CoSMo: a Framework for Implementing Conditioned Process Simulation Models^{*}

Rafael S. Oyamada, Gabriel M. Tavares, and Paolo Ceravolo

Department of Computer Science, Università degli Studi di Milano, Milan, Italy {rafael.oyamada,gabriel.tavares,paolo.ceravolo}@unimi.it

Abstract. Process simulation is an analysis tool in process mining that allows users to measure the impact of changes, prevent losses, and update the process without risks or costs. In the literature, several process simulation techniques are available and they are usually built upon process models discovered from a given event log or learned via deep learning. Each group of approaches has its own strengths and limitations. The former is usually restricted to the control-flow but it is more interpretable, whereas the latter is not interpretable by nature but has a greater generalization capability on large event logs. Despite the great performance achieved by deep learning approaches, they are still not suitable to be applied to real scenarios and generate value for users. This issue is mainly due to fact their stochasticity is hard to control. To address this problem, we propose the CoSMo framework for implementing process simulation models fully based on deep learning. This framework enables simulating event logs that satisfy a constraint by conditioning the learning phase of a deep neural network. Throughout experiments, the simulation is validated from both control-flow and data-flow perspectives, demonstrating the proposed framework's capability of simulating cases while satisfying imposed conditions.

Keywords: Process Mining \cdot Business Process Simulation \cdot Deep learning \cdot What-if Analysis

1 Introduction

Process mining refers to a set of tools used for analyzing recorded data collected over time from information systems. The overall goal is to obtain insights that allow users to improve their business processes or support them in decision-making. Among the existing techniques devoted to this, process simulation models have gained renewed attention in recent research papers [12, 6, 11]. Simulating processes allows researchers and practitioners to improve and support their processes in various ways, such as validating processes before implementation or diagnosing ongoing processes [1]. In general, the current solutions

^{*} Supported by Università degli Studi di Milano

stochastically simulate traces based on assumptions from the probability distributions obtained or learned from the event logs. Most of the current simulation models available in the literature are either implemented upon process models discovered from event logs [23, 5, 6] or learned from event logs via deep learning techniques [8, 11]. The former group of methods usually requires first discovering a process model, extracting information from it, and then generating simulated traces [18]. This step might introduce limitations and lead to suboptimal solutions since selecting the suitable process discovery algorithm according to the event log characteristics can be challenging [28]. Traditionally, these methods are also restricted to the control-flow and temporal behavior, which means they are not able to take into consideration extra event attributes such as resources and costs. In this sense, deep learning present more flexibility when modeling a solution since these approaches are able to include as many event attributes as available [14, 15, 20]. Moreover, Camargo et al. [10] have demonstrated that simulation models based on deep learning outperform simulation models based on process models for larger event logs and perform similarly for smaller event logs. Despite these promising results, deep learning models still suffer from a lack of interpretability, which can be a major limitation for decision-makers. However, we believe that exploring innovative deep learning design ideas in process mining can help to mitigate this issue and advance the state-of-the-art of process simulation.

Recently, Camargo et al. [11] have proposed a hybrid solution based on process mining and deep learning techniques to overcome the limitations of both groups of methods. Although hybrid solutions tend to be more powerful since they leverage the strengths of different techniques, approaches fully based on deep learning have not been widely and properly explored so far regarding the process simulation problem. To the best of our knowledge, the only contribution in the literature is the DeepGenerator [10], which has been proposed for the generation of event logs from scratch. However, simply generating data via deep learning might not be so beneficial due to the stochasticity introduced by the learned models. Process simulation models should be able to answer questions in order to compare possible changes with respect to key performance indicators [1]. For example, teaching models how to satisfy conditions imposed by users. Although stochasticity is an intrinsic property of many simulation methods, it is possible to constrain the output of a deep neural network by providing additional information during training. By incorporating auxiliary data into the training process, it is possible to limit the randomness of the network's output by conducting them into desired directions guided by conditions. This can effectively reduce the stochastic nature of the output and increase the control over the model's behavior, which can be valuable when performing what-if analysis.

Thus, considering the recent successful deep learning applications in process mining and the lack of alternative solutions derived from it, in this paper we propose CoSMo: a framework for developing COnditioned Simulation MOdels. CoSMo is capable of learning how to simulate processes by satisfying constraints. An example of a constraint that can be taught to condition the simulation model is resource usage. We study in this work how to simulate processes that make usage (or not) of a specific resource, which basically consists of teaching neural networks how to perform simulation considering this condition of resource availability. Moreover, we take into consideration the existing deep neural architecture designs in the literature of process mining in order to develop our proposal. This way, we demonstrate through experiments that CoSMo is capable of learning how to satisfy conditions regardless of the underlying architecture. More specifically, we instantiate the DeepGenerator and a simpler architecture with fewer parameters to serve as baselines. Results show that our framework instantiations are capable of generating reasonable event logs from scratch by satisfying the imposed conditions and performing what-if analysis by simulating desired scenarios on ongoing cases.

