

# УПРАВЛІННЯ У ТЕХНІЧНИХ СИСТЕМАХ

## CONTROL IN TECHNICAL SYSTEMS

UDC 004.93

### IMPROVED MULTI-OBJECTIVE OPTIMIZATION IN BUSINESS PROCESS MANAGEMENT USING R-NSGA-II

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#### ABSTRACT

**Context.** Business process management is a critical component in contemporary organizations for maintaining efficiency and achieving operational objectives. Optimization of these processes in terms of time and cost can lead to significant improvements in overall business performance. However, traditional optimization techniques often face challenges in handling multi-objective problems with a known time-cost trade-off, necessitating more effective solutions. The integration of a business process model and notation for a stochastic process simulation provides a robust foundation for analyzing these business processes and complies with state-of-the-art business process management. In prior studies, we applied several heuristic algorithms, including the evolutionary NSGA-II, to find a Pareto-optimal set of solutions. We defined a solution as a pair of cost and time associated with a specific resource allocation. For one of the selected processes, the performance of NSGA-II was subpar compared to other techniques.

**Objective.** The goal of this study is to improve upon the NSGA-II's performance and, in turn, enhance the efficiency of multi-objective business process optimization. Specifically, we aim to incorporate reference points into NSGA-II. Our goal is to identify an optimized set of solutions that represent a trade-off between process execution time and the associated cost. We expect this set to have a higher spread and other quality metrics, compared to the prior outputs.

**Method.** To accomplish our objective, we adopted a two-step approach. Firstly, we modified the original genetic algorithm by selecting and integrating the reference points that served to guide the search towards the Pareto-optimal front. This integration was designed to enhance the exploration and exploitation capabilities of the algorithm. Secondly, we employed the improved algorithm, namely R-NSGA-II, in the stochastic simulations of the business processes. The BPMN provided the input for these simulations, wherein we altered the resource allocation to observe the impact on process time and cost.

**Results.** Our experimental results demonstrated that the R-NSGA-II significantly outperformed the original NSGA-II algorithm for the given process model, derived from the event log. The modified algorithm was able to identify a wider and more diverse Pareto-optimal front, thus providing a more comprehensive set of optimal solutions concerning cost and time.

**Conclusions.** The study confirmed and underscored the potential of integrating the reference points into NSGA-II for optimizing business processes. The improved performance of R-NSGA-II, evident from the better Pareto-optimal front it identified, highlights its efficacy in multi-objective optimization problems, as well as the simplicity of the reference-based approaches in the scope of BPM. Our research poses the direction for the further exploration of the heuristics to improve the outcomes of the optimization techniques or their execution performance.

**KEYWORDS:** business process, genetic algorithm, reference points, multi-objective optimization, spacing.

#### ABBREVIATIONS

BPM is a business process management;  
BPMN is a business process model and notation;  
BPS is a business process simulation;  
MOEA is a multi-objective evolutionary algorithm;  
MOOP is a multi-objective optimization problem;  
MORAP is a multi-objective resource allocation problem;  
NSGA-II is a non-sorting genetic algorithm;  
R-NSGA-II is a reference non-sorting genetic algorithm;  
CT is the cycle time;  
TC is the total cost;  
TCT is the theoretical cycle time;

OMG is Object Management Group;  
HA is hyperarea;  
SP is spacing;  
IGD is inverted generational distance.

#### NOMENCLATURE

$M$  is the number of the conflicting objective functions;  
 $R^M$  is the objective function space;  
 $f()$  is a process simulation function;  
 $S$  is a constrained search space;  
 $a$  is a lower bound for the allocation;  
 $b$  is an upper bound for the allocation;  
 $x^*$  is a Pareto-optimal solution;

