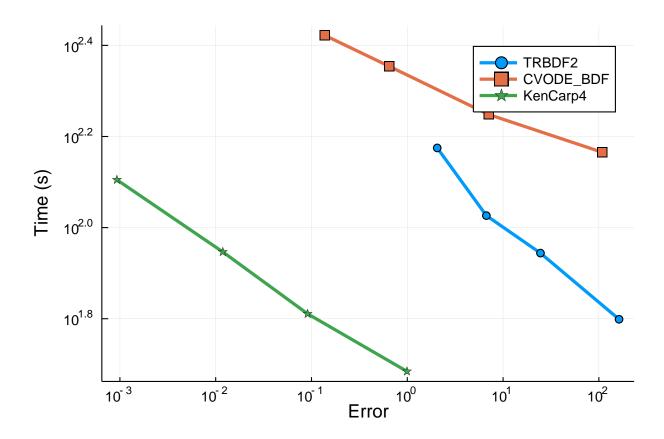
Dict(:alg => Sundials.CVODE\_BDF{:Newton,:Dense,Nothing,Nothing}(0, 0, 0, 0
, false, 10, 5, 7, 3, 10, nothing, nothing, 0))

Dict(:alg => OrdinaryDiffEq.KenCarp4{0,false,DiffEqBase.DefaultLinSolve,DiffEqBase.NLNewton{Rational{Int64},Rational{Int64}},DataType}(DiffEqBase.DefaultLinSolve(nothing, nothing), DiffEqBase.NLNewton{Rational{Int64},Rational{Int64}},(1//100, 10, 1//5, 1//5), Val{:forward}, true, :linear, :PI))

## 0.5 Automatic Jacobian Solves

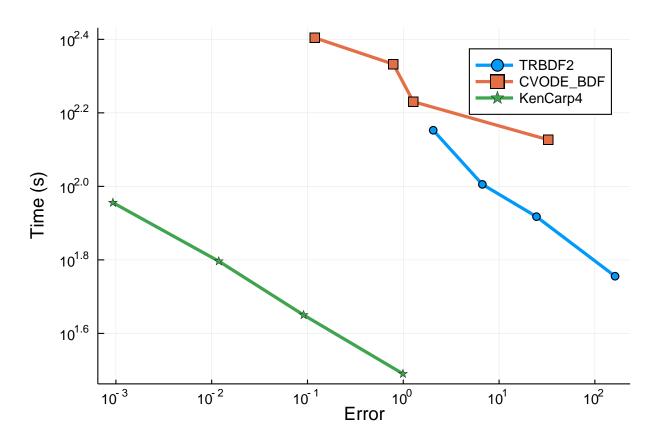
Due to the computational cost of the problem, we are only going to focus on the methods which demonstrated computational efficiency on the smaller biochemical benchmark problems. This excludes the exponential integrator, stabilized explicit, and extrapolation classes of methods.

First we test using auto-generated Jacobians (finite difference)



# 0.6 Analytical Jacobian

Now we test using the generated analytic Jacobian function.



# 0.7 Sparse Jacobian

Finally we test using the generated sparse analytic Jacobian function.

