Multi-parameter detector optimization: SHiP case

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Abstract. SHiP (Search for Hidden Particles) and the associated SPS Beam Dump Facility is a new general-purpose experiment proposed at the SPS to search for "hidden" particles as predicted by a very large number of recently elaborated models of Hidden Sectors which are capable of accommodating dark matter, neutrino oscillations, and the origin of the full baryon asymmetry in the Universe. SHiP is declared as an experiment with zero background. The Muon Shield is the key element to do this. So on the one hand it has to provide a good background suppression, on the other hand it has not be too heavy. In this paper we present the results of obtaining the new Muon Shield shape using the Bayesian Optimization. This allowed to reduce the background rate by the factor of 2.5, while keeping the weight of the shield at the same level.

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1 Introduction

The Standard Model (SM) of elementary particles proved its success in the theoretical prediction of all the experimental observations in high-energy physics [1]. But it has several drawbacks related to the cosmological evidence of the existence of dark matter and baryon asymmetry of the Universe [2]. In this regard, models of Hidden Sector (beyond the SM) are actively being developed, in which new weakly interacting particles with which these problems can be described are introduced. Given the absence of signals of new particles in GeV-TeV mass range, numerous experiments have focused on searching for GeV-scale long-lived feebly interacting particles (FIPs). The best physics potential was shown by heavy neutral leptons (HNL), dark photons (DP), dark scalars (DS), axion-like particles (ALP), light dark matter (LDM) [3, 4].

The main goal of the currently developed fixed-target experiment SHiP (Search For Hidden Particles) at the SPS (400 GeV proton beam energy) at CERN is to search for Hidden Sector [5, 6]. For this purpose, a detector system will be implemented in SHiP to register possible decay products or direct signal from new particles.

The detector incorporates two complementary apparatuses which are capable of searching for hidden particles through both visible decays and through scattering signatures from recoil of electrons or nuclei. Moreover, the facility is ideally suited to study the interactions of tau neutrinos.

During the last 2 years the study of alternative locations for the BDF has been focused on three existing underground facilities. The main candidate for now is ECN3, see figure 1. The main acThe ECN3 experimental area was constructed at the end of the 1970s as part of the SPS North Area High-Intensity Facility for fixed-target experiments [7]. After the new location has been considered some new restrictions on Muon Shield sizes have been added. This induced the new search for the optimal shield configuration.

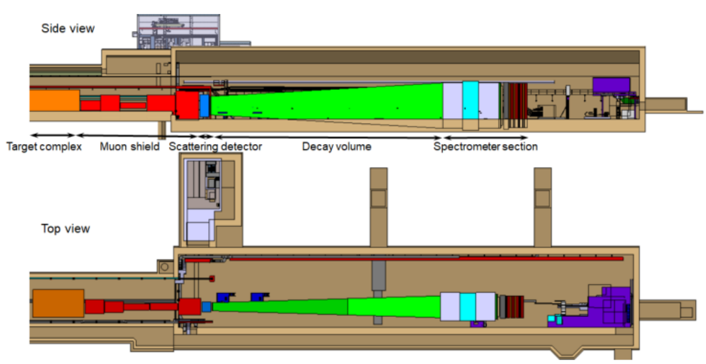

Figure 1. Views of the SHiP ECN3 option. Top view shows the ground profile along the relevant section of TCC8 and ECN3. The two bottom views shows a preliminary integration of the SHiP detector [7].

2 Muon Shield

SHiP is declared as an experiment with zero background. After the beam hits the target a lot of different particles are produced. Most of them should be somehow removed before they reach the decay vessel. The Hadron Absorber deals with high cross section particles. The Muon Shield is the key element to remove muons as a main source of the background. The goal is to reduce the flux from $\sim 10^{11}$ muons per spill by 6 ordes of magnitude. So on the one hand it has to provide a good background suppression, on the other hand not to be too heavy or expensive.

2.1 Shield magnets shape and parametrization

Muon Shield consists of 6 warm Grain Oriented steel magnets with identical parametrization and 1.7T magnetic field. The directions of the field are opposite for the first and last halfs of the shield. The idea behind: the high energy muons supposed to be deflected out of the acceptance by magnet core at the first 3 magnets, and by yoke at the last 3 magnets. See Fig. 2.

It takes 7 parameters to define one magnet shape: 3 parameters for IN plane, 3 paramters for OUT plane and the length of the magnet, see Fig. 3. Considering 6 magnets with fixed gaps between them we got 42 overall parameters to fix the whole shield shape.