$P_{ref}$  is a Pareto front containing Pareto-dominating points from the different applied algorithms;  
 $P_{ref}'$  is  $P_{ref}$  including R-NSGA-II;  
 $x$  is an allocation parameter used in Tabu Search;  
 $x'$  is an allocation parameter used in R-NSGA-II;  
 $H$  is a set of heuristics used;  
 $C_i$  is the hourly cost for the resource;  
 $t_i$  is the number of hours spent by the resource;  
 $p()$  is a purity metric function;  
 $p_i$  is the probability of the outgoing sequence flow;  
 $T_i$  is the average task execution time;  
 $p_{rew}$  is the probability of necessity to rework the task;  
 $r_i$  is the resource pool;  
 $cTime$  is an average CT of the process;  
 $N$  is the number of resources assigned;  
 $TC_r$  is the total cost for the resource pool;  
 $R_p$  is a sequence of resource pools;  
 $rtCost$  is the function that retrieves TC for  $r_i$ ;  
 $\epsilon$  is a threshold parameter;  
 $RP_c$  is a cost reference point;  
 $RP_t$  is a time reference point;  
 $RP_h$  is a reference point to optimize HA;  
 $P_{approx}$  is a Pareto front obtained by a specific algorithm;  
 $\mu$  is the population size;  
 $\lambda$  is the size of the offspring;  
 $rp$  is the number of reference points.

## INTRODUCTION

Resource optimization in business processes is a critical aspect of the organizational efficacy and profitability of enterprises. The process of resource management and assigning resources to the work roles, as well as simulating their behaviour in a business process has been widely addressed using various Petri net models [1, 2]. Although the Petri nets are generally compliant and transformable with the newer industry standard of BPMN [3], they possess a small toolset for modelling complex business processes that involve multiple objectives and high-level business concepts [4]. The descriptive possibilities of the core Petri nets and their' extensions (e.g. stochastic Petri nets or differential Petri nets) are of limited applicability to the modern well-defined business flows, and not coupled to the industry processes requirements. It leads to the necessity for the specific enterprise to develop a model with a custom architecture, which might require manual changes to be compliant with other models.

From a practical standpoint, the classical Petri nets typically aimed for a precise simulation of the basic mechanisms present in the system and clearly communicating its state. If the system becomes more complicated, considering privacy requirements, unequal resources, and other constraints, the specification complexity of this Petri net increases. Since the Places, Transitions, and Tokens are not self-descriptive, the built model has to carry all the rules and assumptions for each element. While not all of these constraints might be necessary for the simulation, they are required to explicitly define an AS-IS process and make it possible to interpret the results by manage-

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ment representatives. Moreover, BPMN provides a number of time-related primitives out-of-the-box, which are often critical to describe the simulation scenarios, whereas the notion of time is not natively defined in classical Petri nets [5].

There are a number of extended notations of Petri nets, such as stochastic, hierarchical, and differential Petri nets, that were attempting to address multi-level processes, multi-agent systems, stochastic transitions, and others. The diversity of non-standardized solutions could be a ground that led the industry to create a conventional standard, which includes the necessary primitives to exhaustively describe the business process and its scenarios, without the necessity to introduce the common definitions for each model.

BPMN 2.0 has become a standard, which expresses the control logic such as choice, sequences, parallel execution, and iteration and introduces the respective common concepts such as Task, Event, and Resource Pool instead of operating abstract places, transitions, and tokens. The more advanced elements such as timer event, lane, or data object allow to cover typical use cases with less architectural effort. BPMN has been approved by OMG, it describes and formalizes the manifold of use cases of the enterprise systems. Nevertheless, BPMN is two-way compatible with the majority kinds of Petri nets and other industrial frameworks, which are used by different simulation engines by building the mapping between BPMN and Petri nets [6, 7].

One of the classical problems of enterprise management concerns choosing the number of people or, more generally, resources to assign to a specific unit of work. Increasing the number of resources typically leads to lower execution times of the work units, which implies a faster business process cycle. In its turn, the amount of money (cost) required to spend on these resources also increases. The improvement of the cost or time efficacy of the business process is usually achieved by qualitative and quantitative analysis. In this research we prioritize the quantitative analysis, employing and assessing various optimization methods in the scope of business process modelling. However, enterprises usually do not seek to minimize only the cost of their business process or to make execution time the lowest possible. Instead, both cost and time are objectives, and the goal is to find a suitable trade-off from a set of existing allocations. This is a so-called MORAP.

