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COSY MODEL-MACHINE OPTIMIZATION

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Abstract

Successful operation of a particle accelerator requires accompanying model calculations. The model helps in understanding the machine and predicts the impact of a change in the settings (e.g. current of magnetic elements). For the **Co**oler **Sy**nchrotron (COSY) at FZ Jülich the accelerator simulation software MAD-X is used to model the accelerator. The model parameters are steadily being improved based on various manual (human) and analytical observations, but hardly optimized all at once, which can be solved with machine learning methods. The model can be used to predict measurable quantities, like the Orbit Response Matrix (ORM) or betatron tunes. Several observables for different particle energies have been measured recently and the corresponding machine settings are available.

We describe the effort to optimize the agreement between measured and calculated ORMs and hence improve the agreement between model and (real) machine and report on the optimization using a multivariate algorithm (e.g. genetic algorithm). This facilitates the setup of COSY and will allow to perform high precision experiments e.g. a measurement of an electric dipole moment of deuterons at COSY.

MODEL OF COSY

Within MAD-X [1] the accelerator is described by a lattice (see Fig. 1) that comprises the position, the size and the function of each element, e.g. a beam-steering magnet (steerer) or a beam-position monitor (BPM). At COSY the lattice comprises approximately 200 individual elements [2, 3]. The validity of the model is only given if the parameters of all elements closely match the reality.

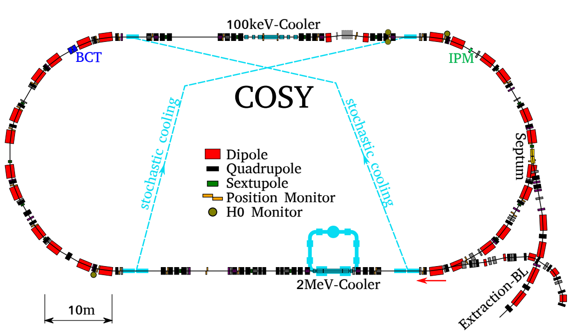

Figure 1: COSY lattice diagram. 184 m circumference, split and extended 6-segment symmetry.

The model has about 1500 parameters: each non-infinitesimal element - apart from nominal coordinates on S,X,Y axes - also has three each lateral and rotational MAD-X-defined displacements. Magnetic elements - apart from respective main coefficient and higher multipole coefficients - also have nominal length, while for main dipoles an artificial effective kick is used to represent the magnetic shortening. Precise parametrisation is an ongoing effort. The parameters which are accessible for measurement (in geodetic surveys, manufacturer specifications, in-house measurements and beam studies) have been provided to the model.

Using the provided model MAD-X calculates the global machine parameters such as betatron tune and chromaticity as well as optics (also called twiss) functions.

MEASUREMENTS VS. SIMULATION

The measurement of several observables shows discrepancies to the simulated values from the model - see tune in Fig. 2.

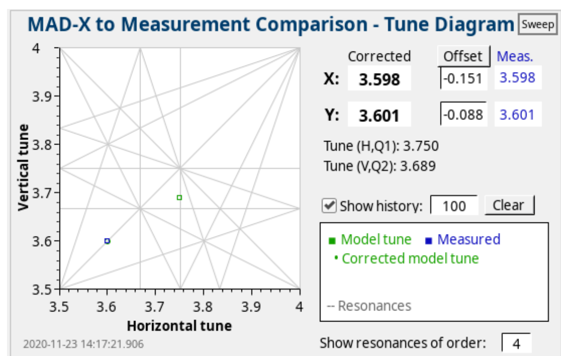

Figure 2: A betatron tune simulation from the model and its measurement on a simplified operations screen. A correction offset has to be applied to obtain the correct simulated tune.

Orbit Response Matrix (ORM), as another example of an observable, encodes orbit change for certain settings of the steerer magnets. Measured ORM (see Fig. 3(b)) can be compared to the calculated (see Fig. 3(a)) from simulated parameters. The discrepancy (see Fig. 3(c)) does not hinder usage of the ORM in accelerator operation e.g. for orbit correction, but strongly indicates the incompleteness of the model.

At COSY an ORM consists of 3149 entries (67 BPM responses times 47 used steerers), and depends non-linearly on various twiss parameters (cf. [2]), with non-trivial correlations between them. For this analysis only the diagonal quadrants are analytically accessible (although XY quadrants can be calculated numerically) and some devices (steerers or BPMs) may not have been available at the time of measurement.

