# **Medartis Wrist Plates**

## Experiment 2 - bending and shear matched

2024-07-23

#### setup

Load any needed libraries and define some constants.

```
library(dplyr) # for manipulating dataframes
library(ggplot2) # for plotting

# If you don't have bluer install it with
# inatall.packages("devtools")
# devtools::install_github(repo = "yadbor/bluer")
library(bluer) # routines for analysing mechanical test data

data_root <- here::here("data-raw", "Experiment 2", "Results", "VIC-3D data")

data_col_names <- "File Number,U [mm],V [mm],W [mm],Time_1,position,load"
data_cols <- stringr::str_split_1(data_col_names, ",")</pre>
```

#### read the data files

Get all the .csv file names under the data\_root folder and store them in a list.

Then run the list of file paths names through a pipeline that does the following:

- 1. Name every list element with the basename from the path (i.e. just the file name with no path or extension)
- 2. Read each .csv file into the list as a dataframe
- 3. Keep only the wanted columns in each dataframe
- 4. Stack the read dataframes, adding the names from the list as a column

all\_results is now a big dataframe (actually a tibble) holding all the results from all tests, labelled with their file name. This will work for studies like this one where all the meta-data are in the file names. For some studies some of the meta-data can be in the folder name as well. In those cases the final folder name can be extracted using basename(pathname(full\_path)).

### extract test information

The filenames have the plate type, id and repeat encoded as:

```
"{Long|Short} Plate {id} T{repeat}_Data.csv"
```

Extract these into separate columns to identify each test. Because the filenames don't have clean delimiters use a regex to break them up.

Some names have special issues, like the two that were repeated (T1.2 & T2.2). Clean those up here as well.

Replace the column names with names that are easier to manipulate in code but still convey their purpose

#### save clean data

Write the cleaned data to a .csv file before starting the analysis.

```
all_results |>
  readr::write_csv(file = here::here("data", "all_results.csv"))
```

### analyse cycles

Each test has multiple load-unload cycles. Data are recorded on the  $9^{\rm th}$  and  $10^{\rm th}$  cycles, and this is repeated every 10 cycles up to a total of 60 cyles. We are interested in the loading part of each cycle.

Divide test into cycles by finding peaks and troughs. The loading phase is the one going towards a peak, and the unloading phase is towards a trough.

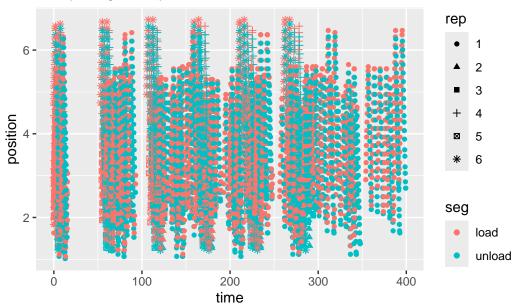
The bluer package has routines for finding peaks and labelling cycles and phases.

But first, as these tests are all in compression, the load and position are all negative. Invert them both so that graphs read better for most people.

```
cycles <- all_results |>
  mutate(position = -1.0 * position, load = -1.0 * load) |> # Invert these axes
  group_by(plate, id, rep) |> # group each test
  mutate(as_tibble(bluer::label_cycles(position))) |> # and label the cycles
  mutate(cycle = factor(cycle)) |> # Make the cycle a factor for easier plotting
  mutate(uid = paste0(plate,id,rep,cycle)) # uniquely identify each cycle

# Check what we have done
cycles |> ggplot() +
  aes(x = time, y = position, colour = seg, group = rep) +
  geom_point(aes(shape = rep)) +
  facet_grid(rows = vars(plate), cols = vars(id)) |>
  labs(title = "everything, everywhere, all at once")
```