In [8] the solution was developed to employ three algorithms for finding the Pareto front containing resource allocations for the given BPMN, so that there is not any single allocation in the set with a better cost and time simultaneously, compared to another allocation from the set. The Pareto front represents the trade-offs between multiple objectives and allows one to select a suitable solution depending on the management priority. The performance metrics of the algorithms were compared across multiple business processes. In particular, the output Pareto front for the business process of the call center, acquired by NSGA-II, diverged significantly with the

reference front accumulated from all of the three approaches.

In this paper, we plan to set up a more advanced variant of the NSGA-II evolutionary algorithm, namely R-NSGA-II, to assess the possibility to narrow the gap between accumulated outcomes of the regression descent algorithms and NSGA-II. We will select the reference points that fit the common sense bounds of the selected process, run the adjusted algorithm, and record the metrics of the updated Pareto front.

**The object of study** is the Pareto fronts of the dominating resource allocations in the business processes, their quality metrics, and the input data features.

**The subject of study** is the methods for identifying the Pareto-optimal set of resource allocations in a business process derived from the call center event log.

**The purpose of the work** is to improve the metrics of the outputting Pareto front for the selected BPMN model, by adding the reference points to the NSGA-II experimental run.

## 1 PROBLEM STATEMENT

Suppose given a classical MOOP, to find a single solution we can use the formalism as follows:

$$\begin{aligned} \text{minimize } f(x) &= (f_1(x), \dots, f_m(x))^T, \\ x &\in S \subseteq R^M, \\ m &\in \{1, 2, \dots, M\}, \end{aligned} \quad (1)$$

where  $f: S \rightarrow R^M$ .  $S$  is limited by the boundaries:

$$\begin{aligned} x &= (x_1, \dots, x_M), \\ a_i &\leq x_i \leq b_i, \end{aligned} \quad (2)$$

considering the  $i$ -th resource. We say that the allocation  $x_{i_1}$  dominates  $x_{i_2}$  only if  $f_i(x_{i_1}) \leq f_i(x_{i_2})$  for all  $i \in \{1, \dots, M\}$  and  $f_i(x_{i_1}) < f_i(x_{i_2})$  for at least one sequence entry, therefore we denote  $x_{i_1} \prec x_{i_2}$ .  $x^*$  encompasses a Pareto-optimal solution if  $\nexists x \in S$  such that  $x \prec x^*$ . The aggregated set of solutions using H is a Pareto front

$$P_{ref} = \{f(x_1^*), \dots, f(x_M^*)\} \in S \quad (3)$$

that contains global dominating points.

Then the overall goal of MOOP in this research is finding a set of well-spread non-dominated solutions using  $H_j$  wherein  $p(P_{ref}^j) \rightarrow p(P_{ref})$ .

## 2 REVIEW OF THE LITERATURE

In this section, we start with the state-of-the-art research and applications for MOOP and MORAP related to the BPM and proceed with the guided search methods.

In [9], the authors investigate the parcel delivery being procured by Employees and Drones. The resource-to-process assignment is assessed in two ways. Firstly, they selected a static allocation for both resources and measured how do those resources handle the variable workload, considering the execution time and the resource utilization. Secondly, they fixated on the number of work units and tracked how resource utilization and time are affected depending on the lower or higher number of drones and employees involved. The authors explored all possible allocations since the possible pool sizes were limited; the search space consisted of less than a hundred variants. This approach is not well-applicable to the larger search spaces and also does not consider the stochastic nature of the real-life business process.

Other than resource utilization, the measure of cost is typical and natural for human-related tasks. In [10] authors proposed a modification of the ant-colony algorithm for finding the global optimum of the multi-objective function. In their experimental setup, the global Pareto-optimal solutions are stored in the form of the Pareto front. The algorithm is aimed at the resource allocation problem but is also applicable to grouping and scheduling problems. The advantage of the algorithm is the ability to continue the exploration of the richer areas after reaching the local optimum, which reminds the Tabu Search in this regard. In the experiment, authors used cost and profit as the optimization objectives, but it is also possible to work with higher dimensionality. Authors claim a better computational time in comparison with genetic algorithms. On the other hand, the authors do not assess the quality of the resulting Pareto front.

