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Handling Noise in Search-Based Scenario Generation for Autonomous Driving Systems

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Abstract—This paper presents the first evaluation of k-nearest neighbours-Averaging (kNN-Avg) on a real-world case study. kNN-Avg is a novel technique that tackles the challenges of noisy multi-objective optimisation (MOO). Existing studies suggest the use of repetition to overcome noise. In contrast, kNN-Avg approximates these repetitions and exploits previous executions, thereby avoiding the cost of re-running. We use kNN-Avg for the scenario generation of a real-world autonomous driving system (ADS) and show that it is better than the noisy baseline. Furthermore, we compare it to the repetition-method and outline indicators as to which approach to choose in which situations.

Index Terms—Search-Based Testing, Multi-Objective Optimization, kNN-Averaging, Noisy Systems, Autonomous Driving System

I. INTRODUCTION

Noisy system executions—e.g. due to use of volatile communication means, complex and distributed system architectures, and non-deterministic execution times—are a challenging, but common characteristic of many modern cyber-physical systems (CPSs) [1]. In a growing number of systems, a given randomness cannot be avoided at all, for instance, when a system’s architecture is built on asynchronous message passing between multi-process / multi-node systems. The popular Robot Operating System (ROS) framework is a well-known representative of this type of system, causing challenges throughout all phases of a CPS’s lifecycle, including development, testing, and deployment.

In our ongoing research on the testing of the Autonomoose\textsuperscript{1} autonomous driving system (ADS), we came across this problem when we applied search-based testing (SBT) using multi-objective optimisation (MOO) [2] for the creation of crash scenarios. Our goal here is to automatically adapt the parameters of an ADS scenario, s.t. the Ego vehicle collides with another road participant, V1 for instance (see Fig. 1). Subsequently, these crashes can be analysed by experts to identify whether Ego acted correctly or whether there is a problem. Nonetheless, being based on ROS, our ADS simulator experiences noise and, therefore, suffers from the well-known problems of noisy search-based optimisation, namely the unwarranted preference of outliers and the selection of non-representative, volatile solutions [3], [4].

The ADS’s noisy inter-process communication causes differing observations for repeated executions of the same setting, s.t. the distance between two cars may vary up to several meters. To illustrate the effect and magnitude in our system, Fig. 2 shows the results of an upfront evaluation of the scenario in Fig. 1. In this experiment, we systematically modify V1’s position in a value range where we suspect a collision. Each valuation is repeated 30 times where Fig. 2 plots the valuation against the smallest Euclidean distance observed between Ego and V1 and marks whether a collision occurred. As can be easily seen, not only do the ordinate-values differ vastly for a given situation, there is also not a single configuration that always leads to a collision. Logically, this problem becomes even more severe once the number of search variables is

\textsuperscript{1}https://www.autonomoose.net/
increased and the complexity raised to MOO for SBT.

A naive solution to tackle the problem in MOO would be to repeat the evaluation of each configuration and calculate the average fitness value to account for the noise [5]. The problem, however, is that a typical simulation run takes roughly 1 to 2 minutes and requires a GPU. Assuming 1000 total optimisation steps (a typical SBT setting), five-fold averaging would easily add some 80 to 160 hours of simulation time to each individual scenario search; or significantly lower the number of optimisation cycles, potentially causing worse results. Both situations reduce this method’s applicability for our purposes and broad application.

This paper describes the application of the k-nearest neighbours (kNN)-Averaging [3] technique to ADS scenario generation. kNN-Avg is a recently proposed approach that avoids the costly need for re-running by relying on results from previous, neighbouring configurations. The advantage of kNN-Avg is that it increases the robustness of MOO searches, without requiring any additional simulation effort. In [3], kNN-Avg showed good success when applied to synthetic benchmark problems from literature [6]. In the rest of this paper, we show its viability on a real-world case study and compare it to the default, noisy setup and the naive repetition-solution.

Paper structure. § II briefly discusses noisy MOO and re-states the kNN-Avg concept. Next, § III introduces our experimental setup. § IV outlines the results of the experiments and discusses the insights we draw. § V explores threats to validity of our approach. § VI explores related works, § VII concludes and outlines future works.

