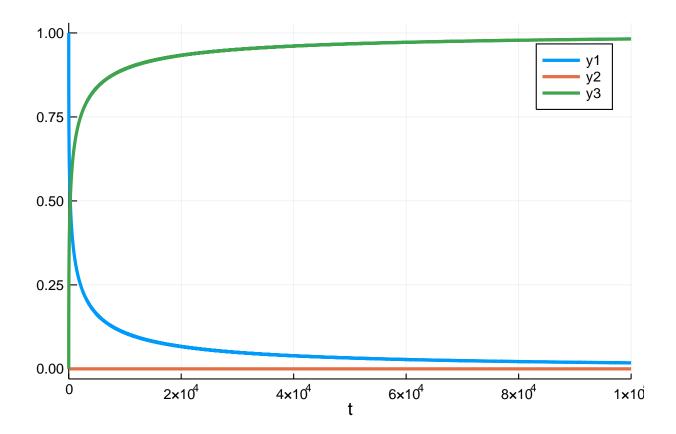
# ROBER Work-Precision Diagrams

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```
using OrdinaryDiffEq, DiffEqDevTools, Sundials, ParameterizedFunctions, Plots, ODE,
    ODEInterfaceDiffEq, LSODA
gr()
rober = @ode_def begin
 dy_1 = -k_1*y_1+k_3*y_2*y_3
 dy_2 = k_1*y_1-k_2*y_2^2-k_3*y_2*y_3
 dy_3 = k_2*y_2^2
\verb"end k\_1 k\_2 k\_3"
prob = ODEProblem(rober, [1.0,0.0,0.0], (0.0,1e5), (0.04,3e7,1e4))
sol = solve(prob,CVODE_BDF(),abstol=1/10^14,reltol=1/10^14)
test_sol = TestSolution(sol)
abstols = 1.0 ./ 10.0 .^{(4:11)}
8-element Array{Float64,1}:
 0.0001
 1.0e-5
 1.0e-6
 1.0e-7
 1.0e-8
 1.0e-9
 1.0e-10
 1.0e-11
plot(sol,labels=["y1","y2","y3"])
```



## 0.1 Omissions And Tweaking

The following were omitted from the tests due to convergence failures. ODE.jl's adaptivity is not able to stabilize its algorithms, while GeometricIntegratorsDiffEq has not upgraded to Julia 1.0. GeometricIntegrators.jl's methods used to be either fail to converge at comparable dts (or on some computers errors due to type conversions).

```
 \#sol = solve(prob,ode23s()); \ println("Total ODE.jl \ steps: \ \$(length(sol))") \\ \#using \ GeometricIntegratorsDiffEq \\ \#try \\ \#sol = solve(prob,GIRadIIA3(),dt=1/10) \\ \#catch \ e \\ \# \ println(e) \\ \#end
```

ARKODE needs a lower nonlinear\_convergence\_coefficient in order to not diverge.

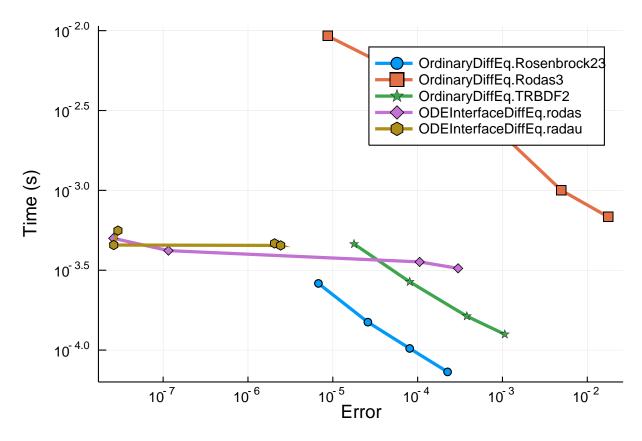
Note that 1e-7 matches the value from the Sundials manual which was required for their example to converge on this problem. The default is 1e-1.

