

R Package **FME** : Inverse Modelling, Sensitivity, Monte Carlo – Applied to a Dynamic Simulation Model

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Abstract

Rpackage **FME** (Soetaert and Petzoldt 2010) contains functions for model calibration, sensitivity, identifiability, and Monte Carlo analysis of nonlinear models.

This vignette (`vignette("FMEdyna")`) applies the functions to a dynamic simulation model, solved with integration routines from package **deSolve**. A similar vignette, (`vignette("FMEsteady")`), applies **FME** to a partial differential equation, solved with a steady-state solver from package **rootSolve**. A third vignette (`vignette("FMEother")`), applies the functions to a simple nonlinear model. `vignette("FMEcmc")` tests the Markov chain Monte Carlo (MCMC) implementation.

Keywords: dynamic simulation models, differential equations, fitting, sensitivity, Monte Carlo, identifiability, R.

1. Introduction

R-package **FME** contains part of the functions present in the software environment **FEMME** (Soetaert, deClippele, and Herman 2002), a *Flexible Environment for Mathematically Modeling the Environment*. **FEMME** was written in FORTRAN. **FME** is – obviously – written in R.

Although **FME** can work with many types of functions, it is mainly meant to be used with models that are written as (a system of) differential equations (ordinary or partial), which are solved either with routines from package **deSolve** (Soetaert, Petzoldt, and Setzer 2010), which integrate the model in time, or from package **rootSolve** (Soetaert 2009) which estimate steady-state conditions. With **FME** it is possible to:

- perform local and global sensitivity analysis (Brun, Reichert, and Kunsch 2001; Soetaert and Herman 2009),
- perform parameter identifiability analysis (Brun *et al.* 2001),
- fit a model to data,
- run a Markov chain Monte Carlo (MCMC, Haario, Laine, Mira, and Saksman 2006).

Most of these functions have suitable methods for printing, visualising output etc. In addition, there are functions to generate parameter combinations corresponding to a certain distribution. In this document a – very quick – survey of the functionality is given, based on a simple model from (Soetaert and Herman 2009).

2. The example model

The example model describes growth of bacteria (BACT) on a substrate (SUB) in a closed vessel. The model equations are:

$$\begin{aligned}\frac{dBact}{dt} &= gmax \cdot eff \cdot \frac{Sub}{Sub + ks} \cdot Bact - d \cdot Bact - rB \cdot Bact \\ \frac{dSub}{dt} &= -gmax \cdot \frac{Sub}{Sub + ks} \cdot Bact + d \cdot Bact\end{aligned}$$

where the first, second and third term of the rate of change of **Bact** is growth of bacteria, death and respiration respectively. In R, this model is implemented and solved as follows (see help pages of **deSolve**). First the parameters are defined, as a list (a vector would also do)

```
> pars <- list(gmax = 0.5, eff = 0.5,
+             ks = 0.5, rB = 0.01, dB = 0.01)
```

The model function **solveBact** takes as input the parameters and the time sequence at which output is wanted. Within this function, **derivs** is defined, which is the *derivative* function, called at each time step by the solver. It takes as input the current time (**t**), the current values of the state variables (**state**) and the parameters (**pars**). It returns the rate of change of the state variables, packed as a list. Also within function **solveBact**, the state variables are given an initial condition (**state**) and the model is solved by integration, using function **ode** from package **deSolve**. The results of the integration are returned, packed as a data.frame.

```
> solveBact <- function(pars, times=seq(0,50,by=0.5)) {
+   derivs <- function(t,state,pars) { # returns rate of change
+     with(as.list(c(state,pars)), {
+
+       dBact = gmax*eff*Sub/(Sub+ks)*Bact - dB*Bact - rB*Bact
+       dSub  = -gmax      *Sub/(Sub+ks)*Bact + dB*Bact
+       return(list(c(dBact,dSub)))
+     })
+   }
+   state <- c(Bact = 0.1, Sub = 100)
+   ## ode solves the model by integration...
+   return(as.data.frame(ode(y=state,times=times,func=derivs,parms=pars)))
+ }
```

The model is then solved by calling **solveBact** with the default parameters:

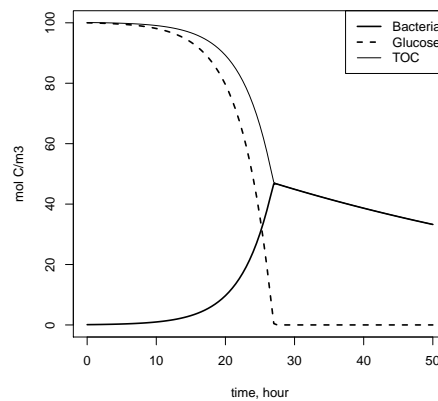


Figure 1: Solution of the simple bacterial growth model - see text for R-code

```
> out <- solveBact(pars)
```

and output plotted as:

```
> plot(out$time, out$Bact, ylim=range(c(out$Bact, out$Sub)),
+       xlab="time, hour", ylab="mol C/m3", type="l", lwd=2)
> lines(out$time, out$Sub, lty=2, lwd=2)
> lines(out$time, out$Sub+out$Bact)
> legend("topright", c("Bacteria", "Glucose", "TOC"),
+       lty=c(1, 2, 1), lwd=c(2, 2, 1))
```

3. Global sensitivity

In global sensitivity analysis, certain parameters are changed over a large range, and the effect on certain model output variables assessed. In **FME** this is done via function **sensRange**.

First the sensitivity parameters are defined and a distribution is assigned; here we specify the minimum and maximum values of three parameters in a **data.frame**:

```
> parRanges <- data.frame(min=c(0.4, 0.4, 0.0), max=c(0.6, 0.6, 0.02))
> rownames(parRanges) <- c("gmax", "eff", "rB")
> parRanges
```

	min	max
gmax	0.4	0.60
eff	0.4	0.60
rB	0.0	0.02

Then we estimate the sensitivity to one parameter, `rB` (parameter 3), varying its values according to a regular grid (`dist=grid`). The effect of that on sensitivity variables `Bact` and `Sub` are estimated. To do this, the model is run 100 times (`num=100`). The `system.time` is printed (in seconds):

```
> tout    <- 0:50
> print(system.time(
+   sR<-sensRange(func=solveBact,parms=pars,dist="grid",
+                 sensvar=c("Bact","Sub"),parRange=parRanges[3,],num=50)
+ ))
```

```
user  system elapsed
2.21   0.00   2.20
```

```
> head(summary(sR))
```