Genetic algorithms have become a baseline to approach multi-objective problems. Specifically, NSGA-II is among the most popular and widely used algorithms because of the simplicity of tuning. In [11] authors developed the hybrid algorithm to minimize the number of simulations for multi-objective optimization. The paper describes the custom algorithm based on the evolutionary approach mixed with the predictions model. The authors used the hypervolume metric to compare and assess the Pareto front quality. The results are compared with the conventional genetic algorithms such as NSGA-2 and SPEA2 and claimed to be more efficient in the simulations usage.

A common drawback of the evolutionary search algorithms is a fixed sample size. While it is a convenient parameter to specify the degree of reduction of the search space, it may imply some uneven distribution of the solutions [12]. As a result, we might see some poorly explored areas, some parts of the Pareto set being distant from the reference figure or not present at all. In [12-15] the different methods proposed to guide the evolutionary algorithms towards the areas of interest. They do not focus on the BPM field, however, demonstrate a clear improvement in the convergence, diversity, and quality of the outputting Pareto front. In our paper, we decided to follow the approach described in [16], since it proved to work well on the two-objective problem, allows us to specify

more than one reference point, and is tuned to expand toward particular areas of interest.

Finally, we refer to [8] as a baseline for our experiment. The research introduces a comprehensive setup with the multiple BPMN models, concerns the different facets of MORAP in BPM, such as building the simulation model out of the event log, the accuracy of the simulation model, and proposes metrics to compare the outputting Pareto front from the applied algorithms. The authors selected the well-known Hill Climbing, Tabu Search, and NSGA-II to run. For one of the case studies, namely a business process of a call center, there is a gap that we try to cover in this paper.

### 3 MATERIALS AND METHODS

To estimate the business process performance, there are two traditional measures: average cycle time and cost of the process execution. In our case study, we assume that the cost is a static measure meaning it has a predefined value counted for a unit of time for each resource, therefore the total cost value is described as:

$$TC = \sum_{i=1}^n C_i t_i. \quad (4)$$

Calculating the cycle time for a flat single-lane business process is straightforward: we calculate the average execution time for each task and sum it up. However, there are additional constraints that add up to additional calculations:

– Alternative paths with the probability of choosing one sequence flow over another; in this case cycle time

$$CT_{\text{alternative}} = \sum_{i=1}^n p_i T_i, \text{ considering the tasks and their}$$

respective sequence flows;

– Parallel  $CT_{\text{parallel}} = \text{Max}\{T_1, T_2 \dots T_m\}$ ;

– Rework  $CT_{\text{rework}} = T/(1 - p_{\text{rew}})$ .

Combining these three rules, we can calculate TCT, although it does not include waiting time, handover time, or other non-value-adding activities [17]. Queueing theory can be used to address those real-life parameters, however, it has its own drawbacks. To calculate factual CT, there is a BPS approach, which allows the tuning of the resources' waiting and handover times to calculate factual CT in a versatile way, given that the BPMN model can undergo frequent changes. Due to the high level of output noise, it is common to run multiple simulations, hence in our research we repeat the simulation 15 times for each resource allocation and assume *cTime* is an average CT of the process.

The accuracy of a BPS, and hence the usefulness of the outcomes, to a large extent relies on how accurately the process model and simulation parameters capture the observed reality. In general, process models are manually designed by enterprise analysts for the sake of management convenience. Typically, process models do not capture all the details and mechanisms of how the process is actually carried out. If there is a significant variation in

service times the actual cycle time of the business process can diverge significantly from the predicted BPS metrics using flow analysis. The simulation parameters for BPS are commonly estimated based on the process manager's expertise and manual fitting, which does not always comply with the real-life process execution [18].

As an input for the simulation, we denote a resource allocation as a sequence of resource pools in the business process  $R_p = \langle r_1, \dots, r_n \rangle$ , each corresponding to a subset of tasks in a business process. The function  $rtCost: R_p \rightarrow TC_{r_i}$  retrieves the total cost of the selected resource pool  $r_i, r_j \in \{N, T, Ci\}$ .