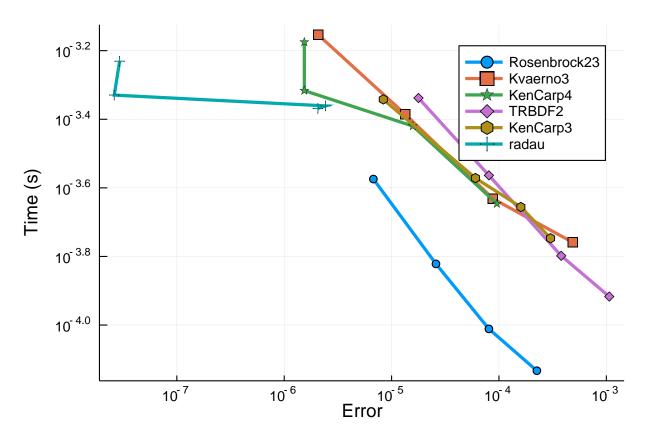
```
#sol = solve(prob,ARKODE(order=5,nonlinear_convergence_coefficient = 1e-9),abstol=1e-5,reltol=1e-1); # Noisy, output omitted
```

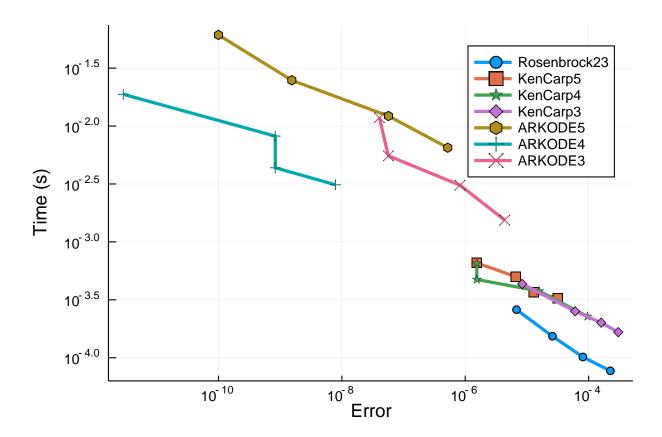
## 0.2 High Tolerances

This is the speed when you just want the answer. ode23s from ODE.jl was removed since it fails. Note that at high tolerances Sundials' CVODE\_BDF fails as well so it's excluded from this test.

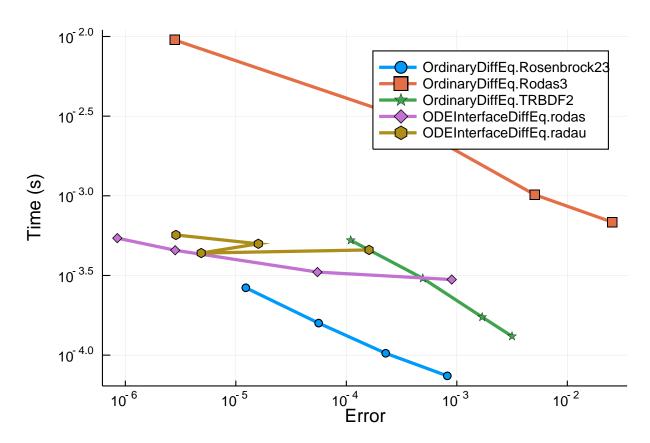
```
solve(prob, ddebdf())
solve(prob, rodas())
solve(prob, radau())
abstols = 1.0 ./ 10.0 .^ (5:8)
reltols = 1.0 ./ 10.0 .^ (1:4);
setups = [Dict(:alg=>Rosenbrock23()),
          Dict(:alg=>Rodas3()),
          Dict(:alg=>TRBDF2()),
          Dict(:alg=>rodas()),
          #Dict(:alg=>lsoda()),