	x	Mean	Sd	Min	Max	q05	q25
Bact0	0.0	0.1000000	0.00000000000	0.1000000	0.1000000	0.1000000	0.1000000
Bact0.5	0.5	0.1121194	0.0003335405	0.1115597	0.1126809	0.1116155	0.1118390
Bact1	1.0	0.1257062	0.0007479668	0.1244532	0.1269674	0.1245777	0.1250770
Bact1.5	1.5	0.1409422	0.0012579439	0.1388384	0.1430668	0.1390468	0.1398836
Bact2	2.0	0.1580263	0.0018805072	0.1548863	0.1612075	0.1551964	0.1564430
Bact2.5	2.5	0.1771819	0.0026354918	0.1727886	0.1816476	0.1732211	0.1749620
		q50	q75	q95			
Bact0		0.1000000	0.1000000	0.1000000			
Bact0.5		0.1121189	0.1123996	0.1126246			
Bact1		0.1257040	0.1263341	0.1268405			
Bact1.5		0.1409367	0.1419978	0.1428524			
Bact2		0.1580153	0.1596034	0.1608854			
Bact2.5		0.1771627	0.1793911	0.1811941			

The results are represented as a data.frame, containing summary information of the value of the sensitivity variable (`var`) at each time step (`x`). It is relatively simple to plot the ranges, either as $\text{min} \pm \text{sd}$ or using quantiles:

```
> par(mfrow=c(2,2))
> plot(summary(sR),xlab="time, hour",ylab="molC/m3",
+       legpos="topright")
> plot(summary(sR),xlab="time, hour",ylab="molC/m3",
+       quant=TRUE,col=c("lightblue","darkblue"),legpos="topright")
> mtext(outer=TRUE,line=-1.5,side=3,"Sensitivity to rB",cex=1.25)
> par(mfrow=c(1,1))
```

Sensitivity ranges can also be estimated for a combination of parameters. Here we use all 3 parameters, and select the latin hypercube sampling algorithm.

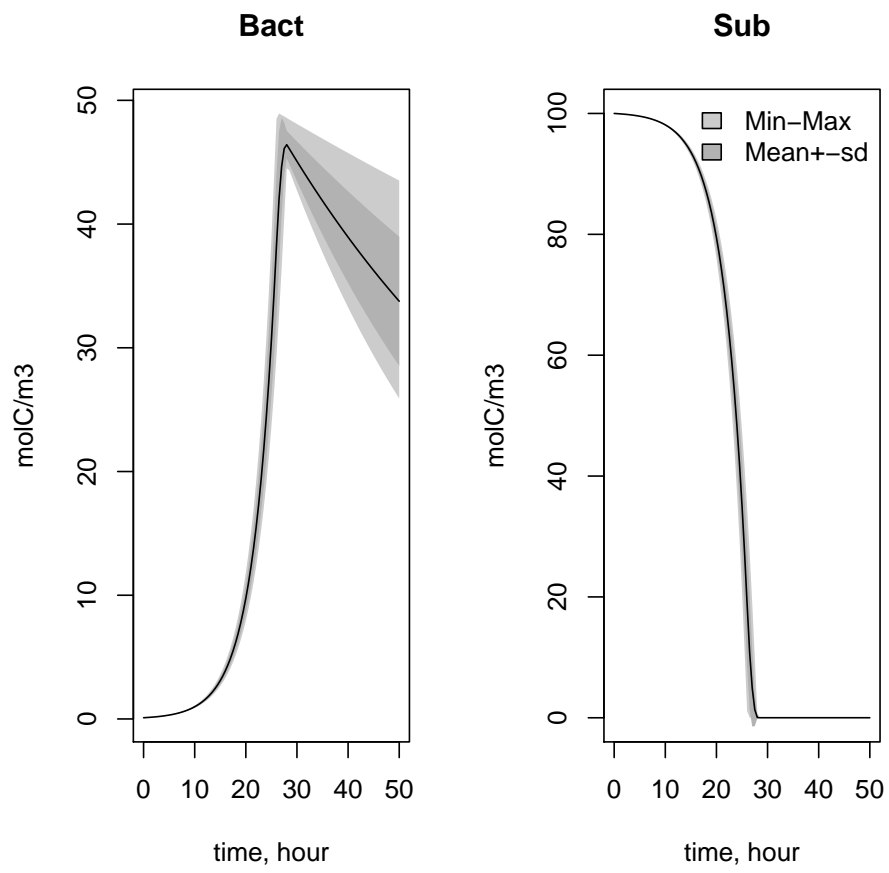


Figure 2: Sensitivity range for one parameter - see text for R-code

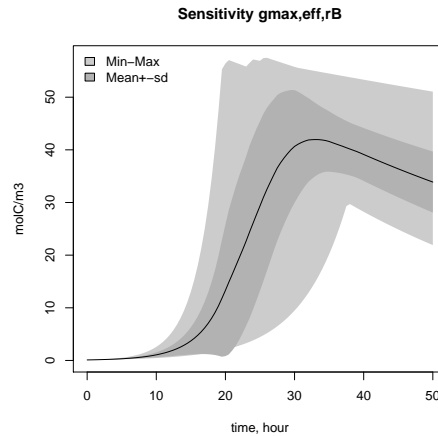


Figure 3: Sensitivity range for a combination of parameters - see text for R-code

```
> Sens2 <- summary(sensRange(func=solveBact,parms=pars,
+                           dist="latin",sensvar="Bact",parRange=parRanges,num=100))

> plot(Sens2,main="Sensitivity gmax,eff,rB",xlab="time, hour",ylab="molC/m3")
```

4. Local sensitivity

In local sensitivity, the effect of a parameter value in a very small region near its nominal value is estimated. The methods implemented in **FME** are based on [Brun *et al.* \(2001\)](#) which should be consulted for details. They are based on so-called “sensitivity functions”.