II. MULTI-OBJECTIVE OPTIMISATION & K-NEAREST NEIGHBOURS-AVERAGING

a) Multi-objective optimisation (MOO) [2]: MOO refers to a collection of methods whose aim is to find a set of solution vectors \( \vec{x} \in \mathbb{X} \) which minimise the outcome of a set of objective functions \( f \). The dimensions of \( \mathbb{X} \) relate, for instance, to the position and velocity of \( \forall \) in Fig. 1.

\[
\min_{\vec{x} \in \mathbb{X}} f(\vec{x}) = \{ f_1(x), \ldots, f_m(x) \}, \forall i \in \{1, \ldots, m\}, f_i : \mathbb{X} \to \mathbb{R}
\]

(1)

The output \( f(\vec{x}) \in \mathbb{Y} \) is called the objective value of \( \vec{x}; \mathbb{Y} \subseteq \mathbb{R}^m \) being the objective space. An optimisation problem is called multi-objective if \( m > 1 \).

The complexity of the approach is that in many cases it is not possible to find a configuration that minimises all \( f_i \in f \). As a result, we might observe a so-called Pareto front, consisting of Pareto optimal points. These points are optimal in the sense that there is no point that minimises any of the objective dimensions without worsening another objective. Fig. 3 displays the Pareto front of a search as red crosses \( \times \). Note, how for any \( \times \) there is no other \( \times \) whose \( y_0 \) value is lower, while its \( y_1 \) value is equally good or better, or vice-versa. Fig. 3 also displays the ideal Pareto front \( \circ \), representing the theoretically best values that can be obtained for the underlying ZDT1 [6] problem. The goal of the MOO is to push the objectives \( \times \) as close as possible to the ideal Pareto front \( \circ \).

b) Genetic algorithms (GAs) [7]: GAs are a family of evolutionary algorithms (EAs). Their goal is to iteratively generate new populations (sets of solutions) for a given number of generations, by selecting good candidates and producing offspring (combinations of two existing candidates) and mutants (variants of one existing, good candidate). GAs have been shown to be robust and continuously produce good results in various fields such as evolutionary design, biological and chemical modelling, and artificial intelligence. In this work, we apply the well-known NSGA-II algorithm [8] implemented in the pymoo Python library [9].

c) Noisy MOO [2]: Noisy MOO is a research domain that aims to overcome the problems introduced by non-deterministic objective functions. This means that for repeated executions, it is possible that some or all \( f_i \in f \) may produce different results on exactly the same input \( \vec{x} \). In most studies, it is assumed that the noise is Gaussian-distributed [2], which also seems to match the observations in the problems of the Autonomoose ADS. When applying a GA to noisy problems, we observe that it typically prefers outlier solutions, that have coincidentally good, non-representative objective values [3], [4]. When rerunning the yielded Pareto front’s values, the effective value (averaged over repeated runs) can be significantly different, and is typically worse than the one predicted by the GA. Fig. 3 shows an example of this behaviour, obtained from a noisy variant of the ZDT1 problem. As can be seen, the noisy Pareto front \( \circ \) is remarkably good. The effective Pareto front \( \bullet \) for this experiment is significantly worse than the noisy one. Clearly, we see that the noisy Pareto front \( \circ \) is non-representative.

The goal of our research is to reduce the effect of noise, such that the Pareto front yielded by the GA is more representative, while still producing good effective results. Casually speaking, we aim to push the \( \bullet \) closer towards \( \circ \), while at the same time reduce the length of arrows in Fig. 3.

d) KNN-Averaging (kNN-Avg) [3]: kNN-Avg is a recently introduced method to overcome the problem of noisy MOO. Its goal is to approximate the repetition of \( f(\vec{x}) \), without the actual need for rerunning expensive simulations. Given an individual \( \vec{x} \), kNN-Avg searches previously executed “neighbour” solutions (i.e. close in solution space). Then, after

Fig. 3: Standard, Noisy and Effective Pareto front for ZDT1 [6], showing the problem of noise and outliers in MOO.
obtaining the objective of $\bar{x}$ (e.g. through simulation), kNN-Avg calculates the mean of the new objective value with the neighbours’ objectives and reports this as fitness to the GA.