# everything, everywhere, all at once

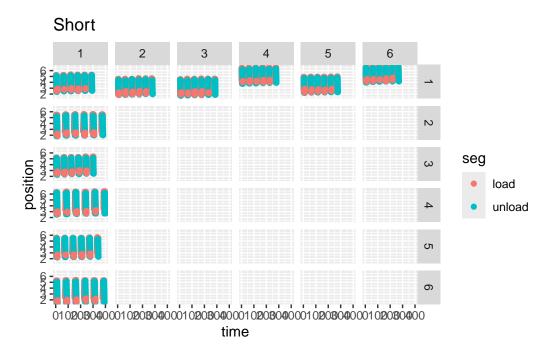


```
# that plot was crowded, so do separate ones for each plate
#

cycles |>
   filter(plate == "Long") |>
    ggplot() +
   aes(x = time, y = position, colour = seg, group = rep) +
   geom_point() +
   facet_grid(rows = vars(id), cols = vars(rep)) +
   labs(title = "Long")
```



```
cycles |>
  filter(plate == "Short") |>
  ggplot() +
  aes(x = time, y = position, colour = seg, group = rep) +
  geom_point() +
  facet_grid(rows = vars(id), cols = vars(rep)) +
  labs(title = "Short")
```

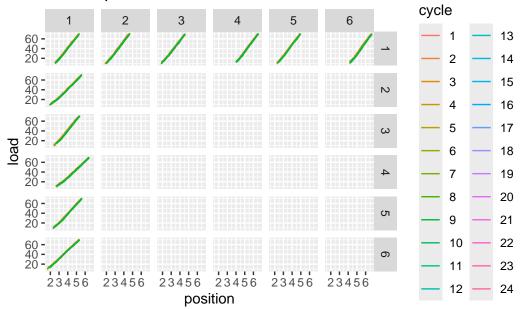


Plot just the loading portion of each cycle, as load vs position.

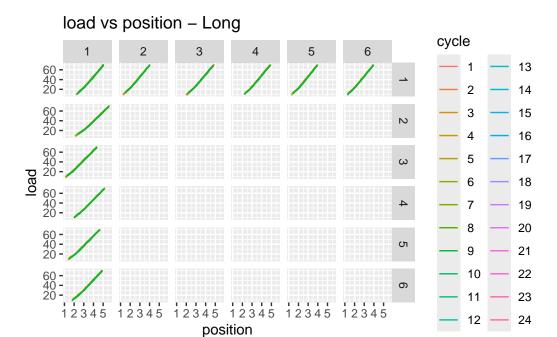
```
loading <- cycles |>
    filter(seg == "load")

loading |>
    filter(plate == "Short") |>
    ggplot() +
    aes(x = position, y = load, colour = cycle, group = uid) +
    geom_line() +
    facet_grid(rows = vars(id), cols = vars(rep)) +
    labs(title = "load vs position - Short")
```

# load vs position - Short



```
loading |>
  filter(plate == "Long") |>
  ggplot() +
  aes(x = position, y = load, colour = cycle, group = uid) +
  geom_line() +
  facet_grid(rows = vars(id), cols = vars(rep)) +
  labs(title = "load vs position - Long")
```



### analysis

To get the stiffness of each test we fit a linear model by least squares.

```
loading_models <- loading |>
  #group_by(uid) |>
  group_by(plate, id, rep, cycle) |>
  summarise(
   model = list(
    lm(load ~ position, data = pick(everything()))
  )
)
```

`summarise()` has grouped output by 'plate', 'id', 'rep'. You can override using the `.groups` argument.

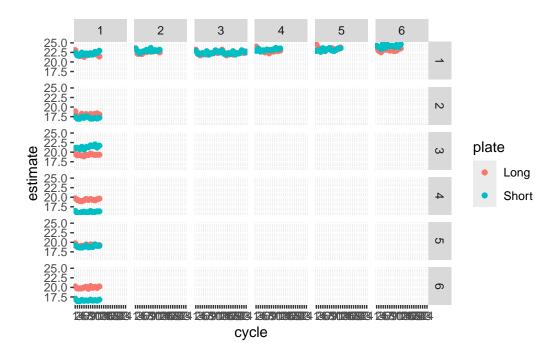
```
loading_models |>
  mutate(glance = purrr::map(model, broom::glance))|>
  tidyr::unnest(glance)
```