4.1. Sensitivity functions

Sensitivity functions are generated with `sensFun`, and estimate the effect of a selection of parameters (here all parameters are selected) on a selection of variables (here only `Bact`).

```
> SnsBact<- sensFun(func=solveBact,parms=pars,
+                  sensvar="Bact",varscale=1)
> head(SnsBact)
```

	x	var	gmax	eff	ks	rB	dB
1	0.0	Bact	0.00000000	0.00000000	0.0000000000	0.0000000000	0.0000000000
2	0.5	Bact	0.01394713	0.01394714	-0.0000703354	-0.000560559	-0.0005605588
3	1.0	Bact	0.03127214	0.03127218	-0.0001562084	-0.001257071	-0.0012570697
4	1.5	Bact	0.05259210	0.05259221	-0.0002623735	-0.002114135	-0.0021141330
5	2.0	Bact	0.07861787	0.07861810	-0.0003921211	-0.003160362	-0.0031603571
6	2.5	Bact	0.11017714	0.11017756	-0.0005495271	-0.004429033	-0.0044290250

They can easily be plotted (Fig. 3):

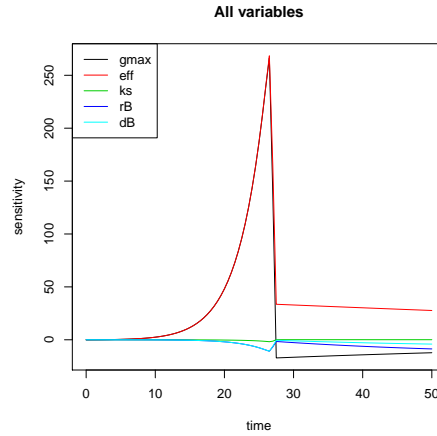


Figure 4: Sensitivity functions - see text for R-code

```
> plot(SnsBact)
```

4.2. Univariate sensitivity

Based on the sensitivity functions, several summaries are generated, which allow to rank the parameters based on their influence on the selected variables.

```
> summary(SnsBact)
```

	value	scale	L1	L2	Mean	Min	Max	N
gmax	0.50	0.50	29.51	5.859	16.2	-17.1	266.361	101
eff	0.50	0.50	37.12	6.212	37.1	0.0	268.408	101
ks	0.50	0.50	0.17	0.037	-0.1	-1.8	0.097	101
rB	0.01	0.01	3.47	0.463	-3.5	-10.8	0.000	101
dB	0.01	0.01	2.06	0.297	-2.1	-10.8	0.000	101

Here

- L1 is the L1-norm, $\sum |S_{ij}|/n$
- L2 is the L2-norm, $\sqrt{\sum (S_{ij}^2)/n}$
- Mean: the mean of the sensitivity functions
- Min: the minimal value of the sensitivity functions
- Max: the maximal value of the sensitivity functions

Sensitivity analysis can also be performed on several variables:

```
> summary(sensFun(solveBact,pars,varscale=1),var=TRUE)
```

	value	scale	L1	L2	Mean	Min	Max	N	var
gmax1	0.50	0.50	29.51	58.88	16.25	-1.7e+01	2.7e+02	101	Bact
gmax2	0.50	0.50	48.40	122.95	-48.40	-5.6e+02	0.0e+00	101	Sub
eff1	0.50	0.50	37.12	62.43	37.12	0.0e+00	2.7e+02	101	Bact
eff2	0.50	0.50	39.64	102.50	-39.64	-4.8e+02	6.8e-06	101	Sub
ks1	0.50	0.50	0.17	0.37	-0.10	-1.8e+00	9.7e-02	101	Bact
ks2	0.50	0.50	0.29	0.77	0.29	0.0e+00	3.8e+00	101	Sub
rB1	0.01	0.01	3.47	4.65	-3.47	-1.1e+01	0.0e+00	101	Bact
rB2	0.01	0.01	1.59	4.12	1.59	-2.8e-07	1.9e+01	101	Sub
dB1	0.01	0.01	2.06	2.98	-2.06	-1.1e+01	0.0e+00	101	Bact
dB2	0.01	0.01	1.78	4.54	1.78	0.0e+00	2.1e+01	101	Sub

4.3. Bivariate sensitivity

The pairwise relationships in parameter sensitivity is easily assessed by plotting the sensitivity functions using R-function `pairs`, and by calculating the correlation.

```
> cor(SnsBact[,-(1:2)])
```

	gmax	eff	ks	rB	dB
gmax	1.0000000	0.9184218	-0.9879349	-0.2602262	-0.7165956
eff	0.9184218	1.0000000	-0.9265098	-0.5575106	-0.8883636
ks	-0.9879349	-0.9265098	1.0000000	0.2878336	0.7302580
rB	-0.2602262	-0.5575106	0.2878336	1.0000000	0.8599353
dB	-0.7165956	-0.8883636	0.7302580	0.8599353	1.0000000

```
> pairs(SnsBact)
```

4.4. Monte Carlo runs

Function `modCRL` runs a Monte Carlo simulation, outputting single variables.

This is in contrast to `sensRange` which outputs vectors of variables, e.g. a time-sequence, or a spatially-dependent variable.

It can be used to test what-if scenarios. Here it is used to calculate the final concentration of bacteria and substrate as a function of the maximal growth rate.

```
> SF <- function (pars) {
+   out <- solveBact(pars)
+   return(out[nrow(out),2:3])
+ }
> CRL <- modCRL(func=SF,parms=pars,parRange=parRanges[1,])

> plot(CRL)
```