To avoid any bias on the search space dimensions and scaling, kNN-Avg uses standardised Euclidean distance $\text{sed}(\bar{x}_1, \bar{x}_2) = \sqrt{\sum_{i=1}^{N} \frac{(x_{1,i} - x_{2,i})^2}{\sigma_i^2}}$, which relates all summands to their respective dimensional variance. kNN-Avg can be configured using several hyperparameters. The first (obvious) one is the number of neighbours taken into account. By convention, $\text{KNN}_1$ represents the (noisy) baseline approach (called B in the experiments), where only the noisy observation is used. $\text{KNN}_{10}$, on the other hand, means that the algorithm will calculate the mean of the observation’s value and those of the solution’s nine closest neighbours.

Furthermore, a maximum-distance can be configured to impose a limit on the distance of neighbours. This asserts that, especially in the beginning of the search or in generally sparsely populated areas of the search space, the algorithm does not use (probably) non-representative, distant solutions.

For more details, we refer to the original publication [3].

III. EXPERIMENT DESIGN

A. Experiment approaches

We compare our kNN-Avg approaches $\text{KNN}_{10}$ (with $k = 10$ considered neighbours) and $\text{KNN}_{50}$ ($k = 50$) to the baseline approach B that does not perform any mitigation action for noise, i.e. the fully noisy approach. Moreover, we also compare them to the repetition approaches $\text{Rep}_2$ and $\text{Rep}_5$, which repeat each scenario configuration $n$ times ($n = 2, 5$) and use their mean objective values.

Similar to $\text{KNN}_k$, B and Rep algorithms were implemented in pymoo, using the same NSGA-II optimisation algorithm, so rendering our results comparable. As our goal is not to optimise the GA parameterisation, but to study the KNN-Avg impact, we left the GA in its default configuration. A study on any potential influence between GA settings and KNN-Avg is left as future work.

For each experimental setting, the total budget $B_{gt}$—i.e. the total number of simulator executions—is equal, and so B and both KNN-settings cycled through twice as many optimisation generations as $\text{Rep}_2$, and five times more generations than $\text{Rep}_5$. We believe that this configuration is practical and fair, since we assume a fixed total budget $B_{gt}$ as in realistic practical settings, and each approach decides how to allocate it.

B. Definition of search objective and search spaces

The specific search problem under study is the scenario shown in Fig. 1, for which we defined two search spaces. Search space $SS_1$ is a simple version modifying $V_1$’s position and velocity in the ranges $[-100, 60]$ and $[35, 65]$, respectively. The position value indicates the offset from the scenario’s default position, corresponding to how many metres $V_1$ is moved left or right in Fig. 1. The absolute velocity is in km/h.

Search space $SS_2$ is more complex in several ways. First, it extends $SS_1$ and increases the velocity range to $[3, 100]$, and second, it adds two more search variables, trigger delay (in seconds; range $[0, 10]$) and trigger position (in metres; range $[-20, 20]$) which moves the trigger closer or further away from Ego’s starting position.

Since our goal is to find avoidable collisions between the vehicles, we defined two objective functions that we compute from the simulation results. Minimum Euclidean Distance represents the closest distance of the two vehicles throughout the simulation. If this value is small enough, a crash is signalled by the simulator. The second objective is to minimise the Velocity of $V_1$ as, clearly, collisions at fast speeds are more often unavoidable, while at low speeds Ego should be capable of making up for other driver’s mistakes.

C. Performance Indicators

To quantify the benefit and allow objective comparisons between the kNN-Avg settings and the other compared approaches, we use the following performance indicators.

First, we use $\Delta F$ as the mean distance between a solution’s calculated and effective objective values, as suggested in [10]. Thus, $\Delta F$ corresponds to the mean length of arrows in Fig. 3.

Secondly, we calculate the hypervolume $HV^\text{pred}$ and $HV^\text{eff}$. The predicted hypervolume $HV^\text{pred}$ is based on the noisy predicted solutions, that may look exceptionally good only due to noise. Therefore, we also calculate the effective hypervolume $HV^\text{eff}$, that is the hypervolume computed over the averaged values of 30 repetitions of each solution, that should give a more trustworthy indication of the quality of the final solutions. The difference between $HV^\text{pred}$ and $HV^\text{eff}$ was already observed in [10], although the authors used their proportion to judge the relative quality (similar to $\Delta F$). As we also aim to compare against baseline approaches, we will use the actual HV values.