          Dict(:alg=>radau())
          #Dict(:alg=>ROCK2()) #Unstable
          #Dict(:alg=>ROCK3()) #needs more iterations
gr()
wp = WorkPrecisionSet(prob,abstols,reltols,setups;
                      save_everystep=false,appxsol=test_sol,maxiters=Int(1e5),numruns=10)
plot(wp)
```

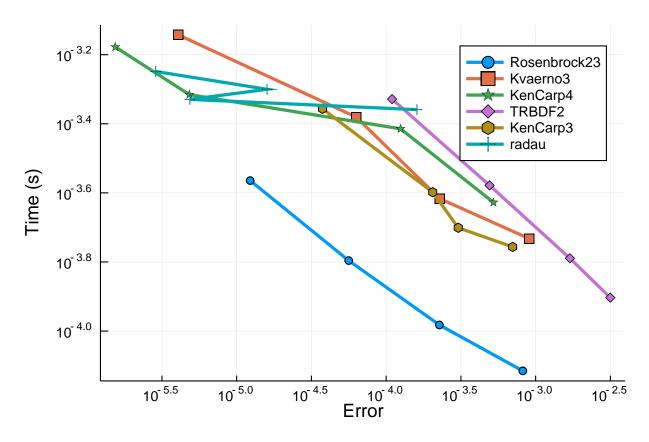






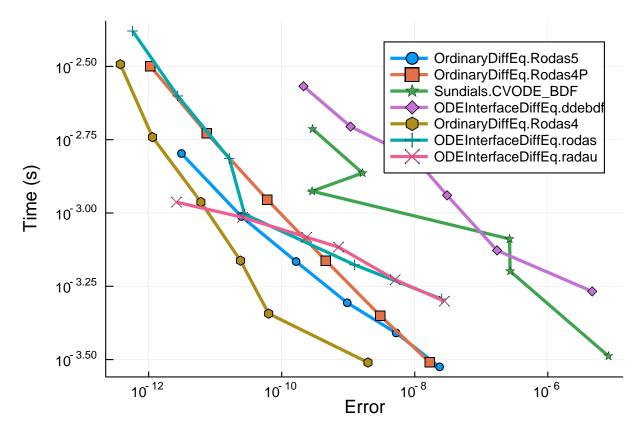
#### 0.2.1 Timeseries Errors

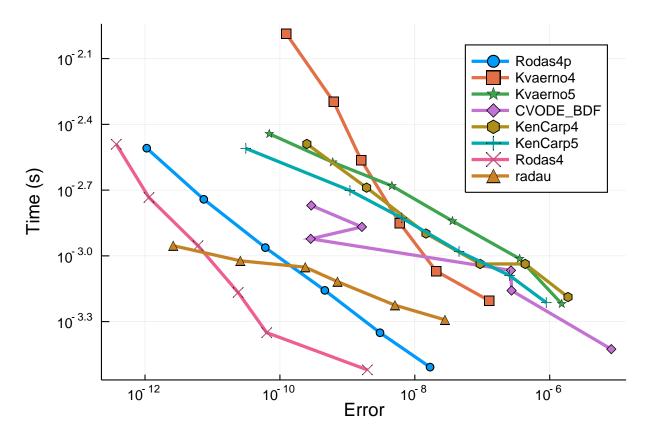


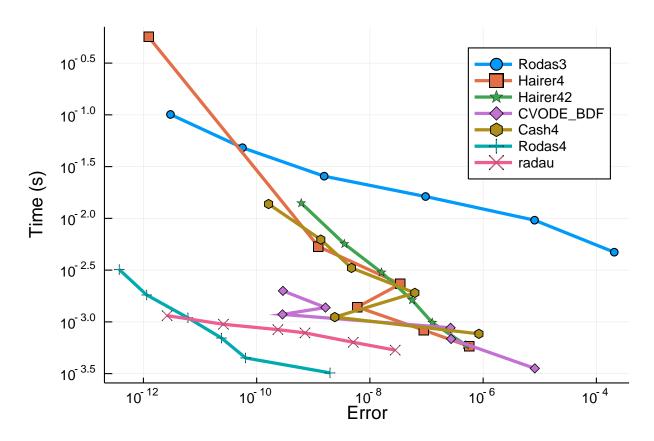


## 0.2.2 Low Tolerances

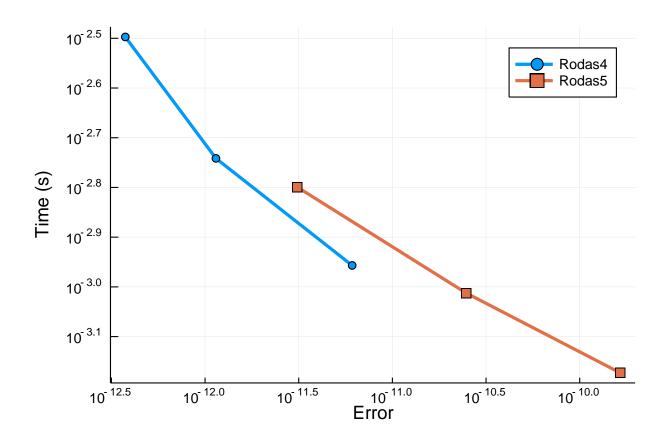
This is the speed at lower tolerances, measuring what's good when accuracy is needed.







Rodas5 requires much lower tolerances to be stable here. Even then, it does not outdo Rodas4.