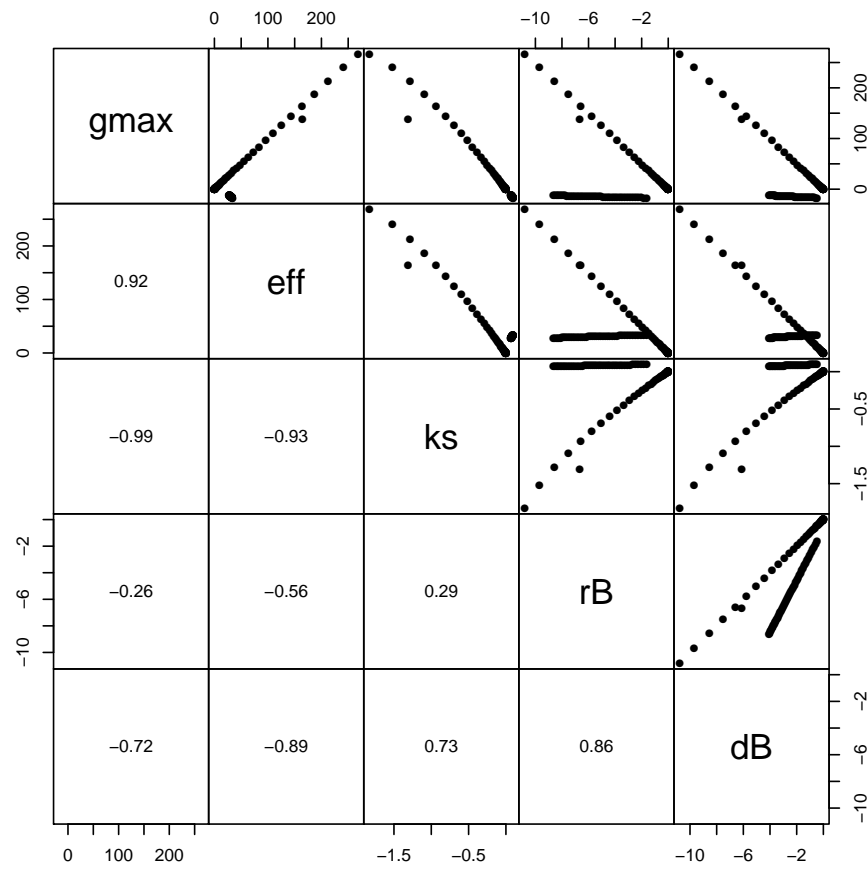



Figure 5: Pairs of sensitivity functions - see text for R-code

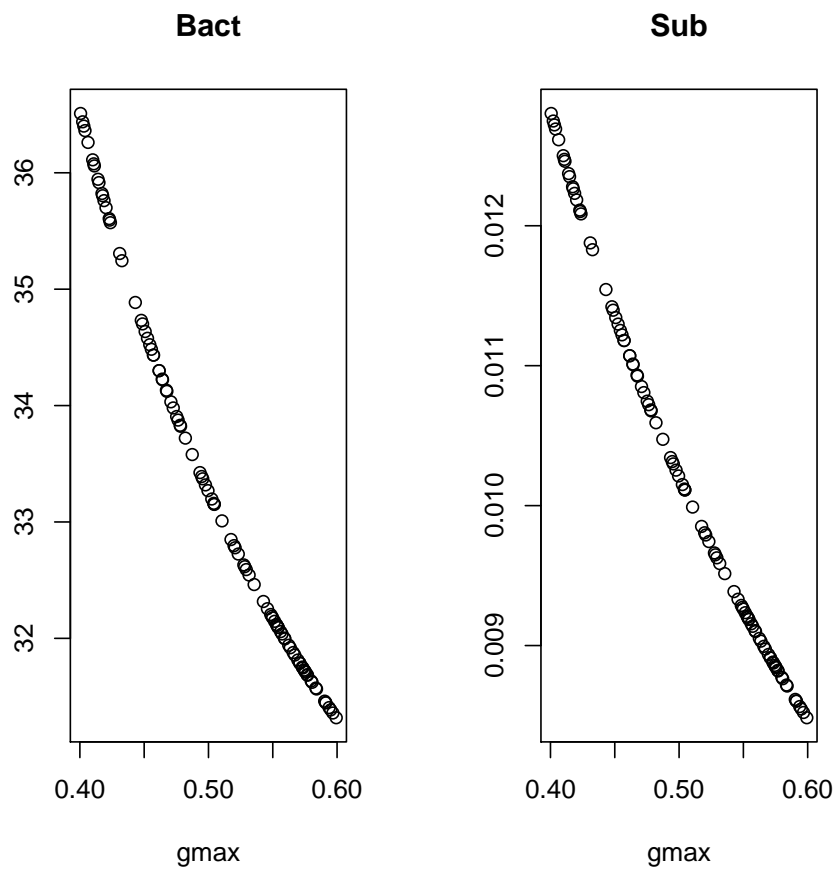


Figure 6: Monte carlo analysis - see text for R-code

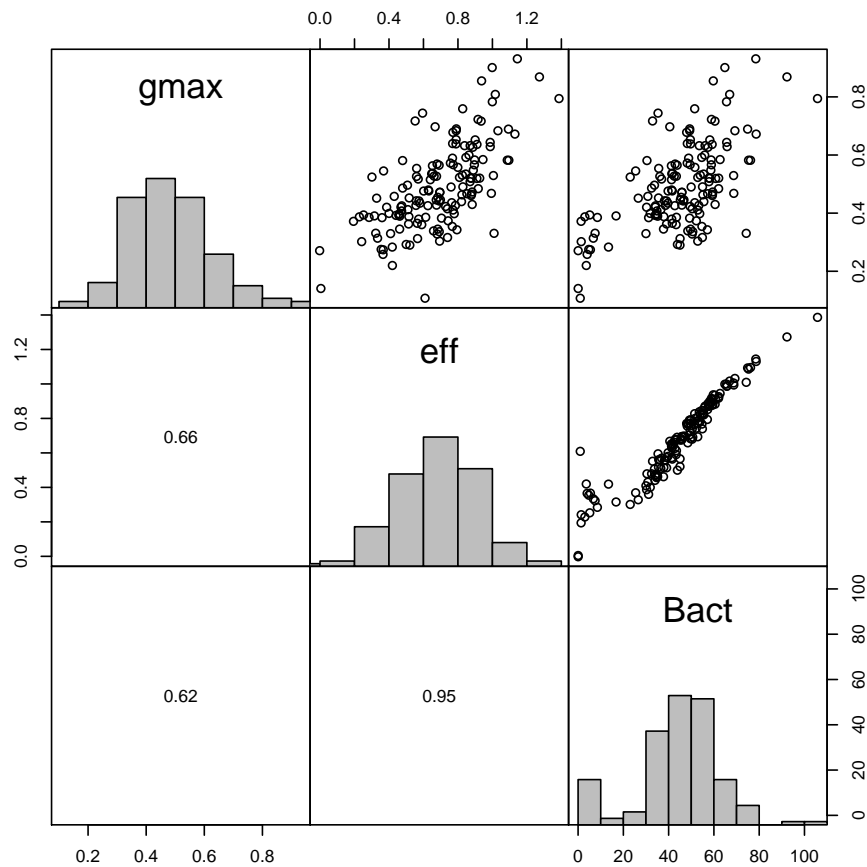


Figure 7: Multivariate Monte Carlo analysis - see text for R-code

Monte Carlo methods can also be used to see how parameter uncertainties propagate, i.e. to derive the distribution of output variables as a function of parameter distribution.