D. Experimental setup

The experiments were conducted using the Autonomoose simulation platform, following the default installation and configuration. No changes were made to the simulator or vehicle configuration, except the direct modification of the nhtsa_run_stopsign scenario during the search using prescribed solution values. The simulation runs were executed on AWS EC2 machines of flavour $g4dn.xlarge$ under Ubuntu 18.04.

By following a guideline to conduct experiments with randomised algorithms [12], each experiment was repeated ten times to account for the randomness of the search algorithm.\footnote{see https://git.uwaterloo.ca/wise-lab/wise-sim-scenarios}

\footnote{Due to cost and time constraints we could not repeat the experiment 30 times, but instead took particular care in comparing the results with appropriate statistical tests, as suggested in [12].}
We compare each pair of approaches in terms of \( HV^{\text{pred}} \), \( HV^{\text{eff}} \), and \( \Delta F \). Given a metric \( M \) and two approaches \( \text{App}_1 \) and \( \text{App}_2 \), we compare the distributions of the values of \( M \) using the Mann-Whitney U test\(^4\) for the statistical significance (at significance level \( \alpha = 0.05 \)), and the Vargha-Delaney’s \( \hat{A}_{12} \) as effect size. If the p-value of the Mann-Whitney U test is less than \( \alpha \), we reject the null hypothesis and we claim that there is a significant difference; the \( \hat{A}_{12} \) value tells us which approach is higher and the strength of the difference.

To avoid interference between simulations, each simulation was run on its own machine on Amazon Web Services’ EC2, avoiding interference of running parallel simulations, leading to a total of nearly 180 machine computation days for pure computation of the data.

### IV. Experiment results

We here introduce the experimental results, and discuss them using three research questions. Fig. 4 reports the distributions of the results of the three metrics for the five compared approaches. Table I reports the comparison between all the approaches for the three metrics; \( \checkmark \) means that the first approach is statistically better than the second approach, \( \times \) that the second is better, and \( = \) means that there is no difference.

\(^4\)We use a non-parametric test because, in general, the compared values are not normally distributed.

### A. RQ1: Can kNN-Avg be better than the baseline approach and the repetition approach?

In this RQ, we are interested in assessing whether the kNN-Avg is advantageous in test generation settings with limited budget. We have run, in the two search spaces \( SS_1 \) and \( SS_2 \), all the approaches with population size 10, and a total budget \( Bgt = 500 \) simulations. This means that \( B \), \( \text{KNN}_{10} \), and \( \text{KNN}_{50} \) are run for 50 generations, \( \text{Rep}_3 \) is run for 25 generations, and \( \text{Rep}_5 \) is run for 10 generations.

Results are reported in Tables Ia-Ib for the two search spaces. Regarding \( HV^{\text{pred}} \) (i.e. the hypervolume value computed on the final solutions), it is apparent that \( B \) is better than any other approach. This is expected, as \( B \) does not apply any technique to mitigate the noise (neither repeating nor k-nn averaging), and so noisy solutions that are exceptionally good will survive during the search and be returned as final solutions. We further notice that controlling the noise more (by more repetitions in the repetition approach \( \text{Rep}_n \)), or considering more neighbours in the proposed approach \( \text{KNN}_{k} \), lead to worse \( HV^{\text{pred}} \) results: \( \text{Rep}_5 \) is worse than \( \text{Rep}_2 \), and \( \text{KNN}_{50} \) is worse than, or equivalent to, \( \text{KNN}_{10} \). Again, this is reasonable, as the approaches that control the noise more are more precautious, and avoid to keep in the population very noisy solutions that are coincidentally very good.
comparing the repetition approach and our approach, it seems that there is no unique trend: Rep₂ can be worse than \( \text{kNN}_{10} \), but can also be better than \( \text{kNN}_{50} \); on the other hand, \( \text{kNN}_{10} \) and \( \text{kNN}_{50} \) are always better than, or equivalent to, Rep₅.