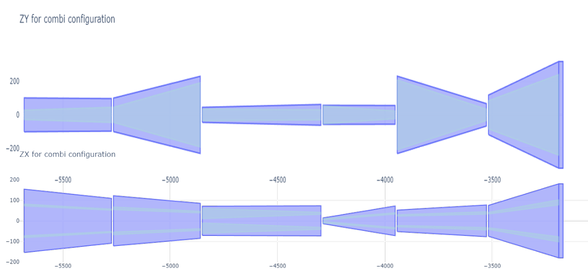

Figure 2. ZX and ZY shield projections. Light blue - the inner gap projections.

2.2 Shield quality

To establish Muon Shield quality in numbers the Geant4-based simulation software with fixed generated weighted muon sample corresponding to the one spill as input is used. The number of muon tracks at the spectrometer strawtube Tracking Stations is used as a main metric. To avoid the possible problems with full track reconstruction code we treated as "reconstructed tracks" the set of hits at least at 3 out of 4 tracking stations. The first and the last one station hits are mandatory.

Beside the shielding quality the mass of the shield also is an important numeric characteristic. There are some limits on how heavy the overall setup can be. Also the price of material is the largest part of overall shield price.

3 Muon Shield optimization

During the last year the SHiP experiment has undergone a number changes. One of them is the Muon Shield length reduction from 35m down to 30m. The previously used configuration was obtained during the optimization cycle and have been fine tuned to work on the peak performance only for previous dimensions.

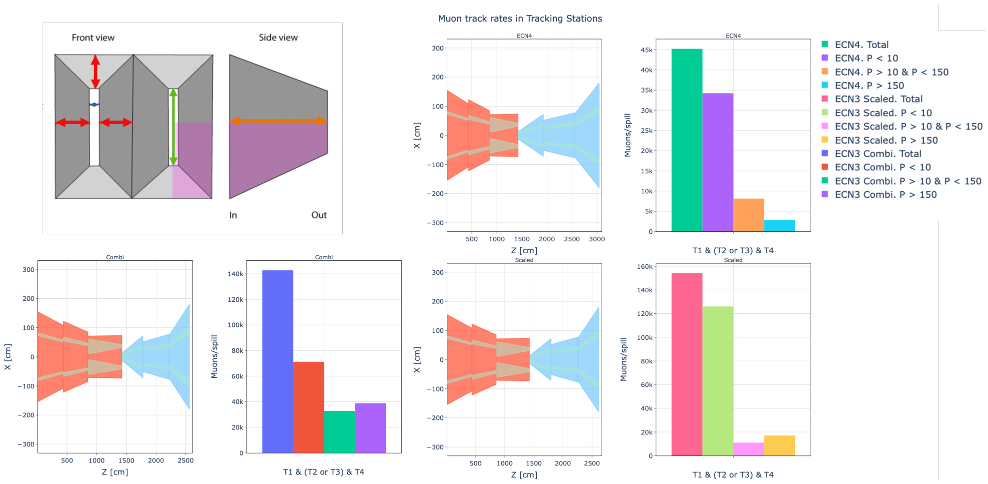

Figure 3. Front and side view of the shield magnet (on the top-left). All unique parameters are marked by the arrow of a different color. Manually adapted Muon Shield and corresponding metrics(on the right).

3.1 Manual approach

The most direct approach to reduce the overall shield length is just to scale every magnet length by the same number. Unfortunately this increased the muon flux rate by the factor of 4. At the detailed view it become clear, that high energy tracks were not deflected enough by the first half of the shield and instead of yoke hit the hole in the magnet #4. This formed 2 clear spots at the tracking stations.

To avoid this effect another manually adapted configuration was suggested — "combi" shield. The first half of the old shield had no changes at all, instead only the last 3 magnets have been shortened. This allowed to half the high energy muon rate comparing to the direct scaled shield by the price of low and medium momentum muons rate slightly increased. Overall results are presented at Fig. 3.

3.2 Bayesian optimization

Bayesian optimization was chosen as a main technic to optimize the muon shield parameters. It is a sequential design strategy for global optimization of black-box functions that does not assume any functional forms. It is usually employed to optimize expensive-to-evaluate functions. The overall optimization loop is presented on the Fig.4. The cost function used for the optimization was chosen as:

$$F_{cost} = (1 + e^{\frac{10\cdot(M-M^*)}{M^*}}) \cdot (1 + \Sigma\sqrt{\frac{400-(x+200)}{400}}) \quad (1)$$

where M - is the mass of the shield, M^* - some constant and x is the x-coordinate of the hit on the reference plane. The first half doesn't allow the shield to become too big, while the second lead to muon flux decrease. The non-linear function of x hit coordinate instead of just direct muon counts is chosen to increase the sensitivity of the optimization to the minor flux changes.