The paper is organized as follows. Section 2 introduces the basic concepts for the understanding of this work along with a discussion on the related works. Subsequently, in Section 3 we discuss the limitations of existing process simulation models, and in Section 4 we introduce our proposed solution. Section 5 describes the employed experimental setup and the experimental evaluation. Finally, we conclude our work and discuss future directions in Section 6.

2 Background and Related Works

An event log consists of a set of cases (a.k.a. process executions) [2]. Each case is composed of an ordered sequence of events, where each event refers to the execution of a system activity and is characterized by a set of attributes. A sequence of events related to a given case is called a trace. The most common attributes that can be found in an event are the activity label and the timestamp denoting, for instance, when the activity started. Moreover, an event might present other attributes, such as a resource needed to execute the activity or the cost of this execution.

Process simulation models aim at abstracting details from the event logs in order to simulate reality [1]. They are employed as a tool by the process mining community for several applications, such as conformance checking [24], event log generation [5, 10], purposed-oriented event log generation [6], what-if analysis [12], and predictive process monitoring [26, 14, 8]. The existing simulation solutions in the literature can be mainly divided into two groups: simulation models built upon a discovered process model or models learned from event logs via deep learning. For the sake of simplicity, in this work, we shorten the process simulation based on process models term as PSPM approaches and process simulation based on deep learning as PSDL approaches.

In general, the *PSPM* approaches discover a process model and extract statistical characteristics from a given event log [23]. Thus, the simulation is usually performed by replaying a process model (e.g. Colored Petri Net [21] or BPMN [6]) in a stochastic fashion to make simulations more realistic [1]. Moreover, the obtained statistics are usually managed according to each scenario's specifications and user requirements, although guidelines and automated solutions have

been proposed [18, 7]. This group of simulation models is the most popular in the current literature and includes several proposals such as the PGL2 [5] and SIMOD [9]. These methods are usually designed to simulate different control-flow patterns by manipulating user-based requirements, such as the number of gates and the amount of noise. A weakness of this group of methods is the restriction of capturing only the control-flow and temporal behavior, whereas the strengths consist of higher interpretability since they rely on white-box representations (i.e., the discovered process model).

On the other hand, *PSDL* solutions are very recent in the process mining literature. These methods can be seen as extensions of the wide range of applications related to the predictive process monitoring field. Predictive process monitoring consists of a set of process mining techniques that aim mostly at solving the problems of the next activities, remaining time, and outcome predictions [22]. Thus, the simulation might be thought of as the problem of iteratively predicting the next activities or the whole remaining trace (a.k.a. suffix) of an ongoing execution [26]. Leveraging the recent achievements in this field, the first simulation model fully based on deep learning, named DeepGenerator, was proposed by Camargo et al. [8]. This process simulator differs from the traditional *PSPM* approaches since it learns directly from an event log instead of relying on discovering a process model and extracting additional information. Later, the same authors demonstrated that this group of simulation models is capable of outperforming PSPM approaches for larger event logs while performing similarly for smaller event logs in the event log generation task [10]. Furthermore, deep learning provides more flexibility for multi-dimensional modeling, i.e., including extra event attributes such as resources and costs.

In order to mitigate or overcome the mentioned limitations of both groups of simulation models, hybrid approaches have been proposed recently. For example, Pourbafrani and van der Aalst [21] combined process mining and system dynamics techniques, which in a nutshell leverages the details captured by process mining with higher-level information extracted by system dynamics. On the other hand, Camargo et al. [11] proposed the DeepSimulator, which employs a process model for simulating the control-flow and a deep learning model for estimating the remaining time of activities.

3 Motivation

We stress the motivation of our work by considering the current limitations of existing process simulation solutions. The *PSPM* approaches might be influenced by the underlying process model [28] and they are restricted to control-flow aspects and temporal behaviors. This means they are affected by the bias introduced by the discovery algorithms. Indeed, there is no common sense for selecting the optimal discovery algorithm according to the given event log characteristics, which may lead to suboptimal performances [28].

A common characteristic among process simulation models is the stochasticity inserted during simulation. For example, simulations by replaying process models are supported by statistical information extracted from the event logs, such as branches' probabilities and activity duration time distributions. On the other hand, *PSDL* approaches consist of learning the underlying data distributions and drawing event attributes from the probability distributions returned by the learned model. Although this stochastic approach makes simulations more realistic [1, 8], fully depending on randomness limits the users' flexibility to control the simulated behaviors based on desired conditions. To the best of our knowledge, the first deep learning application in process mining was proposed in 2017 by Evermann et al. [13] to introduce a solution for the problem of next activity prediction. Since then, many variations have been proposed and extended for other tasks [22], but a very small effort has been dedicated to process simulation exclusively.