We recall that \( H_{\text{pred}} \) is based on the computed solutions, that may look exceptionally good only due to noise; therefore, we also calculate the effective hypervolume \( H_{\text{eff}} \), that gives a real indication of the quality of the solutions (see § III-C). From Tables Ia-Ib, we observe that, in this case, there is almost always no difference for \( H_{\text{eff}} \), even in the cases in which one approach was better for \( H_{\text{pred}} \); this confirms that not controlling the noise can indeed produce noisy solutions that only look better, but are actually similar to other solutions when the noise is taken into consideration. A notable result is that the proposed approach \( \text{kNN}_{50} \) is actually always better than Rep₅, and it was better or equivalent for \( H_{\text{pred}} \).

As said before, the final solutions report fitness values that could be noisy, i.e. they could deviate significantly from the real (effective) value. A good approach should return solutions whose computed fitness value is already close to the real value: such an approach is more trustworthy, as the user can have more confidence on the correctness of the results. Therefore, we here compare the different approaches w.r.t. the average error \( \Delta F \) of the returned solutions. From Tables Ia-Ib, we observe that Rep₅ is better than B and Rep₂, showing that (as expected) simulating the solution multiple times leads to accurate results. We also observe that \( \text{kNN}_{10} \) provides worse results than Rep₅, and is equivalent to B and Rep₂; this could mean that 10 neighbour solutions may not be enough to completely mitigate the noise. \( \text{kNN}_{50} \) is significantly better than \( \text{kNN}_{10} \), B, and Rep₂ in Table Ia, and equivalent to the same approaches in Table Ib. Note that \( \text{kNN}_{50} \) is once equivalent and once worse than Rep₅; however, as we have observed before, it is always better than Rep₅ in terms of \( H_{\text{eff}} \); this could mean that Rep₅, given this budget, is too precautious and is not able to find very good solutions, i.e. it spends too much time in obtaining very accurate results, but it does not have time to explore more alternative solutions.

B. RQ2: How do the results change by changing the configuration of the search algorithm?

In a search algorithm, different hyperparameters (e.g. population size, probability of crossover, etc.) can be selected, that affect the effectiveness of the approach. Since the ADS system under study is extremely costly, we can not perform a systematic study on the influence of the hyperparameters. Instead, we only perform a preliminary study, by increasing, in the test generation for search space \( SS_2 \), the population size to 20, by keeping the same budget \( Bgt \) of 500 simulations. This means that B, \( \text{kNN}_{10} \), and \( \text{kNN}_{50} \) are run for 25 generations, Rep₂ is run for 13 generations, and Rep₅ is run for 5 generations. Experimental results are reported in Table Ic. By comparing the results with those of Table Ib, we observe that the performance of the proposed approaches \( \text{kNN}_k \) has in general decreased: \( \text{kNN}_{50} \) is no more better than Rep₂ and Rep₅ for \( H_{\text{eff}} \), and \( \text{kNN}_{50} \) is now also worse than Rep₂ for \( \Delta F \). This can be explained by the fact that the accuracy of \( \text{kNN}_k \) improves with increasing generations (when solutions are converging towards optimum), while it is not particularly good for initial generations in which the solutions are more spread and so the averaging is less accurate.

C. RQ3: How do the results change by increasing the budget?

Another aspect that can be controlled in a search algorithm is the budget \( Bgt \). For ADS testing, having high budget is not feasible, due to the high cost of ADS simulations. In any case, we still try the experiments with a larger budget, by increasing it w.r.t. the one used in the experiment in RQ2. We run all the approaches using population size 20, and 1000 simulations as budget \( Bgt \). This means that B, \( \text{kNN}_{10} \), and \( \text{kNN}_{50} \) are run for 50 generations, Rep₂ is run for 25 generations, and Rep₅ is run for 10 generations. Experimental results are reported in Table Id. As expected, Rep₅ still provides the best results in terms of \( \Delta F \); however, we observe that \( \text{kNN}_k \) does not degrade its performance in terms of \( H_{\text{eff}} \), i.e. there is no risk of obtaining more noisy results by running longer.

D. Conclusions

From the previous results, we observe that the proposed kNN-Avg approach is effective w.r.t. the baseline approach (no noise handling) and the repeat approach (in which the noise is handle by multiple repetitions), when the budget is not too big (Figs. 4a and 4b, and Tables Ia and Ib), as it always the case in ADS testing that relies on costly simulations. Given the same budget, increasing the population size and reducing the number of generations does not seem to be effective (Fig. 4c and Table Ic). Of course, using a very large budget, the kNN-Avg and the repeat approaches converge in terms of \( H_{\text{eff}} \) (Fig. 4d and Table Id); however, using such large budget is not feasible in the development practice, and so the repeat approaches are not a feasible option.