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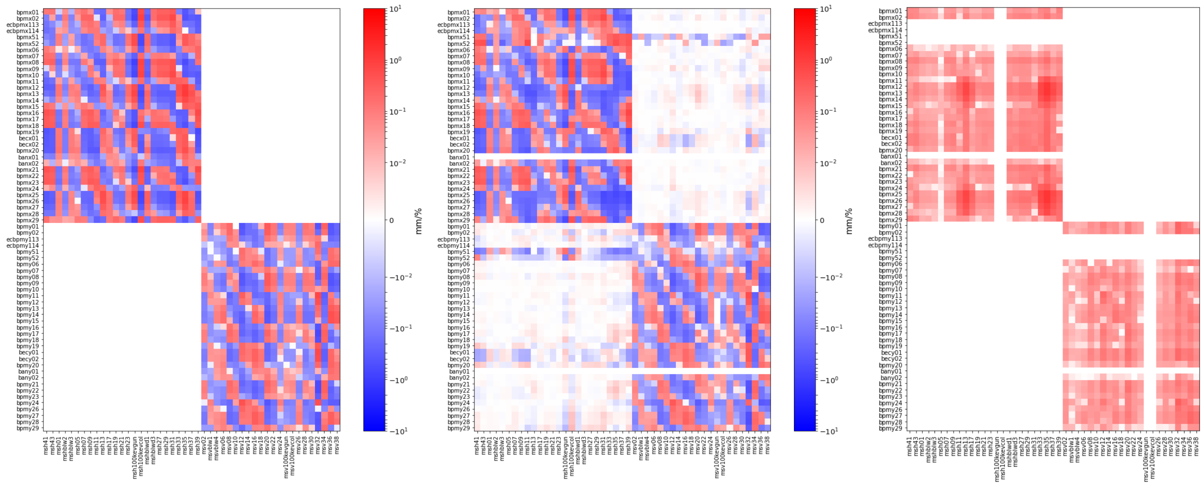

Figure 3: Example ORM: (a) sim_{init} i.e. simulated, (b) *meas* i.e. measured, (c) $|meas - sim_{init}|$ as (initial) discrepancy; color-code: log $\pm(0.001..10)$ mm/% from blue to red. For ORM difference only the diagonal quadrants and also only operational devices contributing to the measurement are considered.

OPTIMIZATION GOAL AND DATA SET

The ongoing analysis effort at COSY aims to optimize the agreement between measured and calculated observables and hence improve the agreement between the model and the (real) machine. This facilitates the setup of COSY and will allow to perform high precision experiments.

In this paper a promising subset (further referred to as variables) of the previously described parameters is selected for optimization (see Table 1) with limits mainly encompassing uncertainties of currently known values.

Table 1: Summary of Parameters Let Free for Optimization, with Respective Allowed Ranges and Reference Indeces

Type	**Correction**	**Lim.**	**Unit**	**Idx.**
Dipole	shortening kick	[-3,3]	mrad	0
Quad	roll (S-axis)	[-6,6]	mrad	25
Quad	displacement X	[-1,1]	mm	81
Quad	displacement Y	[-1,1]	mm	137
Quad	displacement S	[-20,20]	mm	193

249 variables

We use measurements of the vertical and horizontal tunes, as well as of the ORMs (further called observables) each for 5 different optics settings with respective beam setups performed during COSY beam time (CBAC A014.3 [4]) of 2021CW5 (further called benchmark points): deuterons at 970 MeV/c and 3000 MeV/c with minimal development to achieve stable beam conditions, and at 600 MeV/c, 970 MeV/c and 3000 MeV/c in productive conditions with optimal tune, dispersion, orbit correction, beam lifetime.

The defining parameters of these benchmark points (beam momentum, magnet currents) are distinct and disjunct from the variables - which in turn apply to all benchmark points.

GENETIC ALGORITHM

We use a variant of genetic algorithms (cf. [5]) in order to perform the multivariate optimization with composite fitness function (not multi-objective at this point); implementation is based on the `DEAP` framework [6] in combination with `cpymad` [7].

In the framework of the algorithm an individual (also genome) is defined as a set of variables (see above) - each comparable to a gene - completing a parametrization of the model. A population is a collection of individuals with genome variations, its size is one of the main algorithm parameters and was chosen to be 1000 for singular runs and 200 for serial runs.

A fundamental property of an individual is its fitness, i.e. how well the model with this parameter set matches the measurement for all benchmark points. The *fitness* is calculated as weighted sum of absolute differences between simulated and measured observables over all benchmark points, such that lower value of fitness corresponds to better model-machine matching. A typical discrepancy of both tune measurements (offset in Fig. 2) is $\mathcal{O}(0.1)$. The weight is chosen to be 2 and scaled (down) by uncertainty on the measurement if needed.

For ORM (absolute difference) an average over all used entries (see Fig. 3) is calculated and is $\mathcal{O}(0.1)$. The weight is chosen to be 1.

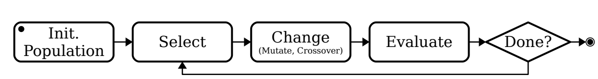

Figure 4: Genetic algorithm flow.

The procedure of the algorithm is sketched in Fig. 4; the initial population is produced from standard variable values by customized mutation (applied to randomly selected 40% of the population), where 50% of randomly selected genes

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are shuffled with gaussian probability around the initial value within 5 sigma inside their limit. The same mutation is applied to the iteratively generated offspring generations - with individual genes gaussian width of 2 sigma. 50% of individuals are also put through uniform cross-over, where 90% of genes are swapped between random pairs. Such newly created individuals have their fitness evaluated and are selected for the next offspring iteration via a repeated tournament process over 5% of the population.