Conditioning the simulation of a process is relevant since it provides more flexibility to users by allowing them to restrict the simulation according to the desired scenario. The idea of this approach is to be more adaptable by learning how processes might behave under possible changes or desired constraints. The most related solution to ours in the literature is the Purple framework, recently introduced by [6]. The authors proposed a purpose-guided solution capable of simulating entire event logs by following a given purpose. For instance, Purple is capable of generating synthetic event logs specifically designed to evaluate and possibly benchmark process discovery algorithms. However, it is still harmed by the greatest limitation of PMPS approaches since it focuses mainly on the control-flow aspects.

In order to clarify the problem of control-flow restriction and fully rely on the stochasticity nature of simulation models, consider the following example. Consider an activity A which might be followed by one out of two possible activities: activity B, if A is executed by the resource R_1 ; or activity C, if A is executed by a resource R_2 . A stochastic process simulation model will randomly associate a resource to A based on the learned probability distributions from the given event log. However, the intuitive idea of CoSMo is providing the user an alternative for restricting the simulations based on the condition that only R_1 can be employed at that moment, i.e., A should always be followed by B. More examples of naive and intuitive conditions in the process mining context might include the usage of given resources (e.g. if a resource is available or not for the process execution), time-based constraints (e.g. restricting allowed time for a process that fails or succeeds w.r.t. a key process indicator).

Now, consider the abstraction of a neural network as $p(y|x) = \hat{y}$ with some abuse of notation, where \hat{y} is a probability distribution returned by the neural network p [3]. Hence, a naive neural network is naturally a conditioned probability function that aims at estimating y given a random variable x. In probability theory, we are allowed to jointly measure the probability of the intersection of multiple random variables. For instance, functions that learn the underlying relation of sequential data (e.g. recurrent networks, see [26] for a formal definition in the context of process mining) are interested in knowing the probability distribution $p(x_t|x_{t-1}, ..., x_1)$ where t indicates, for instance, the position or time of the random variable x. Thus, the conditional learning of neural nets in the context of this work can be performed by introducing customized conditions C in the form of auxiliary information, such that $p(y|x, c) = \hat{y}$.

Therefore, in this work, we propose a conditioned process simulation model. The overall idea consists of providing the model with some extra information during the training phase so that at the testing phase (simulation) the outputs might be restricted or manipulated according to the provided extra information. Such extra information can be provided in the form of class labels [19], for instance. However, conditional learning is very popular nowadays in the multi-modal learning context, for example, generation of text conditioned by images [16] or by short text prompts [4].

4 CoSMo: A Framework for Conditioned Simulation Models

In this section, we introduce CoSMo, our proposed framework for implementing process simulation models based on conditioned deep neural nets. We propose a methodology that leverages a basic deep learning technique to mitigate the stochastic nature of process simulation models. Although stochasticity will be always present in simulations, following this conditioned design allows users and practitioners to have more control over the outputs.



Fig. 1. Implementation pipeline for instantiating a process simulator based on the CoSMo framework.

Figure 1 summarizes the pipeline for instantiating CoSMo. The red blocks refer to data preprocessing steps, the yellow block refers to the training of a conditioned network, and the green block refers to the final conditioned simulation model. Given an event log, there are three preprocessing steps, and one of them is optional. The conditioning step regards the labeling of cases based on a constraint. Nevertheless, in this step users are free to design any condition according to their interests. The obtained conditions in form of labels serve as auxiliary information when training a deep neural net. Moreover, alternative preprocessing procedures are included as an optional step. Finally, the *n-gram* method is applied to transform the preprocessed event log into a dataset of conditioned prefixes.

Given the dataset of conditioned prefixes, we can train a conditioned network. A generic design of conditioned networks for process simulation is proposed in Figure 2. We take into consideration two important aspects to propose this abstraction. First, we consider several design ideas of conditional learning from the deep learning community as briefly discussed in Section 3. Second, we also consider all the mentioned related works in predictive process monitoring since they follow a similar neural architecture design in general. Usually, the overall architectures employ a block for learning a representation of input features (a.k.a. encoding), e.g. RNNs to represent temporal dependencies [26] or CNNs to extract new features [29], followed by a linear (a.k.a. dense or fully connected) layer. Therefore, the overall idea of designing generic conditioned networks is first to learn feature representations of the input prefix and concatenate the outputs with the provided condition label. The next blocks are hence responsible for performing non-linear transformations in order to learn how to solve downstream tasks, for instance, the next activity prediction or remaining time estimation.