R-NSGA-II is a multi-objective optimization algorithm. It is an improved version of the original NSGA-II algorithm, which aims to solve multi-objective optimization problems. While both of them keep the population of the Pareto-optimal points, R-NSGA-2 incorporates a reference point-based approach for selecting the individuals from the offspring. By using the reference points, R-NSGA-2 can effectively explore diverse and evenly-distributed solutions along the Pareto front, allowing decision-makers to make informed choices when dealing with multiple conflicting objectives.

The algorithm ranks the current Pareto-optimal points by Euclidean distance to each reference point in ascending order. The solution closest to the reference point obtains the rank of one. The next step ranks the solutions by crowding distance, meaning the solution should be closest to a set of reference points. Then the solutions are grouped by the sum of normalized distances between them using  $\epsilon$  threshold parameter. The farther groups are discouraged from being promoted to the next generation. The higher value of  $\epsilon$  increases the range of explored solutions.

By employing the aforementioned selection algorithm, it becomes possible to allocate equal attention to solutions that are in close proximity to each reference point. This enables the identification of multiple regions of interest concurrently.

### 4 EXPERIMENTS

In this research, we outline the three stages of multi-objective business process optimization: Process Discovery, Optimization, and Evaluation, which are denoted in Figure 1 in BPMN format. We aim to improve and focus on the latter two stages.

In the Process Discovery stage, we obtain the XES event log as input for the business process. This is a common data source for existing enterprises since building the BPMN model requires certain expertise and effort from the management resources. The process mining technique is used to build the BPMN simulation model. Specifically, we use the Simod tool to obtain the BPMN model approximation with the necessary simulation parameters described in [19]. These parameters include the initial resource allocation: resource pools, the number of resources for each of the resource pools, resource cost per

hour, resource pool linked to each of the BPMN tasks, and the distribution of the processing time for each task.

In the Optimization stage, we try to change the initial resource allocation, which means overriding the number of resources in the BPMN pool of the simulation model. To compare two resource allocations, we run the simulation using the BIMP tool. For a given resource allocation, it produces an output in CSV format. Among all of the simulation outcomes, we are interested in the average cycle time  $cTime$  of the simulation and the TC. In general, better allocation means both lower cycle time and lower total cost, making it Pareto-dominating. However, if only one parameter is better in one allocation than another, we cannot prefer a single solution. We have to keep a set of non-dominating solutions as a  $P_{ref}'$ .

Due to the computationally intensive nature of simulating the BPMN model, employing a brute-force approach to explore the vast search space of all potential resource allocations is not feasible. Therefore, we adopt established strategies to navigate the search space of solutions and iterate through various allocation possibilities.

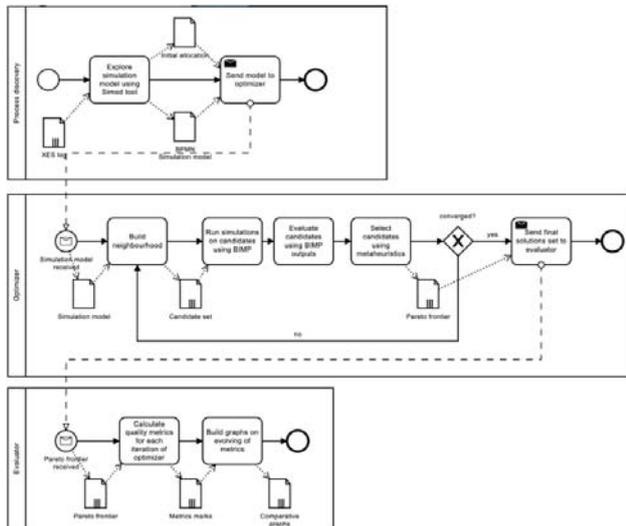


Figure 1 – The experiment outline in a BPMN format

During the Evaluation stage, we compare the quality of the output Pareto fronts obtained by different algorithms and assess the selected quality metrics proposed in [20]. To apply the reference point-based approach, we extended the experimental setup introduced in [8] using the R-NSGA-II from the Pymoo toolset [21]. During the experiment run, we want to measure and compare the efficacy of R-NSGA-II with a conventional regression descent algorithm – Tabu Search. In the prior study, Tabu Search outperformed the original NSGA-II evolutionary algorithm on one of the business processes describing a call center enterprise.