# A tibble: 288 x 17

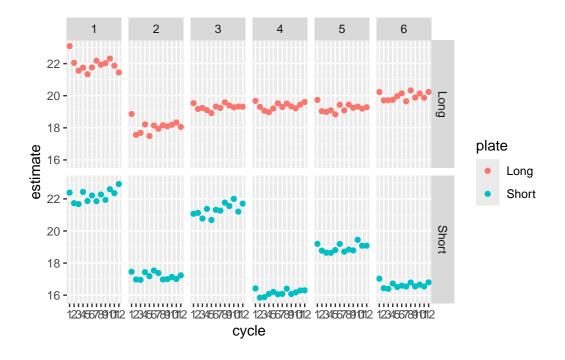
```
# Groups:
            plate, id, rep [22]
   plate id
                rep
                      cycle model r.squared adj.r.squared sigma statistic
   <chr> <chr> <chr> <fct> <fct> <list>
                                        <dbl>
                                                       <dbl> <dbl>
                                                                        <dbl>
 1 Long
                      1
                            <1m>
                                        0.996
                                                       0.996 1.05
                                                                        2776.
        1
                1
 2 Long
                1
                      2
                            <1m>
                                        0.996
                                                       0.996 1.22
                                                                        2981.
 3 Long
                                                       0.995 1.27
                                                                        3034.
                1
                            <1m>
                                        0.996
 4 Long
                1
                      4
                            <1m>
                                        0.998
                                                       0.997 0.934
                                                                        4936.
 5 Long 1
                1
                      5
                            <1m>
                                        0.995
                                                       0.995 1.37
                                                                        2824.
 6 Long 1
                            <1m>
                1
                      6
                                        0.997
                                                       0.997 1.01
                                                                        4165.
 7 Long
        1
                1
                      7
                            <1m>
                                        0.997
                                                       0.996 1.14
                                                                        3162.
                                                       0.998 0.781
                                                                        7017.
 8 Long
                      8
                            <1m>
                                        0.998
        1
                1
                      9
                            <1m>
 9 Long
                1
                                        0.995
                                                       0.995 1.38
                                                                        2797.
10 Long
                      10
                            <1m>
                                        0.997
                                                       0.997 1.08
                                                                        3903.
                1
# i 278 more rows
# i 8 more variables: p.value <dbl>, df <dbl>, logLik <dbl>, AIC <dbl>,
    BIC <dbl>, deviance <dbl>, df.residual <int>, nobs <int>
# Extract the slope components of the models
lm_fits <- loading_models |>
  mutate(tidy = purrr::map(model, broom::tidy)) |>
  tidyr::unnest(tidy) |>
  filter(term != '(Intercept)')
lm_fits
# A tibble: 288 x 10
# Groups:
            plate, id, rep [22]
                      cycle model
   plate id
               rep
                                   term
   <chr> <chr> <chr> <fct> <chr> <fct> <chr>
                                                <dbl>
                                                                      <dbl>
                                                           <dbl>
                                                  23.1
                      1
                            <1m>
                                                           0.438
 1 Long
        1
                1
                                    position
 2 Long
                      2
                            <1m>
                                                  22.0
                1
                                    position
                                                           0.404
 3 Long
                      3
                            <1m>
                                    position
                                                  21.6
                                                           0.391
```

estimate std.error statistic p.value <dbl> 52.7 1.47e-13 54.6 9.38e-16 55.1 8.56e-17 4 Long <1m> 21.7 0.310 70.3 4.59e-17 1 position 5 Long 5 <1m> 21.3 53.1 1.36e-16 1 1 position 0.402 6 Long 1 1 6 <1m> 21.8 0.337 64.5 1.27e-16 position 7 Long 1 1 7 <1m> position 22.2 0.394 56.2 6.95e-15 21.9 83.8 5.59e-18 8 Long 1 1 8 <1m> 0.262 position 9 Long 1 9 <1m> 22.0 52.9 1.45e-16 1 position 0.417 62.5 1.87e-16 10 Long 10 <1m> position 22.3 0.357 # i 278 more rows

```
lm_fits |> ggplot() +
  aes(x= cycle, y = estimate, colour = plate) +
  geom_point() +
  facet_grid(rows = vars(id), cols = vars(rep))
```



```
lm_fits |> filter(rep == 1) |> ggplot() +
aes(x= cycle, y = estimate, colour = plate) +
geom_point() +
facet_grid(cols = vars(id), rows = vars(plate))
```



## check for effect of cycling

We have six plates, each tested mutiple times, and each test consisting of multiple cycles. To test if the number of cycles is having an effect we need a two way repeated measured ANOVA, because both the tests and the cycles are repeated for each plate.

```
# lm_fits |>
# summarise(
# anova = list(aov(estimate ~ rep * cycle + Error(id / (rep * cycle))))
# )
```