Here the effect of the parameters **gmax** and **eff** on final bacterial concentration is assessed. The parameter values are generated according to a multi-normal distribution; they are positively correlated (with a correlation = 0.63).

```
> CRL2 <- modCRL(func=SF,parms=pars,parMean=c("gmax"=0.5,"eff"=0.7),
+               parCovar=matrix(nr=2,data=c(0.02,0.02,0.02,0.05)),
+               dist="norm",sensvar="Bact",num=150)

> pairs(CRL2)
```

5. Multivariate sensitivity analysis

Based on the sensitivity functions of model variables to selection of parameters, function **collin** calculates the *collinearity* or *identifiability* of sets of parameters.

```
> Coll <- collin(SnsBact)
> Coll
```

	gmax	eff	ks	rB	dB	N	collinearity
1	1	1	0	0	0	2	2.8
2	1	0	1	0	0	2	9.5
3	1	0	0	1	0	2	1.3
4	1	0	0	0	1	2	1.8
5	0	1	1	0	0	2	2.9
6	0	1	0	1	0	2	2.0
7	0	1	0	0	1	2	3.7
8	0	0	1	1	0	2	1.3
9	0	0	1	0	1	2	1.8
10	0	0	0	1	1	2	3.8
11	1	1	1	0	0	3	9.5
12	1	1	0	1	0	3	7.0
13	1	1	0	0	1	3	6.8
14	1	0	1	1	0	3	9.5
15	1	0	1	0	1	3	9.5
16	1	0	0	1	1	3	2261.4
17	0	1	1	1	0	3	6.7
18	0	1	1	0	1	3	6.8
19	0	1	0	1	1	3	12.2
20	0	0	1	1	1	3	22.6
21	1	1	1	1	0	4	9.6
22	1	1	1	0	1	4	9.5
23	1	1	0	1	1	4	3631.3
24	1	0	1	1	1	4	3451.1
25	0	1	1	1	1	4	23.5
26	1	1	1	1	1	5	2421318.6

```
> Coll [Coll[,"collinearity"]<20&Coll[,"N"]==4,]
```

	gmax	eff	ks	rB	dB	N	collinearity
1	1	1	1	1	0	4	9.6
2	1	1	1	0	1	4	9.5

```
> collin(SnsBact,parset=1:5)
```

	gmax	eff	ks	rB	dB	N	collinearity
1	1	1	1	1	1	5	2421319

The higher the value, the larger the (approximate) linear dependence. This function is mainly useful to derive suitable parameter sets that can be calibrated based on data (see next section).

6. Fitting the model to data

6.1. Data structures

There are two modes of data input:

- *data table (long) format*; this is a two to four column `data.frame` that contains the **name** of the observed variable (always the **FIRST** column), the (optional) **value of the independent variable** (default = "time"), the **value of the observation** and the (optional) **value of the error**.
- *crosstable format*; this is a matrix, where each column denotes one dependent (or independent) variable; the column name is the name of the observed variable.

As an example of both formats consider the data, called `Dat` consisting of two observed variables, called "Obs1" and "Obs2", both containing two observations, at time 1 and 2:

name	time	val	err
Obs1	1	50	5
Obs1	2	150	15
Obs2	1	1	0.1
Obs2	2	2	0.2

for the long format and

time	Obs1	Obs2
1	50	1
2	150	2

for the crosstable format. Note, that in the latter case it is not possible to provide separate errors per data point.

6.2. The model cost function

FME function `modCost` estimates the "model cost", which the sum of (weighted) squared residuals of the model versus the data. This function is central to parameter identifiability analysis, model fitting or running a Markov chain Monte Carlo.

Assume the following model output (in a matrix or `data.frame` called `Mod`):

time	Obs1	Obs2
0	4	1
1	4	2
2	4	3
3	4	4

Then the `modCost` will give:

```
> Dat<- data.frame(name=c("Obs1","Obs1","Obs2","Obs2"),
+                  time=c(1,2,1,2),val=c(50,150,1,2),
+                  err=c(5,15,0.1,0.2))
> Mod <- Mod <- data.frame(time=0:3,Obs1=rep(4,4),Obs2=1:4)
> modCost(mod=Mod,obs=Dat,y="val")
```

```
$model
[1] 23434
```

```
$minlogp
[1] Inf
```

```
$var
  name scale N SSR.unweighted SSR.unscaled  SSR
1 Obs1     1 2          23432          23432 23432
2 Obs2     1 2              2              2    2
```

```
$residuals
  name x obs mod weight res.unweighted  res
1 Obs1 1  50  4     1          -46 -46
2 Obs1 2 150  4     1         -146 -146
3 Obs2 1   1  2     1           1  1
4 Obs2 2   2  3     1           1  1
```

```
attr("class")
[1] "modCost"
```

in case the residuals are not weighed and

```
> modCost(mod=Mod,obs=Dat,y="val",err="err")
```

```
$model
[1] 304.3778
```

```
$minlogp
[1] Inf
```

```
$var
  name scale N SSR.unweighted SSR.unscaled  SSR
1 Obs1     1 2          23432          179.3778 179.3778
2 Obs2     1 2              2          125.0000 125.0000
```

```
$residuals
  name x obs mod      weight res.unweighted  res
1 Obs1 1  50  4 0.20000000          -46 -9.200000
2 Obs1 2 150  4 0.06666667         -146 -9.733333
3 Obs2 1   1  2 10.00000000           1 10.000000
```

```
4 Obs2 2 2 3 5.00000000 1 5.000000
```

```
attr("class")
[1] "modCost"
```

in case the residuals are weighed by 1/error.

6.3. Model fitting

Assume the following data set (in crosstable (wide) format):

```
> Data <- matrix(nc=2,byrow=2,data=
+ c( 2, 0.14, 4, 0.21, 6, 0.31, 8, 0.40,
+    10, 0.69, 12, 0.97, 14, 1.42, 16, 2.0,
+    18, 3.0, 20, 4.5, 22, 6.5, 24, 9.5,
+    26, 13.5, 28, 20.5, 30, 29, 35, 65, 40, 61)
+ )
> colnames(Data) <- c("time","Bact")
> head(Data)

      time Bact
[1,]    2 0.14
[2,]    4 0.21
[3,]    6 0.31
[4,]    8 0.40
[5,]   10 0.69
[6,]   12 0.97
```

and assume that we want to fit the model parameters `gmax` and `eff` to these data.