The resulting Pareto front significantly diverged in all of the selected quality metrics including the Hyperarea Ratio, IGD, Purity, and Spacing.

The research question to evaluate is as follows: how good is the Pareto front obtained by R-NSGA-II compared with the regression descent with respect to conver-

gence, spread, and distribution, and does it perform better than pure NSGA-II?

Each experimental run constructs two outputs:

- $P_{ref}'$  contains the Pareto front points from all of the applied approaches, in our case study it consists of the points, independently acquired by R-NSGA-II and Tabu Search. Namely,  $P_{ref}'$  represents the cross-dominating solutions from both of the algorithms;

- $P_{approx}$  contains the Pareto front points obtained by a specific algorithm.

To set up R-NSGA-II, we selected three reference points, each one defining the desired direction of expansion:

- $RP_c$  has to attract the Pareto front towards the *Resource Allocation Cost* axis and force the algorithm to explore more solutions with smaller *Cycle Time*. Therefore, we try to improve spread by X-axis;

- $RP_t$  has to attract the Pareto front towards to the *Cycle Time* and force the algorithm to explore more solutions with smaller *Resource Allocation Cost*. Therefore, we try to improve spread by Y axis;

- $RP_h$  aims to extend the Pareto front towards the corner, therefore improving the HA of the resulting Pareto front  $P_{ref}$ . This point stands for the wittingly unreachable solution, with both low cost and time.

According to the guidance in [16, 22], we selected the following parameters to reach the balanced and feasible advancement of a genetic algorithm, considering the modification with the reference points approach:

- The population size  $\mu$  is set to 40;
- The size of the offspring  $\lambda$  is set to 20;
- The number of reference points  $rp$  is set to 3, and they are all infeasible as defined in [16];
- The  $\epsilon$  threshold for the sum of the normalized distances is set to 0.001.

In our experiment, we extend the quality evaluation with two metrics commonly used in MOOP:

- SP is a straightforward measure to assess the spread and distribution. Despite its known issue to process Pareto fronts with clearly distinct groups of points, this downside is not applicable to our output. It is calculated as follows:

$$SP(S) = \sqrt{\frac{1}{|S|-1} \sum_{i=1}^{|S|} (\bar{d} - d_i)^2}, \quad (5)$$

where  $d_i = \min(s_i, s_j) \in S, s_i \neq s_j \|F(s_i) - F(s_j)\|_1$ .

Higher value stands for better spread and diversity, in case Pareto fronts are similarly dispersed.

- IGD is a classical convergence metric, which ranks one Pareto front better than another if and only if the given Pareto front is always preferred according to the Pareto optimality rules:

$$IGD(S, P) = \frac{1}{|P|} \left( \sum_{i=1}^{|P|} d_i^M \right)^{\frac{1}{M}}, \quad (6)$$

where  $d_i = \min x \in S \|F(x) - F(i)\|$ . Lower value stands for better  $P_{approx}$ .

### 5 RESULTS

Figure 2 comprises the Pareto front  $P_{approx}$  discovered by R-NSGA-II and  $P_{ref}'$  containing all Pareto-optimal solutions from all selected algorithms. The filled markers in black stand for the solutions in both  $P_{approx}$  and  $P_{ref}'$ , meaning these Pareto-optimal points were successfully identified by the algorithms. The hollow markers in blue designate the solutions in  $P_{ref}'$  but not in  $P_{approx}$ , which implies the points from the reference Pareto set were not identified by the current algorithm. The ones in red are the points in  $P_{approx}$  but not in  $P_{ref}'$ , they were selected by the current algorithm, however, the more effective Pareto-dominating solution exists in the reference set. Nevertheless, the solutions marked with red might be useful in terms of improving the spread and diversity. Figure 3 denotes the same output for the previously winning TS algorithm. We can observe that R-NSGA-II found 29 of the 45 non-dominated points in  $P_{ref}'$ , while TS found a different set containing only 23 of the points in  $P_{ref}'$ . This is a good entry indicator of the improved performance of R-NSGA-II.