V. Threats to Validity

The validity of our results could be affected by several threats. We discuss them in terms of construct, conclusion, internal, and external validity [13].

Construct validity. One such a threat is that the evaluation metrics are not suitable for evaluating the object of the investigation. In our context, we want to assess the ability of kNN-Avg to return good solutions in terms of the objective functions, but also that are trustworthy, i.e. that are not simply good because they are noisy solutions. To assess this, the three metrics that we use in the experimental evaluation are suitable: \( H_{\text{pred}} \) measures the perceived quality of the (possibly noisy) solutions, \( H_{\text{eff}} \) measures the real quality of the solutions after the noise has been removed, and \( \Delta F \) measures the distance between the returned objective value and the real one (i.e. the one obtained with several repetitions).

Conclusion validity. The ability to draw definitive conclusions could be affected by the random behaviour of search algorithms. Therefore, we repeated each experiment multiple times, as suggested by a guideline on conducting experiments.
with randomised algorithms [12]. Moreover, to draw significant conclusions, we have also compared the results of kNN-Avg and of the other compared approaches with suitable tests that account both for statistical significance and effect size.

Internal validity. One such a threat is that the obtained results could be due to some other factor, rather than the applied technique. To mitigate such a threat, we thoroughly tested the implementation, and checked that bad solutions are not due to other factors such as the simulation timing out, or the simulator crashing.

External validity. It could be that the effectiveness of the proposed approach does not extend to other benchmarks. First of all, the kNN-Avg approach was shown to be effective on several synthetic benchmarks in [3]. In this paper, we show its applicability to a complex real world system. However, due to the cost of running the experiments, we could not assess on multiple search spaces with different objectives. Part of future work is to provide a more extensive evaluation.

VI. RELATED WORK

We here review works related to our approach, namely optimisation approaches handling noise, and search-based approaches for autonomous driving.

Some work have been proposed for handling noise in multi-objective optimisation; see [2] for a survey. For example, Fitzpatrick and Grefenstette use multiple evaluations of the fitness functions; we have used such approach as one of the compared approaches. Park and Ryu [14], instead, handle the noise by doing multiple evaluations of the solutions over several different generations. Some works, instead, modify the ranking methods to take into account the noise, as done, for example, by Hughes [15] and Teich [15].

Search-based testing has been extensively applied to ADSs. For example, Li et al. [16] propose AV-FUZZER, an SBT approach combined with fuzzing, that has the aim of finding safety violations of an ADS implemented in Apollo. Ben Abdessalem et al. [17] used multi-objective search combined with surrogate models to test a Pedestrian Detection Vision based (PeVi) system. Gambi et al. [18] search for road scenarios in which the lane keeping component of the ADS fails and the autonomous vehicle drives off the road. Calò et al. [19], instead, try to find collision scenarios that are avoidable, i.e. in which the ADS configured in a different way would not lead to collision.

VII. CONCLUSIONS & FUTURE WORK

This paper presents the results of applying kNN-Avg in noisy multi-objective optimisation (MOO). Our experiments—stemming from a real-world case study on designing ADS scenarios—show that kNN-Avg clearly outperforms the noisy baseline setting. Furthermore, we show that in certain settings kNN-Avg also outweighs the naive approach of repetition. This shows that kNN-Avg is a valid alternative to the repetition approach, especially in situations with limited budget.

Nonetheless, we observe that the choice of search hyperparameters (e.g. population size) has a big impact on the performance of kNN-Avg and the repetition. Our next steps include a deeper study into various configurations such that we might provide best-practices for hyperparameter selection. Next, we aim to extend our evaluation to additional case studies. As our time and budget constrain our work, we are additionally looking for other noisy real-world systems with less execution time. Finally, we are in the process of integrating kNN-Avg into our general search-based testing (SBT) and scenario generation workflow. To this end, we are developing an extension of the pymoo library, that allows kNN-Avg’s convenient off-the-shelf use.