Due to the *n-gram* nature of data, CoSMo allows users to perform (i) simulations from scratch, i.e., given a zero-like prefix and a desired condition as input, and (ii) simulations from ongoing cases, i.e., simulating the remaining events from a real start point. The former allows users, for example, to simulate synthetic event logs with desired characteristics, e.g., a set of traces executed under the specified condition. The latter is intended for performing what-if analysis. For instance, how a current process execution will behave if a



Fig. 2. Generic design of conditioned networks for training process simulation models.

specific resource is not available. The simulation of an ongoing case leverages the provided information to predict the next events, unlike the simulation from scratch which starts from a zero-like prefix and takes into consideration only the desired condition to be satisfied.

5 Experiments

In this section, we aim at demonstrating how process simulation models based on deep learning can learn to satisfy conditions imposed by the user. Thus, we first describe our experimental setup to evaluate the CoSMo pipeline and we conclude by discussing the performance evaluation.

5.1 CoSMo Pipeline

Datasets. We employ almost all datasets benchmarked¹ by Weytjens and Weerdt [30], which are detailed in the Table 1². We disregard the *BPI15* and *BPI12* event logs since the former has never been considered (to the best of our knowledge) by papers related to predictive process monitoring or process simulation based on deep learning and the latter has numerical resources, which does not fit the scope of this work aiming at the usage of categorical resources. For training, we include the following event attributes: *activity, resource,* and *remaining time³*. Since we aim at evaluating several datasets from a more generic perspective, we consider them since they represent the maximum common set in the employed datasets.

Event Log	#traces	$\# \mathbf{evts}$	#acts	$\#\mathbf{res}$	#vars	Avg act per trace	Avg trace length
BPI13_Closed	652	4025	6	540	283	$2.64{\pm}0.72$	$6.17 {\pm} 4.66$
BPI13_Incidents	5796	88587	4	1432	1963	$2.74{\pm}0.5$	15.28 ± 14.52
BPI17	31497	1210807	26	149	16441	$15.43 {\pm} 2.4$	$38.44{\pm}17.96$
BPI19	148218	843195	40	471	6434	$5.15{\pm}1.16$	$5.69 {\pm} 5.02$
$BPI20_PL$	6831	82190	50	2	1547	$10.66 {\pm} 3.29$	$12.03 {\pm} 5.44$
BPI20_PTC	1781	15233	29	2	194	$8.36{\pm}1.98$	$8.55 {\pm} 2.26$
BPI20_RFP	5692	29887	17	2	73	$5.13{\pm}1.0$	$5.25 {\pm} 1.29$

Table 1. Statistics extracted from each event log: number of traces, number of events, number of activities, number of resources, number of variants, the average number of activities per trace, and average trace length.

Preprocessing. First, we encode traces to be processed by our framework. Similarly to [8], we generate prefixes using the *n-gram* approach to handle multidimensional inputs and demark the end of sequences by including a special token " $\langle eos \rangle$ " for categorical attributes or a *zero value* for numerical attributes. Further, we apply right-padding to the prefixes by also adding a special token " $\langle pad \rangle$ ".

Conditioning. The encoding procedure is completed by introducing the resource usage condition. In order to provide the neural net with such a condition, we first label each case as a binary class if it uses a specific resource at any point of its execution or not. For each event log, we select the second most used resource to be employed as the condition. The reason for choosing the second most frequent one is that for some datasets (e.g. BPI20 - RequestForPayment)

¹ https://github.com/hansweytjens/predictive-process-monitoring-benchmarks/

² Note that it might slightly differ from the original event logs due to the preprocessing steps proposed by the authors. Moreover, we shorten the *BPI20* logs: Permit Log (PL), Prepaid Travel Cost (PTC), and Request For Payment (RFP).

³ The benchmarked versions of the event logs contain the remaining time information. See [30].

the most frequent is present in all cases, which would result in one label for all cases. Thus, a conditioned prefix takes the form of a tuple cp = (prefix, cond), where $prefix \in \mathcal{R}^{l,d}$, with l being the sequence length and d the number of event attributes, and *cond* is a scalar.

CoSMo instantiations. We instantiate the DeepGenerator architecture (see [8]) using our proposed framework, i.e. encoding traces using conditions. We designed the architecture following the descriptions provided in the paper and included an extra concatenation operation (see Figure 2) before feeding the last linear layers. Moreover, we also include a smaller baseline with fewer learnable parameters for comparison. The baseline architecture (Figure 3) contains an embedding layer of categorical features, an LSTM block for encoding the input data, a concatenation operation for conditioning the encoded data, followed by an MLP block (stack of linear layers), and individual linear layers to output each event attribute. The final number of learnable parameters varies for each dataset since the size of the set of activities also varies, and they are summarized in Table 2. As we are concerned specifically about the conditional learning of process simulation models, we attempt to simplify the experimental setup and focus on the methodology by demonstrating how well models are capable of learning how to satisfy user-based conditions. Therefore, we fixed hyperparameters related to the design of both architectures (e.g. number of layers) to reduce the hyperparameter search space for tuning. All details regarding the settings for architecture design and also for reproducibility are available in our repository⁴.