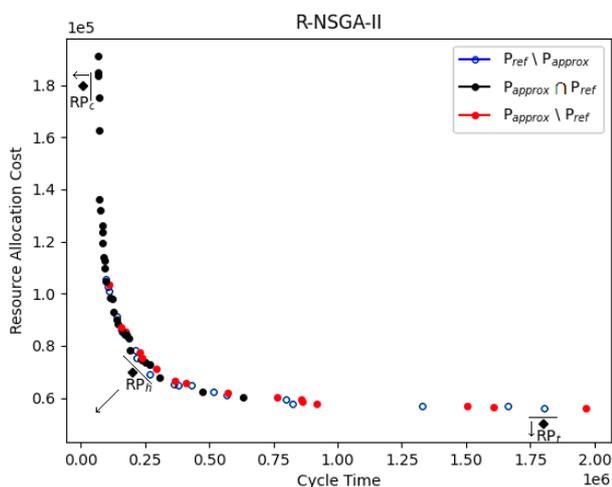


Figure 2 – Pareto front for the R-NSGA-II

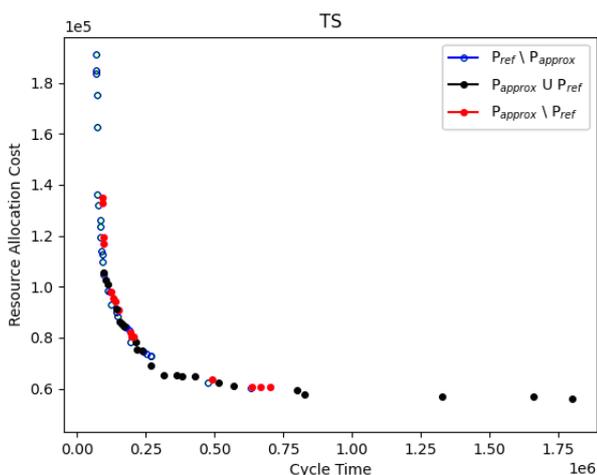


Figure 3 – Pareto front for the Tabu Search

Table 1 compares the quality metrics of the obtained Pareto fronts, and also the metrics for previously used pure NSGA-II. The values in bold designate the best metric across three algorithms. As we can see, adding the reference points significantly improved original NSGA-II efficacy, and overall demonstrated R-NSGA-II more performant than TS in our case study. The HA Ratio and Purity metrics in R-NSGA-II have overcome other algorithms, although the advantage is not very noticeable. The IGD dominance of TS over R-NSGA-II can be explained by the former visually more spread by X-axis and the latter more spread by Y-axis, while the X-axis possesses a higher order of scale. Although TS kept its performance dominance, the reference approach essentially improved this metric of NSGA-II. Regarding the spread and distribution metrics, namely Spacing and Delta, the results are arguable. Although Delta is generally considered a more sustainable and future-proof metric for Pareto fronts, the Spacing metric still might be more applicable in our research since the reference front follows the Gaussian distribution. This means that higher Spacing covers the solutions closer to the extreme points.

Table 1 – Comparative quality metrics of the selected algorithms

	TabuSearch	NSGA-II	R-NSGA-II
HA Ratio	0.998923	0.975051	<b>0.999989</b>
IGD	<b>16820.4</b>	426892.2	32366.9
Purity	0.60	0.0625	<b>0.65</b>
Spacing	88597.2	80713.4	<b>91556.6</b>
Delta	<b>1.07</b>	1.17	1.14

In general, we can observe that adding the reference points to the original genetic algorithm can significantly improve the quality of the output Pareto front, and also outperform the competitor such as Tabu Search in a number of metrics.