REFERENCES

[1] A. Afzal, C. L. Goues, M. Hilton, and C. S. Timperley, “A study on challenges of testing robotic systems,” in 13th Int. Conf. on Software Testing, Validation and Verification (ICST), 2020, pp. 96–107.
[2] C.-K. Goh and K. C. Tan, Evolutionary Multi-objective Optimization in Uncertain Environments – Issues and Algorithms, ser. Studies in Computational Intelligence. Springer, 2009, vol. 186.
[3] S. Klikovits and P. Arcaini, “KNN-Averaging for Noisy Multi-Objective Optimisation,” in 14th Int. Conf. on Quality of Information and Communications Technology (QUATIC). Springer, 2021, pp. 503–518.
[4] C. K. Goh and K. C. Tan, “An investigation on noisy environments in evolutionary multiobjective optimization,” IEEE Transactions on Evolutionary Computation, vol. 11, no. 3, pp. 354–381, 2007.
[5] J. M. Fitzpatrick and J. J. Grefenstette, “Genetic algorithms in noisy environments,” Mach. Learn., vol. 3, no. 2–3, pp. 101–120, Oct. 1988.
[6] E. Zitzler, K. Deb, and L. Thiele, “Comparison of Multiobjective Evolutionary Algorithms: Empirical Results,” Evolutionary Computation, vol. 8, no. 2, pp. 173–195, 06 2000.
[7] A. E. Eiben and J. E. Smith, Introduction to Evolutionary Computing, 2nd ed. Springer, 2015.
[8] K. Deb, A. Pratap, S. Agrawal, and T. A. M. T. Meyarivan, “A fast and elitist multiobjective genetic algorithm: NSGA-II,” IEEE Transactions on Evolutionary Computation, vol. 6, no. 2, pp. 182–197, 2002.
[9] J. Blank and K. Deb, “Pymoo: Multi-objective optimisation in Python,” in 2020 IEEE Congress on Evolutionary Computation, vol. 1. IEEE, 2020, pp. 243–250.
[10] M. Li and X. Yao, “Quality evaluation of solution sets in multiobjective optimisation: A survey,” ACM Computing Surveys, 12 2019.
[11] A. Arcuri and L. Briand, “A practical guide for using statistical tests to assess randomized algorithms in software engineering,” in Proc. of the 33rd International Conference on Software Engineering. ACM, 2011, pp. 1–10.
[12] C. Wohlin, P. Runeson, M. Hst, M. C. Ohlsson, B. Regnell, and A. Wessln, Experimentation in Software Engineering. Springer, 2012.
[13] T. Park and K. R. Ryu, “Accumulative sampling for noisy evolutionary multi-objective optimization,” in Proc. of the 13th Annual Conference on Genetic and Evolutionary Computation. ACM, 2011, pp. 793–800.
[14] J. Teich, “Pareto-front exploration with uncertain objectives,” in Proc. of the First International Conference on Evolutionary Multi-Criterion Optimization, ser. EMO ’01. Springer, 2001, pp. 314–328.
[15] A. G. Li, Y. Li, S. Jha, T. Tsai, M. B. Sullivan, S. L. S. Hari, Z. Kalbarczyk, and R. K. Iyer, “AV-FUZZER: Finding safety violations in autonomous driving systems,” in 2020 IEEE 31st International Symposium on Software Reliability Engineering (ISSRE), 2020, pp. 25–36.
[16] R. Ben Abdessalem, S. Nejati, L. C. Briand, and T. Stüfter, “Testing advanced driver assistance systems using multi-objective search and neural networks,” in Proc. of the 31st IEEE/ACM International Conference on Automated Software Engineering. ACM, 2016, pp. 63–74.
[17] A. Gambi, M. Mueller, and G. Fraser, “Automatically testing self-driving cars with search-based procedural content generation,” in Proc. of the 28th ACM SIGSOFT International Symposium on Software Testing and Analysis. ACM, 2019, pp. 318–328.
[18] A. Calò, P. Arcaini, S. Ali, F. Hauser, and F. Ishikawa, “Generating avoidable collision scenarios for testing autonomous driving systems,” in 2020 IEEE 13th International Conference on Software Testing, Validation and Verification (ICST), 2020, pp. 375–386.