#### 0.2.3 Conclusion

At high tolerances, Rosenbrock23 and lsoda hit the error estimates and are fast. At lower tolerances and normal user tolerances, Rodas4 and Rodas5 are extremely fast. lsoda does quite well across both ends. When you get down to reltol=1e-9 radau begins to become as efficient as Rodas4, and it continues to do well below that.

```
using DiffEqBenchmarks
DiffEqBenchmarks.bench_footer(WEAVE_ARGS[:folder],WEAVE_ARGS[:file])
```

# 0.3 Appendix

These benchmarks are a part of the DiffEqBenchmarks.jl repository, found at: https://github.com/JuliaDirous locally run this tutorial, do the following commands:

```
using DiffEqBenchmarks
DiffEqBenchmarks.weave file("StiffODE","ROBER.jmd")
```

Computer Information:

WORD\_SIZE: 64 LIBM: libopenlibm

LLVM: libLLVM-6.0.1 (ORCJIT, haswell)

#### Package Information:

```
Status: `/home/crackauckas/.julia/environments/v1.1/Project.toml`
[c52e3926-4ff0-5f6e-af25-54175e0327b1] Atom 0.8.7
[bcd4f6db-9728-5f36-b5f7-82caef46ccdb] DelayDiffEq 5.3.0
[bb2cbb15-79fc-5d1e-9bf1-8ae49c7c1650] DiffEqBenchmarks 0.1.0
[459566f4-90b8-5000-8ac3-15dfb0a30def] DiffEqCallbacks 2.5.2
[f3b72e0c-5b89-59e1-b016-84e28bfd966d] DiffEqDevTools 2.8.0
[aae7a2af-3d4f-5e19-a356-7da93b79d9d0] DiffEqFlux 0.5.0
[78ddff82-25fc-5f2b-89aa-309469cbf16f] DiffEqMonteCarlo 0.14.0
[77a26b50-5914-5dd7-bc55-306e6241c503] DiffEqNoiseProcess 3.3.1
[9fdde737-9c7f-55bf-ade8-46b3f136cc48] DiffEqOperators 3.5.0
[055956cb-9e8b-5191-98cc-73ae4a59e68a] DiffEqPhysics 3.1.0
[a077e3f3-b75c-5d7f-a0c6-6bc4c8ec64a9] DiffEqProblemLibrary 4.1.0
[41bf760c-e81c-5289-8e54-58b1f1f8abe2] DiffEqSensitivity 3.2.2
[Oc46a032-eb83-5123-abaf-570d42b7fbaa] DifferentialEquations 6.4.0
[b305315f-e792-5b7a-8f41-49f472929428] Elliptic 0.5.0
[587475ba-b771-5e3f-ad9e-33799f191a9c] Flux 0.8.3
[e5e0dc1b-0480-54bc-9374-aad01c23163d] Juno 0.7.0
[7f56f5a3-f504-529b-bc02-0b1fe5e64312] LSODA 0.4.0
[c030b06c-0b6d-57c2-b091-7029874bd033] ODE 2.4.0
[54ca160b-1b9f-5127-a996-1867f4bc2a2c] ODEInterface 0.4.5
[1dea7af3-3e70-54e6-95c3-0bf5283fa5ed] OrdinaryDiffEq 5.8.1
[2dcacdae-9679-587a-88bb-8b444fb7085b] ParallelDataTransfer 0.5.0
[65888b18-ceab-5e60-b2b9-181511a3b968] ParameterizedFunctions 4.1.1
[91a5bcdd-55d7-5caf-9e0b-520d859cae80] Plots 0.25.1
[d330b81b-6aea-500a-939a-2ce795aea3ee] PyPlot 2.8.1
[731186ca-8d62-57ce-b412-fbd966d074cd] RecursiveArrayTools 0.20.0
[295af30f-e4ad-537b-8983-00126c2a3abe] Revise 2.1.6
[90137ffa-7385-5640-81b9-e52037218182] StaticArrays 0.11.0
[789caeaf-c7a9-5a7d-9973-96adeb23e2a0] StochasticDiffEq 6.2.0
[c3572dad-4567-51f8-b174-8c6c989267f4] Sundials 3.6.0
[92b13dbe-c966-51a2-8445-caca9f8a7d42] TaylorIntegration 0.5.0
[44d3d7a6-8a23-5bf8-98c5-b353f8df5ec9] Weave 0.9.0
[e88e6eb3-aa80-5325-afca-941959d7151f] Zygote 0.3.1
```