To evaluate the cost function for some configuration the MC simulation with a special optimization muon sample as input is used. The optimization sample was created from the one spill sample (see 3.2) by removing generators weights and limiting size of the sample to make an optimization simulation run faster.

An Expected Improvement was used as an acquisition function for the optimization.

The most straitforward surrogate model for the Bayesian Optimization is Gaussian Process. Unfortunately the vanilla GP has an $O(n^3)$ calculating and $O(n^2)$ memory complexities. This doesn't allow to get a stable result for the high dimensional optimization problems. High-Dimensional Bayesian Optimization with Sparse Axis-Aligned Subspaces (SAASBO)[8] and Variational Nearest Neighbor Gaussian Process (VNNGP) [9] was used to avoid these problems.

With the common GP as a surrogate model only $\tilde{1}800$ iterations of BO could be achieved with 32Gb RAM PC. While only after 900 iterations BO overperformed the random search algorithm. SAASBO provided a good start and after $\tilde{2}00$ iterations some good configuration domains have been already found. The VNNGP approach was used to run the optimization up to 5000 iterations with further manual control of some number of the best configurations.

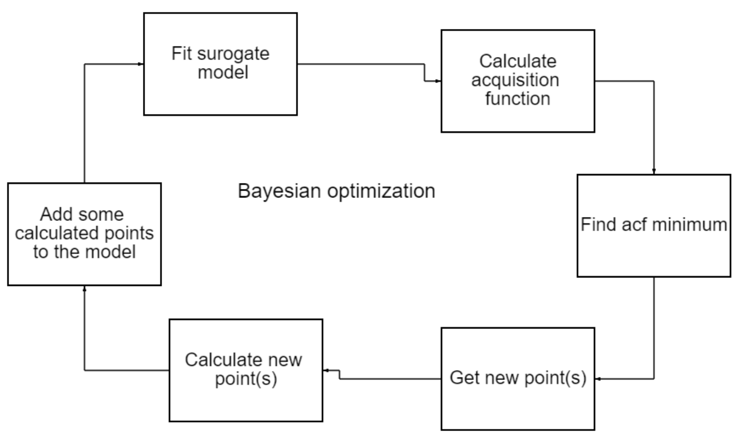

Figure 4. Bayesian optimization block-schema.

4 Muon Shield optimization results

Bayesian optimization significantly outperform the manual shield modifications. Muon shield optimization at ECN3 succeeded in decrease the total muon rate by 2.5 times in comparison with the combi configuration (160 kHz vs. 65 kHz). The most significant decrease was reached in soft momenta P < 10 GeV, see Fig.5.

- The muon rate achieved during the optimization are within the allowed physical limits.
- The overall muon rate was reduced by 2.5 times while keeping weight (and the price) of the Muon Shield nearly the same.
- The muon rates achieved by the optimization are within the allowed physical limits.
- The "curse of dimensionality" has been solved by using special surrogates in the optimization

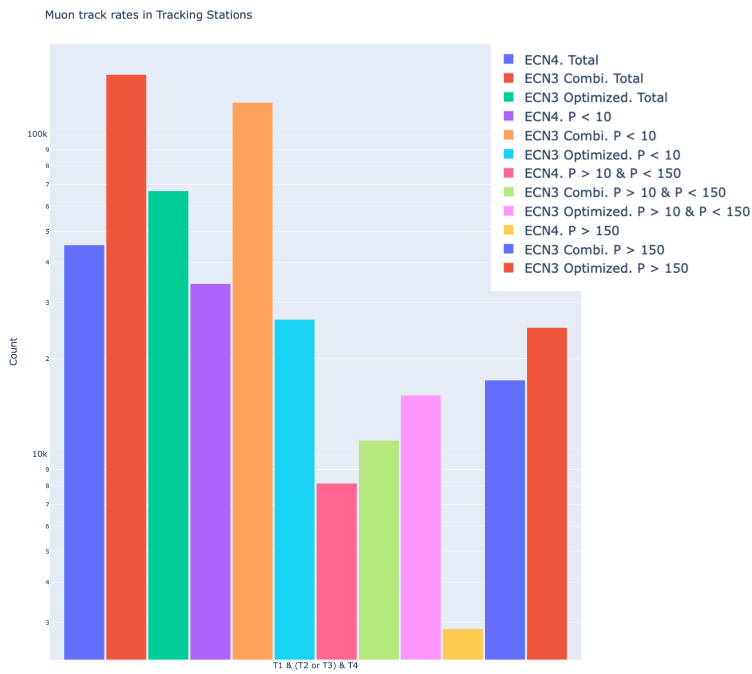

Figure 5. Optimization results

5 Acknowledges

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