We first define an objective function that returns the residuals of the model versus the data, as estimated by `modcost`. Input to the function are the current values of the parameters that need to be finetuned and their names (or position in `par`).

```
> Objective <- function(x,parset=names(x)) {
+   pars[parset]<- x
+   tout <- seq(0,50,by=0.5)
+   ## output times
+   out <- solveBact(pars,tout)
+   ## Model cost
+   return(modCost(obs=Data,model=out))
+ }
```

First it is instructive to establish which parameters can be identified based on the data set. We assess that by means of the identifiability function `collin`, selecting only the output variables at the instances when there is an observation.

```
> Coll <- collin(sF<-sensFun(func=Objective,parms=pars,varscale=1))
> Coll
```

	gmax	eff	ks	rB	dB	N	collinearity
1	1	1	0	0	0	2	4.5
2	1	0	1	0	0	2	21.1
3	1	0	0	1	0	2	2.1
4	1	0	0	0	1	2	3.7
5	0	1	1	0	0	2	4.5
6	0	1	0	1	0	2	3.3
7	0	1	0	0	1	2	9.2
8	0	0	1	1	0	2	2.1
9	0	0	1	0	1	2	3.7
10	0	0	0	1	1	2	4.5
11	1	1	1	0	0	3	21.1
12	1	1	0	1	0	3	10.2
13	1	1	0	0	1	3	10.5
14	1	0	1	1	0	3	21.1
15	1	0	1	0	1	3	21.1
16	1	0	0	1	1	3	3442.4
17	0	1	1	1	0	3	9.9
18	0	1	1	0	1	3	10.5
19	0	1	0	1	1	3	13.8
20	0	0	1	1	1	3	39.2
21	1	1	1	1	0	4	21.3
22	1	1	1	0	1	4	21.1
23	1	1	0	1	1	4	6465.5
24	1	0	1	1	1	4	4198.5
25	0	1	1	1	1	4	40.1
26	1	1	1	1	1	5	16346953.1

The larger the collinearity value, the less identifiable the parameter based on the data. In general a collinearity value less than about 20 is "identifiable". Below we plot the collinearity as a function of the number of parameters selected. We add a line at the height of 20, the critical value:

```
> plot(Coll,log="y")
> abline(h=20,col="red")
```

The collinearity index for parameters **gmax** and **eff** is small enough to enable estimating both parameters.

```
> collin(sF,parset=1:2)
```

	gmax	eff	ks	rB	dB	N	collinearity
1	1	1	0	0	0	2	4.5

We now use function **modFit** to locate the minimum. It includes several fitting procedures; the default one is the Levenberg-Marquardt algorithm.

In the following example, parameters are constrained to be > 0

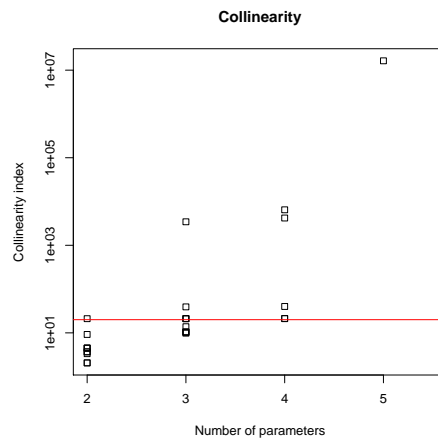


Figure 8: Collinearity analysis - see text for R-code

```
> print(system.time(Fit <- modFit(p=c(gmax=0.5,eff=0.5),
+                                f=Objective,lower=c(0.0, 0.0))))
```

```
user  system elapsed
1.42   0.00   1.44
```

```
> summary(Fit)
```

Parameters:

	Estimate	Std. Error	t value	Pr(> t)
gmax	0.3003277	0.0004744	633.1	<2e-16 ***
eff	0.7006292	0.0010819	647.6	<2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.1531 on 15 degrees of freedom

Parameter correlation:

	gmax	eff
gmax	1.0000	-0.9151
eff	-0.9151	1.0000

The best-fit model is run, the model cost function estimated and the model outcome compared to data.

```
> pars[c("gmax","eff")]<- Fit$par
> out  <- solveBact(pars)
> Cost <- modCost(obs=Data,model=out)
> Cost
```

```

$model
[1] 0.3514637

$minlogp
[1] 15.79769

$var
  name scale  N SSR.unweighted SSR.unscaled      SSR
1 Bact      1 17      0.3514637      0.3514637 0.3514637

$residuals
  name  x  obs      mod weight res.unweighted      res
1 Bact  2  0.14 0.1460459      1  0.0060458809 0.0060458809
2 Bact  4  0.21 0.2132921      1  0.0032921296 0.0032921296
3 Bact  6  0.31 0.3115005      1  0.0015004789 0.0015004789
4 Bact  8  0.40 0.4549261      1  0.0549260945 0.0549260945
5 Bact 10  0.69 0.6643861      1 -0.0256139211 -0.0256139211
6 Bact 12  0.97 0.9702790      1  0.0002789839 0.0002789839
7 Bact 14  1.42 1.4169922      1 -0.0030078325 -0.0030078325
8 Bact 16  2.00 2.0693334      1  0.0693333596 0.0693333596
9 Bact 18  3.00 3.0219120      1  0.0219119911 0.0219119911
10 Bact 20  4.50 4.4128138      1 -0.0871861894 -0.0871861894
11 Bact 22  6.50 6.4435104      1 -0.0564896371 -0.0564896371
12 Bact 24  9.50 9.4077851      1 -0.0922149224 -0.0922149224
13 Bact 26 13.50 13.7335832      1  0.2335831982 0.2335831982
14 Bact 28 20.50 20.0429739      1 -0.4570261141 -0.4570261141
15 Bact 30 29.00 29.2356342      1  0.2356342429 0.2356342429
16 Bact 35 65.00 65.0449095      1  0.0449094734 0.0449094734
17 Bact 40 61.00 60.9533707      1 -0.0466293436 -0.0466293436

attr(,"class")
[1] "modCost"

> plot(out$time,out$Bact,ylim=range(out$Bact),
+       xlab="time, hour",ylab="molC/m3",type="l",lwd=2)
> points(Data,cex=2,pch=18)

Finally, model residuals are plotted:

> plot(Cost, xlab="time",ylab="",main="residuals")

```

7. Markov chain Monte Carlo

We can use the results of the fit to run a MCMC (Gelman, Varlin, Stern, and Rubin 2004). Function `modMCMC` implements the delayed rejection (DR) adaptive Metropolis (AM) algorithm (Haario *et al.* 2006).

