The self-adaptive parameter control mechanism executes the parameters in different individuals and evolves the parameters together with its solution through variation operators.

- Dang and Lehre [3] first presented that a self-adaptive population using two mutation rates can solve PLA$k$EDOLLFunction which is a simple artificial two-peak function.
- Deer et al. [4] rigorously analysed a self-adaptive mechanism on $(1,\lambda)$ EA on OneMax function.
- Case and Lehre [5] showed that the self-adaptation of mutation rate over a continuous interval can be effective on the unknown structure version of LEADINGONES function.

Algorithm 1 Framework for self-adaptive EAs

**Require:** Fitness function $f : \{0,1\}^n \rightarrow \mathbb{R}$. Population size $\lambda \in \mathbb{N}$

1. Sorting mechanism $\mathcal{S}$: Select mutation strategy $\mu$, $\lambda$.
2. Self-adaptation mutation rate strategy $\mathcal{D}$, Initial population $\Pi_0 \in \{0,1\}^n$.
3. for $i = 1, \ldots, \lambda$ do
   a. Sample $i \sim \mathcal{D}(x)$; Set $x_i' = \mathcal{D}_i(x_i)$.
   b. Sample $\chi = \mathcal{D}_0(x)$.
4. Create $x'$ by mutating $x$ with mutation rate $\chi/n$.
5. Set $\Pi_{i+1} = (x', x_1', \ldots, x_{\lambda-1}')$.

**Theoretical Study**

The MOSA-EA can efficiently escape an artificial local optimum with unknown sparsity, while other fixed mutation rate EAs fail.

**Proof Idea:**

- The error thresholds for sparse and dense regions are different.
- The MOSA-EA maximises fitness and mutation rate on Paroto fronts.
- The mutation rates will be closed to its error threshold.
- Individuals with mutation rates larger than error thresholds will vanish in the next generation.
- Use the level-based theorem [9] to derive the runtime.

**MOSA-EA OUTPERFORMS ON COMPLEX PROBLEMS B**

- The probability $p_{\text{mut}}$ of mutation.
- The number of unsatisfied clauses $m$.
- The number of runs $n$.

**MOSA-EA ADAPTS TO NOISE LEVEL B**

- The noise level $q$.
- Initial population $\Pi_0$.
- The number of runs $n$.

**HYPER-PARAMETERS DO NOT NEED CAREFUL TUNING**

- One of the aims of self-adaptation is to reduce the number of parameters that must be set by the user.
- MOSA-EA has three parameters $Q$, $\mu_{\text{m}},$ and $\mu$.
- Adding three new parameters to adapt one parameter seems contrary to the aim of self-adaptation.
- However, as we see the figures to the right, these parameters need not to be tuned carefully.
- We use the same parameters setting of the MOSA-EA for all experiments in this study to show that the MOSA-EA does not pose problem-specific tuning of the hyper-parameters.

**CONCLUSION**

- The MOSA-EA was proposed to optimise single-objective functions, beating parameter control via multi-optimisation.
- The algorithm maximises fitness and mutation rates simultaneously.
- Novelty: treats parameter control as another objective.
- Significant change in one local optima with unknown sparsity. (2) self-adaptation mutation rate to the noise level. (3) outperforms other algorithms on EAs complex problems. (4) no need to set mutation rate manually.