Training phase. We used the bayesian optimization from WandB⁵ with a 4-dimensional hyperparameter search space to tune both architectures. Fixed hyperparameters include the number of epochs as 50, n = 5 regarding the *n*-gram, and the remaining architecture hyperparameters (e.g. number of layers). Subsequently, the optimization method ran for 10 iterations. The evaluated range and set of hyperparameters are described in Table 2.

The architectures share the same loss functions: cross entropy for activity and resource predictions and mean squared error for remaining time prediction. The training is performed in a multi-task fashion, where all loss functions are minimized together. Moreover, we use the He initialization to initialize the neural network parameters and employ a scheduler to decay the learning rate at epochs 25 and 35 by a factor of 0.1. We implemented everything in Python using Pytorch⁶.

Testing phase (Simulation). We employ multinomial sampling to draw the next categorical event attributes from the probability distributions returned by the neural net. This sampling method has shown better results since it presents more diversity in the trace simulation despite the injected randomness [8]. The simulation is performed in two different ways: (i) we simulate traces from scratch, starting from a zero-like array; and (ii) we simulate the remaining trace by starting from different positions given an ongoing case. For instance, considering

⁴ https://github.com/raseidi/cosmo

⁵ https://docs.wandb.ai/guides/sweeps

⁶ https://pytorch.org/



Hyperparam	Values			
Batch size	$\{64, 256, 512\}$			
Learning rate	[1e-3, 1e-6]			
Optmizer	$\{Adam,SGD\}$			
Weight decay	$\{0.0, 1e-2, 1e-3\}$			
Architecture	Avg. number of parameters			
Baseline	$1.71\mathrm{E}{+06}$			
DeepGenerator	$2.39E{+}06$			

Fig. 3. Baseline architecture design. Each output linear layer outputs a different event attribute (i.e., in the sense of this work, activity, resource, and remaining time).

Table 2. Description of hyperparameters values considered for tuning and the average number of learnable parameters for each architecture.

a case of length n, we can simulate remaining traces starting from any position i, where 0 < i < n. However, to save computational resources and accelerate the experiments, we iterate i considering a step of 2. Regarding simulations from scratch, we simulate n traces where n is equal to the testing set size. Since we consider a binary condition in this work, half of these traces are simulated under one condition and the other half is simulated under the other condition. The remaining trace simulation is performed for each case from the testing set.

Evaluation. We organize our evaluation into three steps. First, we consider *event-level* metrics to validate the predictive performance of simulations regarding the next event attribute predictions. Thus, we employ the accuracy for categorical attributes and the mean absolute error for the remaining time. Second, we consider *trace-level* metrics to evaluate the quality of the simulated event logs. We employ the Earth Mover's Distance (*EMD*) to measure the similarity between the distributions of real and simulated remaining time predictions; the Control-Flow Log Similarity (CFLS), which considers the optimal similarity measures between paired traces; and the fitness of the simulated log w.r.t. the process model discovered from the original \log^7 . The first two metrics are also employed by Camargo et al. [10] to measure the quality w.r.t the data-flow and control-flow, whereas the latter metric has never been considered as a strategy to evaluate simulated logs.

Finally, we simulated a what-if scenario and we measure the percentage of traces that were correctly simulated by satisfying the imposed constraint. As previously mentioned, we establish in this work the resource usage condition.

⁷ This is performed by discovering a model from the original log (using inductive miner [17]) and measuring the simulated log fitness via token replay. We do not use the alignment-based fitness algorithm due to computational resource limitations.

Although simple, the main goal of this work is to demonstrate how to learn conditioned process simulation models and how processes might be simulated by satisfying user-based conditions. Therefore, in the scope of this work, the what-if analysis consists of simulating how the processes behave by allowing or not the usage of a given resource.

Although the overall idea of our work is slightly similar to the Purple framework [6], their solution focuses on the control-flow simulation only. Since we are not able to instantiate the proposal by guiding the generation based on resource usage, we are not employing it as a baseline in this work.

5.2 Performance evaluation

We organize this section in three steps. First, we discuss the event-level metrics employed to measure the predictive performances of the architectures instantiated by our CoSMo framework. Second, we present the trace-level metrics that measure the quality of logs simulated by each architecture. Finally, we introduce our what-if scenario and evaluate how well the proposed framework performs by simulating traces under imposed conditions.