Results

The optimization is let to run several times with a fixed number of generations and a convergence is observed after around 25 generations (see Fig. 5).

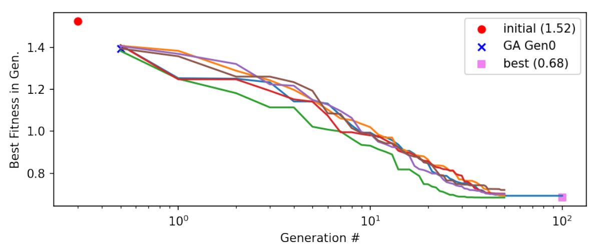

Figure 5: Genetic algorithm execution: 6 runs with 50..100 generations.

This rapid settling can also be seen in the overview over all 249 variables (see indices in 1) in Fig. 6.

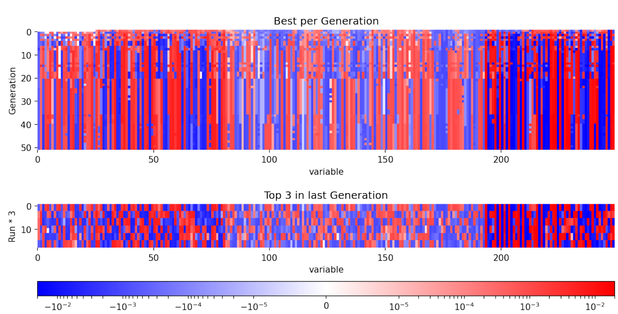

Figure 6: Genomes: (a) One run for variable values (of best individuals per generation) over 50 generations; (b) Top 3 individuals each of 6 runs.

We observe that similar fitness is reached with superficially very different configurations of variables, although some displacements in S show agreement. Many variables are at either side of the allowed limit warranting further investigation.

Figure 7 breaks down the fitness (discrepancy) contributions over all observables before and after the optimization. An improvement can be seen in almost all of them, in the end of all runs the discrepancy is about halved and reduced consistently.

Measurement matching improves for all ORMs, one example is shown in Fig. 8. Although some features (e.g. Dispersion in this example) could not be improved, this is

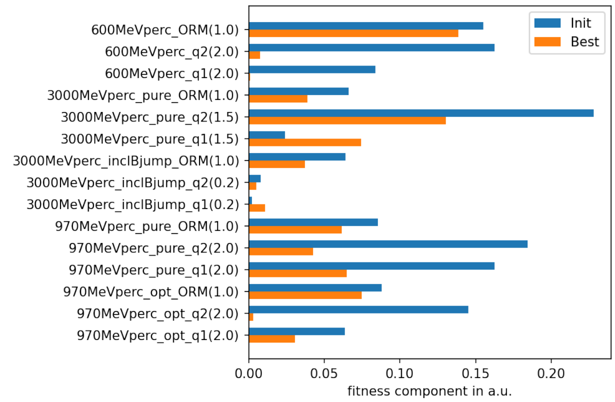

Figure 7: Comparison of individual fitness (discrepancy) contributions of a single run: for initial setting (blue) and best result of the optimization (orange).

not surprising since only a subset of all parameters is let free to optimize.

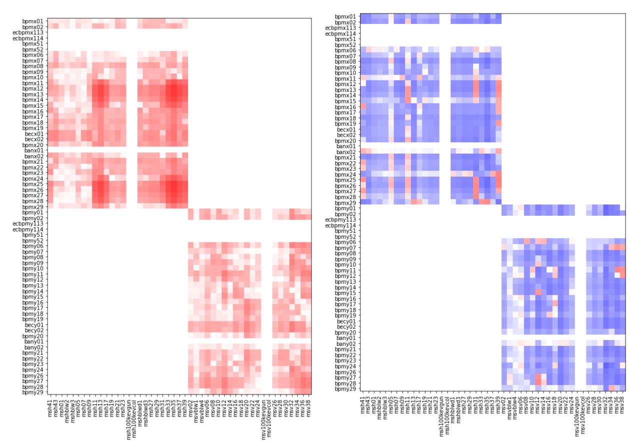

Figure 8: Example of improvement of one ORM prediction: (a) $|meas - sim_{best}|$ as (best) discrepancy, (b) $|meas - sim_{init}| - |meas - sim_{best}|$ as improvement, same colorcode as in Fig. 3.

CONCLUSION

Summarizing COSY model parametrization and measurements were used to improve the model, halving the discrepancy, with the help of a genetic algorithm. Simultaneous optimization against 5 different optics and several observables' measurements is performed.

We plan to use more measurement points at different energies and consider more observables, namely chromaticity and orbit.

Using an ORM simulation instead of analytical calculation will give us the opportunity to consider all quadrants of the ORM directly, and hence to accessing the coupling.

We also need to carefully choose and expand the set of variables to be free and deal with over-determination e.g. by considering their correlations.

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