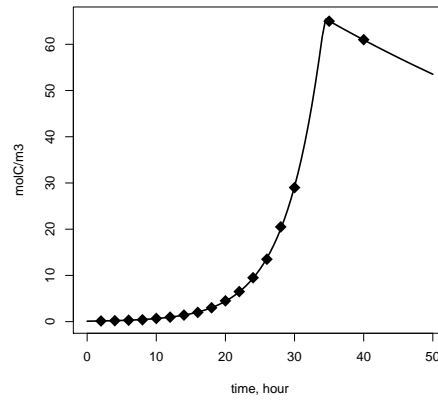


Figure 9: Fitting the model to data - see text for R-code

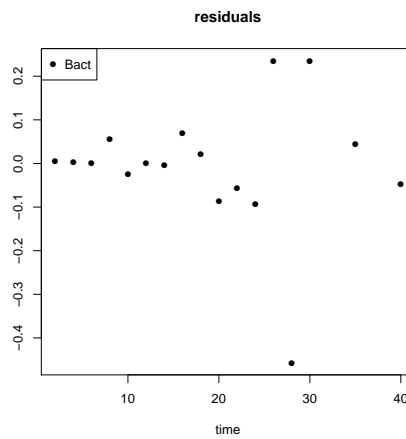


Figure 10: Model-data residuals - see text for R-code

The `summary` method of the best fit returns several useful values:

- The model variance `modVariance` is used as the initial model error variance (`var0`) in the MCMC. In each MCMC step, $1/\text{model variance}$ is drawn from a gamma function with parameters `rate` and `shape`, calculated as: $\text{shape} = 0.5 \cdot N \cdot (1 + \text{pvar0})$, and $\text{rate} = 0.5 \cdot (\text{pvar0} \cdot N \cdot \text{var0} + \text{SS})$ and where `SS` is the current sum of squared residuals, `N` is the number of data points and `pVar0` is a weighing parameter, argument of function `modMCMC`.
- The best-fit parameters are used as initial parameter values for the MCMC (`p`).
- The parameter covariance returned by the `summary` method, scaled with $2.4^2/\text{length}(p)$, gives a suitable covariance matrix, for generating new parameter values (`jump`).

```
> SF<-summary(Fit)
> SF
```

Parameters:

	Estimate	Std. Error	t value	Pr(> t)
<code>gmax</code>	0.3003277	0.0004744	633.1	<2e-16 ***
<code>eff</code>	0.7006292	0.0010819	647.6	<2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.1531 on 15 degrees of freedom

Parameter correlation:

	<code>gmax</code>	<code>eff</code>
<code>gmax</code>	1.0000	-0.9151
<code>eff</code>	-0.9151	1.0000

```
> SF[]
```

\$residuals

	Bact	Bact	Bact	Bact	Bact
	0.0060458809	0.0032921296	0.0015004789	0.0549260945	-0.0256139211
	Bact	Bact	Bact	Bact	Bact
	0.0002789839	-0.0030078325	0.0693333596	0.0219119911	-0.0871861894
	Bact	Bact	Bact	Bact	Bact
	-0.0564896371	-0.0922149224	0.2335831982	-0.4570261141	0.2356342429
	Bact	Bact			
	0.0449094734	-0.0466293436			

\$residualVariance

```
[1] 0.02343091
```

\$sigma

```

[1] 0.1530716

$modVariance
[1] 0.02067434

$df
[1] 2 15

$cov.unscaled
      gmax      eff
gmax 9.604559e-06 -2.004615e-05
eff  -2.004615e-05  4.995865e-05

$cov.scaled
      gmax      eff
gmax 2.250436e-07 -4.696997e-07
eff  -4.696997e-07  1.170577e-06

$info
[1] 3

$niter
[1] 7

$stopmess
[1] "ok"

$par
      Estimate Std. Error t value Pr(>|t|)
gmax 0.3003277 0.0004743876 633.0850 1.274385e-34
eff  0.7006292 0.0010819320 647.5723 9.076375e-35

> Var0<- SF$modVariance
> covIni <-SF$cov.scaled *2.4^2/2
> MCMC<-modMCMC(p=coef(Fit),f=Objective,jump=covIni,
+               var0=Var0,wvar0=1)

```

number of accepted runs: 368 out of 1000 (36.8%)

The `plot` method shows the trace of the parameters and, in `Full` is `TRUE`, also the model function.

```
> plot(MCMC,Full=TRUE)
```

The `pairs` method plots both parameters as a function of one another:

```
> pairs(MCMC)
```

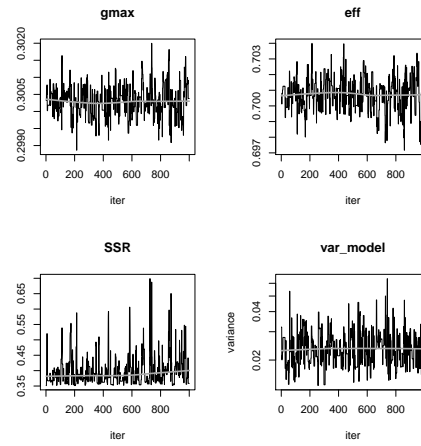


Figure 11: MCMC parameter values per iteration - see text for R-code

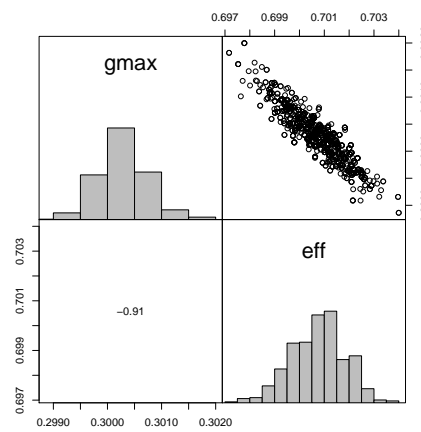


Figure 12: Pairs plot of MCMC results. See text for R-code

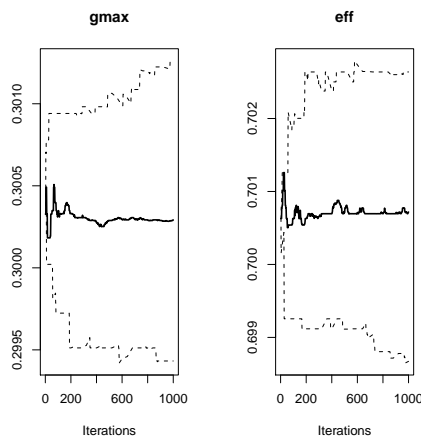


Figure 13: cumulative quantile plot from the MCMC run as from package **coda** - see text for R-code

The MCMC output can be used in the functions from the **coda** package:

```
> MC <- as.mcmc(MCMC$pars)
```

```
> cumuplot(MC)
```