Event Log	Architecture	Acc-ACT	Acc-RES	MAE-RT
BPI13_Closed	Baseline DG	$0.6275 \\ 0.6455$	$0.1838 \\ 0.2087$	$0.0002 \\ 0.0003$
BPI13_Incidents	Baseline DG	$0.7956 \\ 0.7823$	$0.6485 \\ 0.6041$	$0.0001 \\ 0.000$
BPI17	Baseline DG	$0.9026 \\ 0.8969$	$\begin{array}{c} 0.7474 \\ 0.7469 \end{array}$	$0.000 \\ 0.000$
BPI19	Baseline DG	$\begin{array}{c} 0.823 \\ 0.8244 \end{array}$	$\begin{array}{c} 0.5047 \\ 0.5078 \end{array}$	$0.0001 \\ 0.0001$
BPI20_PL	Baseline DG	$0.8227 \\ 0.8121$	$0.9716 \\ 0.9663$	0.000 0.000
BPI20_PTC	Baseline DG	$0.8666 \\ 0.6943$	$0.9976 \\ 0.944$	$0.000 \\ 0.000$
BPI20_RFP	Baseline DG	$0.9277 \\ 0.913$	$0.9996 \\ 0.9949$	0.000 0.000

Table 3. Event-level evaluation metrics achieved by each architecture for each event log. Acc-ACT stands for the accuracy of the next activity prediction, Acc-RES for accuracy of the next resource prediction, and MAE-RT for the mean absolute error of the remaining time prediction (in days).

Event-level metrics. Table 3 shows the performances achieved by each architecture. The employed metrics are, respectively, the accuracy for the next activity and resource predictions and the mean absolute error for the next remaining time prediction. We can notice there is no significant difference between the employed architectures for most processes. This shows that the proposed baseline architecture performs as well as the DeepGenerator using about 30%

fewer parameters. An exception occurs for the dataset *BP120 - Prepaid Travel Cost*, where the DeepGenerator performs poorly. A reason for that might be that the bayesian optimization method was not able to find the best hyperparameters in the defined amount of iterations. On the other hand, we see lower predictive performances for *BP113 - Closed* and *BP113 - Incidents*. Crossing these results with the information from Table 1, we see that there is a certain correlation between the predictive performances and the average number of activities per trace. For the mentioned datasets, although we have traces as long as in other event logs, there is a very low variation of unique activities in the traces.

Trace-level metrics. Figure 4 illustrates the performances of each architecture for each dataset. The lower the EMD the better, whereas the higher the CFLS and fitness the better. Notice that these metrics are measured using the logs simulated from scratch. Both architectures perform similarly again, except for BPI19 and BPI20 - Request For Payment regarding the EMD score. However, the performance can still be considered good since in both cases the score is close to zero. This result matches and complements the event-level metric regarding the remaining time prediction. Furthermore, the variation measured across the optimally paired traces regarding the CFLS score is also similar for both architectures. For BPI13 - Closed and BPI20 - Prepaid Travel Cost both architectures present higher variations, whereas for the remaining datasets the architectures present lower variations. In some cases, the baseline architecture presented CFLS scores slightly better, whereas the DeepGenerator achieved process model fitness scores slightly better in most cases.



Fig. 4. Trace-level evaluation metrics from the employed architectures in this work. Lower values for EMD are better, whereas the higher the better regarding the remaining metrics.

What-if analysis. We now describe how our framework can be employed to perform what-if analysis and demonstrate the effectiveness of our proposal. As mentioned in the previous sections, we simulate traces that make the usage or not of specific resources. Thus, we simulate traces from scratch and from different positions of an ongoing case. The simulations from scratch start from a zero-like array, whereas the ongoing simulations take into consideration the information available so far.



Fig. 5. The percentage of traces that were correctly simulated by satisfying each imposed condition. This score is measured by starting the simulation from different positions in the cases. Case at position zero means simulation from scratch of the entire trace.

Figure 5 illustrates the percentage of traces correctly simulated under each condition. In this Figure, case position equals 0 means simulation from scratch. BPI13 - Closed simulates traces that satisfy the conditions almost perfectly. Despite the low predictive performances, both this dataset and the BPI13 - In*cidents* perform considerably well in this analysis. Although their characteristics (low number of activities and the low average number of activities per trace) affect the learning phase, both architectures are still able to learn how to satisfy the imposed conditions. Overall, all models learned more effectively how to simulate traces that do not make use of the specified resources (i.e. red line). Furthermore, the BPI13 - Incidents, BPI17, BPI20 - Permit Log, and BPI20 - Request For Payment show the expected behavior of improvement in performances as long as more information on the ongoing trace is provided. In this case, we only see an exception for the DeepGenerator for the latter event log, which performed poorly considering the condition of ensuring resource usage. The drastic drop in performance considering the baseline architecture on the BPI20 - Request For Payment is due to the fact this log has fewer longer cases. In this example,

there are only two ongoing cases being simulated from position 12, which means only one of them has not satisfied the condition and dropped the performance by 50%. Similar behavior can be seen for the same event log simulated by the DeepGenerator. *BPI19* was able to learn the simulation of traces without using the given resource, but on the other hand, the performances achieved by both architectures were arbitrary when complying with the condition. Considering the usage of the resource, the baseline architecture performed reasonably well for simulations from scratch and from the beginning of traces, but both architectures performed quite poorly for all the other cases.

6 Conclusion and Future Work

In this work, we introduced the CoSMo framework, which can adapt existing neural network architectures in order to make them learn how to simulate traces that satisfy different conditions. We introduced a very simple and naive condition to serve as an example and demonstrate how models can learn to satisfy this condition when performing simulations. Two instantiations of our proposal were considered using different neural architectures, where one is our proposed baseline and the other refers to the DeepGenerator [10]. Subsequently, we first validate the quality of simulated data through metrics specific to the event- and trace-level evaluation. Finally, we demonstrate the effectiveness of the conditioned simulation models for learning to simulate traces by satisfying an imposed condition. We believe this research introduces in the process mining community a new modeling approach to mitigate the complete stochasticity of current existing simulation models by guiding the simulation based on constraints.

In future directions, we intend to investigate alternative conditions that might be more valuable for real scenarios and stakeholders. Furthermore, the current binary nature of conditions is also a limitation, so future research will also investigate how to perform the simulation based on multiple conditions. The current approach considers a "global" condition w.r.t. a case instance, i.e. it provides one single label for the entire case. However, a more valuable application could rely on "local" conditions, which might change throughout the process cycle time. Finally, although we opted for focusing on the methodology of our proposal, several approaches from the predictive process monitoring community might be leveraged to enhance the final process simulation model. Such techniques include feature engineering based on process mining algorithms [8], robustness enhancement [27, 25], representation learning [20], and hybrid solutions [11].

References

 van der Aalst, W.M.P.: Business process simulation survival guide. In: vom Brocke, J., Rosemann, M. (eds.) Handbook on Business Process Management, 2nd Ed, pp. 337–370, International Handbooks on Information Systems, Springer (2015)

- [2] van der Aalst, W.M.P.: Process Mining Data Science in Action, Second Edition. Springer (2016)
- [3] Bishop, C.M.: Pattern recognition and machine learning, 5th Edition. Information science and statistics, Springer (2007)
- [4] Brown, T.B., Mann, B., Ryder, N., Subbiah, M., Kaplan, J., Dhariwal, P., Neelakantan, A., Shyam, P., Sastry, G., Askell, A., Agarwal, S., Herbert-Voss, A., Krueger, G., Henighan, T., Child, R., Ramesh, A., Ziegler, D.M., Wu, J., Winter, C., Hesse, C., Chen, M., Sigler, E., Litwin, M., Gray, S., Chess, B., Clark, J., Berner, C., McCandlish, S., Radford, A., Sutskever, I., Amodei, D.: Language models are few-shot learners. In: Larochelle, H., Ranzato, M., Hadsell, R., Balcan, M., Lin, H. (eds.) NeurIPS (2020)
- [5] Burattin, A.: PLG2: multiperspective processes randomization and simulation for online and offline settings. CoRR **abs/1506.08415** (2015)
- [6] Burattin, A., Re, B., Rossi, L., Tiezzi, F.: A purpose-guided log generation framework. In: Ciccio, C.D., Dijkman, R.M., del-Río-Ortega, A., Rinderle-Ma, S. (eds.) BPM, LNCS, vol. 13420, pp. 181–198, Springer (2022)
- [7] Camargo, M., Dumas, M., González, O.: Automated discovery of business process simulation models from event logs. Decis. Support Syst. 134, 113284 (2020)
- [8] Camargo, M., Dumas, M., Rojas, O.G.: Learning accurate LSTM models of business processes. In: Hildebrandt, T.T., van Dongen, B.F., Röglinger, M., Mendling, J. (eds.) BPM, LNCS, vol. 11675, pp. 286–302, Springer (2019)
- [9] Camargo, M., Dumas, M., Rojas, O.G.: Simod: A tool for automated discovery of business process simulation models. In: Depaire, B., Smedt, J.D., Dumas, M., Fahland, D., Kumar, A., Leopold, H., Reichert, M., Rinderle-Ma, S., Schulte, S., Seidel, S., van der Aalst, W.M.P. (eds.) BPM, CEUR Workshop Proceedings, vol. 2420, pp. 139–143 (2019)
- [10] Camargo, M., Dumas, M., Rojas, O.G.: Discovering generative models from event logs: data-driven simulation vs deep learning. PeerJ Comput. Sci. 7, e577 (2021)
- [11] Camargo, M., Dumas, M., Rojas, O.G.: Learning accurate business process simulation models from event logs via automated process discovery and deep learning. In: Franch, X., Poels, G., Gailly, F., Snoeck, M. (eds.) CAiSE, LNCS, vol. 13295, pp. 55–71, Springer (2022)
- [12] Dumas, M.: Constructing digital twins for accurate and reliable what-if business process analysis. In: Beerepoot, I., Ciccio, C.D., Marrella, A., Reijers, H.A., Rinderle-Ma, S., Weber, B. (eds.) BPM, CEUR Workshop Proceedings, vol. 2938, pp. 23–27 (2021)
- [13] Evermann, J., Rehse, J., Fettke, P.: Predicting process behaviour using deep learning. Decis. Support Syst. 100, 129–140 (2017)
- [14] Francescomarino, C.D., Ghidini, C., Maggi, F.M., Petrucci, G., Yeshchenko, A.: An eye into the future: Leveraging a-priori knowledge in predictive business process monitoring. In: Carmona, J., Engels, G., Kumar, A. (eds.) BPM, LNCS, vol. 10445, pp. 252–268, Springer (2017)
- [15] Hinkka, M., Lehto, T., Heljanko, K.: Exploiting event log event attributes in RNN based prediction. In: Ceravolo, P., van Keulen, M., López, M.T.G. (eds.) SIMPDA, LNBIP, vol. 379, pp. 67–85, Springer (2019)