Finally, we compare the covariances based on generated parameters with the ones from the fit:

```
> cov(MCMC$pars)
```

	gmax	eff
gmax	2.192628e-07	-4.624050e-07
eff	-4.624050e-07	1.168805e-06

```
> covIni
```

	gmax	eff
gmax	6.481255e-07	-1.352735e-06
eff	-1.352735e-06	3.371261e-06

8. Distributions

Parameter values can be generated according to 4 different distributions:

Grid, Uniform, Normal, Latinhyper:

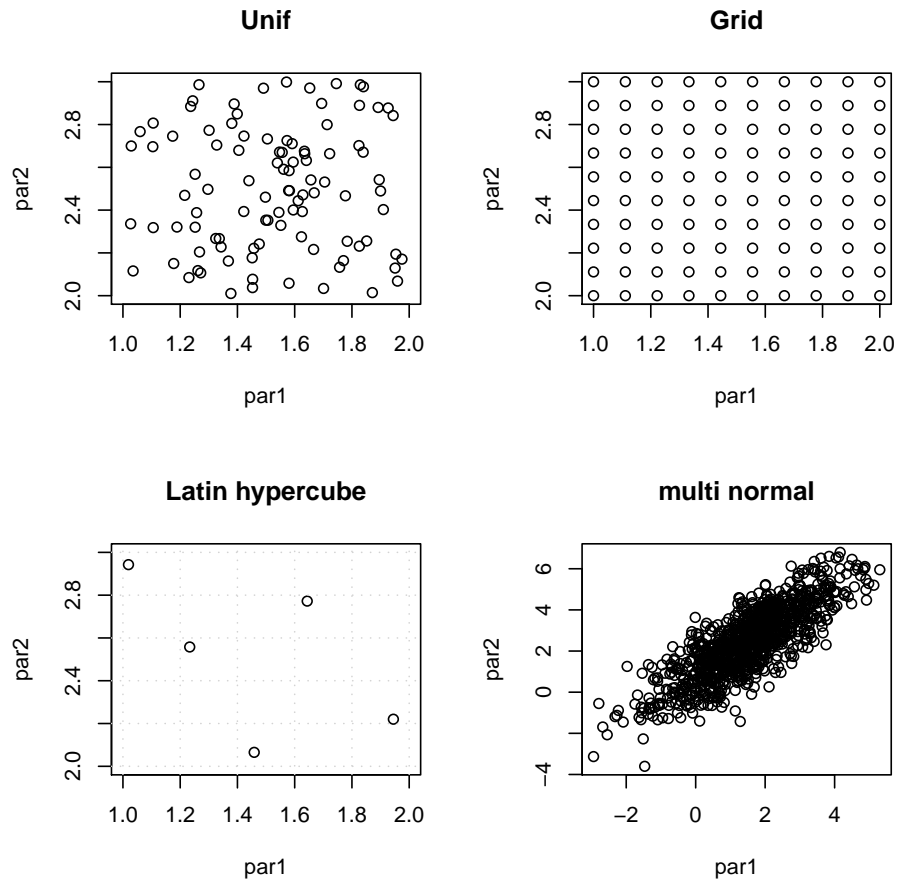


Figure 14: distributions

```
> par(mfrow=c(2,2))
> Minmax <- data.frame(min=c(1,2),max=c(2,3))
> rownames(Minmax) <-c("par1","par2")
> Mean <- c(par1=1.5,par2=2.5)
> Covar <- matrix(nr=2,data=c(2,2,2,3))
> plot(Unif(Minmax,100),main="Unif",xlim=c(1,2),ylim=c(2,3))
> plot(Grid(Minmax,100),main="Grid",xlim=c(1,2),ylim=c(2,3))
> plot(Latinhyper(Minmax,5),main="Latin hypercube",xlim=c(1,2),ylim=c(2,3))
> grid()
> plot(Norm(parMean=Mean,parCovar=Covar,num=1000),main="multi normal")
```

9. Examples

Several examples are present in subdirectory examples of the package. They include, a.o.:

- BOD02_FME.R, a 1-D model of oxygen dynamics in a river. This model consists of two

coupled partial differential equations, which are solved to steady-state.

- `ccl4model_FME.R`. Here the functions are applied to "ccl4model", one of the models included in package **deSolve** . This is a model that has been written in FORTRAN.
- `Omexdia_FME.R`. Here the functions are applied to a model implemented in **simecol**, an object-oriented framework for ecological modeling ([Petzoldt and Rinke 2007](#)), more specifically in package **simecolModels** ([Petzoldt and Soetaert 2008](#)). The omexdia model is a 1-D diagenetic model.
- `O2profile_FME.R`. This contains a simple model of oxygen, diffusing along a spatial gradient, with imposed upper and lower boundary concentration

10. Finally

This vignette is made with Sweave ([Leisch 2002](#)).

Table 1: Summary of the functions in package FME

Function	Description
sensFun	Sensitivity functions
sensRange	Sensitivity ranges
modCost	Estimates cost functions
modFit	Fits a model to data
modMCMC	Runs a Markov chain Monte Carlo
collin	Estimates collinearity based on sensitivity functions
Grid, Norm, Unif, Latinhyper	Generates parameter sets based on grid, normal, uniform or latin hypercube design

Table 2: Summary of the methods in package FME

Method	Function	Description
summary	modFit	Summary statistics, including parameter std deviations, significance, parameter correlation
deviance	modFit	Model deviance (sum of squared residuals)
coef	modFit	Values of fitted parameters
residuals	modFit	Residuals of model and data
df.residual	modFit	Degrees of freedom
plot	modFit	Plots results of the fitting
print.summary	modFit	Printout of model summary
plot	modCost	Plots model-data residuals
summary	modMCMC	Summary statistics of sampled parameters
plot	modMCMC	Plots all sampled parameters
pairs	modMCMC	Pairwise plots all sampled parameters
hist	modMCMC	Histogram of all sampled parameters
summary	modCRL	Summary statistics of monte carlo variables
plot	modCRL	Plots Monte Carlo variables
pairs	modCRL	Pairwise plots of Monte Carlo variables
hist	modCRL	Histogram of Monte Carlo variables
summary	sensFun	Summary statistics of sensitivity functions
plot	sensFun	Plots sensitivity functions
pairs	sensFun	Pairwise plots of sensitivity functions
print.summary	sensFun	Prints summary of sensitivity functions
plot.summary	sensFun	Plots summary of sensitivity functions
summary	sensRange	Summary statistics of sensitivity range
plot	sensRange	Plots sensitivity ranges
plot.summary	sensRange	Plots summary of sensitivity ranges
print	collin	Prints collinearity results
plot	collin	Plots collinearity results

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