- 16 Oyamada et al.
- [16] Karpathy, A., Fei-Fei, L.: Deep visual-semantic alignments for generating image descriptions. In: CVPR, pp. 3128–3137, IEEE Computer Society (2015)
- [17] Leemans, S.J.J., Fahland, D., van der Aalst, W.M.P.: Discovering blockstructured process models from event logs - A constructive approach. In: Colom, J.M., Desel, J. (eds.) PETRI NETS, LNCS, vol. 7927, pp. 311–329, Springer (2013)
- [18] Martin, N., Depaire, B., Caris, A.: The use of process mining in business process simulation model construction - structuring the field. Bus. Inf. Syst. Eng. 58(1), 73–87 (2016)
- [19] Mirza, M., Osindero, S.: Conditional generative adversarial nets. CoRR abs/1411.1784 (2014)
- [20] Pfeiffer, P., Lahann, J., Fettke, P.: Multivariate business process representation learning utilizing gramian angular fields and convolutional neural networks. In: Polyvyanyy, A., Wynn, M.T., Looy, A.V., Reichert, M. (eds.) BPM, LNCS, vol. 12875, pp. 327–344, Springer (2021)
- [21] Pourbafrani, M., van der Aalst, W.M.P.: Hybrid business process simulation: Updating detailed process simulation models using high-level simulations. In: Guizzardi, R.S.S., Ralyté, J., Franch, X. (eds.) RCIS, LNBIP, vol. 446, pp. 177–194, Springer (2022)
- [22] Rama-Maneiro, E., Vidal, J., Lama, M.: Deep learning for predictive business process monitoring: Review and benchmark. IEEE TSC pp. 1–1 (2021)
- [23] Rozinat, A., Mans, R.S., Song, M., van der Aalst, W.M.P.: Discovering simulation models. Inf. Syst. 34(3), 305–327 (2009)
- [24] Sani, M.F., Gonzalez, J.J.G., van Zelst, S.J., van der Aalst, W.M.P.: Conformance checking approximation using simulation. In: van Dongen, B.F., Montali, M., Wynn, M.T. (eds.) ICPM, pp. 105–112, IEEE (2020)
- [25] Stevens, A., Smedt, J.D., Peeperkorn, J., Weerdt, J.D.: Assessing the robustness in predictive process monitoring through adversarial attacks. In: Burattin, A., Polyvyanyy, A., Weber, B. (eds.) ICPM, pp. 56–63, IEEE (2022)
- [26] Tax, N., Verenich, I., Rosa, M.L., Dumas, M.: Predictive business process monitoring with LSTM neural networks. In: Dubois, E., Pohl, K. (eds.) CAiSE, LNCS, vol. 10253, pp. 477–492, Springer (2017)
- [27] Venkateswaran, P., Muthusamy, V., Isahagian, V., Venkatasubramanian, N.: Robust and generalizable predictive models for business processes. In: Polyvyanyy, A., Wynn, M.T., Looy, A.V., Reichert, M. (eds.) BPM, LNCS, vol. 12875, pp. 105–122, Springer (2021)
- [28] Weerdt, J.D., Backer, M.D., Vanthienen, J., Baesens, B.: A multidimensional quality assessment of state-of-the-art process discovery algorithms using real-life event logs. Inf. Syst. 37(7), 654–676 (2012)
- [29] Weytjens, H., Weerdt, J.D.: Process outcome prediction: CNN vs. LSTM (with attention). In: del-Río-Ortega, A., Leopold, H., Santoro, F.M. (eds.) BPM Workshops, LNBIP, vol. 397, pp. 321–333, Springer (2020)
- [30] Weytjens, H., Weerdt, J.D.: Creating unbiased public benchmark datasets with data leakage prevention for predictive process monitoring. In: Marrella, A., Weber, B. (eds.) BPM, LNBIP, vol. 436, pp. 18–29, Springer (2021)