### 6 DISCUSSION

This paper presented an approach to involve a genetic algorithm for computing a set of Pareto-optimal resource allocations for a given business process. In particular, a prior case study evaluated the performance of the NSGA-II algorithm on a given set of business processes. The overall experimental setup remained unchanged and is based on the simulation model to evaluate the noisy value of the objective function. However, we selected a specific business process of a call center to optimize, since the genetic algorithm performed the worst in that example. The output significantly diverged from the Tabu Search output and yielded a less spread Pareto front with a significantly higher HA. We employed a more supervised variant of the algorithm, namely R-NSGA-II, based on the chosen reference points. They provide a clue for a regression run and can improve the convergence and exploration of the new solutions for the Pareto front. The evaluation found that providing three reference points made the Pareto front significantly closer to the one from the Tabu Search, but also explores more of a search field. Overall, providing the reference points can improve the output of NSGA-II, however, requires prior knowledge of the

Pareto front approximation. The further work direction includes comparing other multi-objective algorithms with conventional regression. We also attempt to revisit the actuality of the Spacing metric to assess the spread and the diversity of the Pareto fronts.

### CONCLUSIONS

The resource allocation problem is common in BPM. Although the narrower field of MORAP has a series of research solutions, there are still some methods that are not well-represented in the scope of BPM. If we look at the specific case studies, there arises an even broader spectre of research questions.

**The scientific novelty** of the obtained results is that the method of populating the MOEA with the reference points in the scope of the resource allocation for BPM has been proposed. It characterizes the areas of interest for the management purpose, in a scenario when another evolutionary method did not output the adequate and desired set of the time-cost trade-offs.

**The practical significance** of the obtained results is that the applied reference points approach has improved the existing metrics in a specific scenario. While the experiment shows the potential of reference-based add-ons to explore previously unsearched areas of interest, it also asserts the extensibility of the existing framework to work with the different MOOP methods and BPMN derived from various sources.

**Prospects for further research** are to apply more algorithms to the MORAP. Considering the evolutionary approach, it is possible to extend the experiment with SPEA2; also neural networks are a more profound way to approximate the optimal Pareto front. Since the simulation model captures the stochastic nature of the simulated processes, it enables us to estimate if Bayesian optimization is an applicable strategy.

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## ПОКРАЩЕНА БАГАТОЦІЛЕВА ОПТИМІЗАЦІЯ В УПРАВЛІННІ БІЗНЕС-ПРОЦЕСАМИ ЗА ДОПОМОГОЮ R-NSGA-II

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### АНОТАЦІЯ

**Актуальність.** Управління бізнес-процесами є критично важливим компонентом у сучасних організаціях для підтримки ефективності та досягнення операційних цілей. Оптимізація цих процесів з точки зору часу та витрат може призвести до значного покращення загальної ефективності бізнесу. Однак традиційні методи оптимізації часто стикаються з труднощами при вирішенні багатоцільової проблеми з відомим компромісом часу та вартості, що вимагає більш ефективних рішень. Використання моделі та нотації бізнес-процесів (BPMN) для стохастичного моделювання процесу забезпечує надійну основу для аналізу цих бізнес-процесів і відповідає найсучаснішому управлінню бізнес-процесами. У попередніх дослідженнях ми застосували кілька евристичних алгоритмів, включаючи еволюційний NSGA-II, щоб знайти оптимальний за Парето набір рішень. Ми визначили рішення як пару витрат і часу, пов'язаних із певним розподілом ресурсів. Для одного з вибраних процесів продуктивність NSGA-II була нижчою порівняно з іншими методами.

**Мета роботи** – покращення продуктивності NSGA-II і, у свою чергу, підвищення ефективності багатоцільової оптимізації бізнес-процесів. Зокрема, ми прагнемо включити контрольні точки в NSGA-II. Наша мета полягає в тому, щоб визначити оптимізований набір рішень, що представляє компроміс між часом виконання процесу та пов'язаними витратами. Ми очікуємо, що цей набір матиме вищий розкид та інші показники якості порівняно з попередніми результатами.

**Метод.** Щоб досягти нашої мети, ми застосували двоетапний підхід. По-перше, ми модифікували оригінальний генетичний алгоритм, вибравши та інтегрувавши опорні точки, які слугували для спрямування пошуку до оптимального за Парето фронту. Ця інтеграція була розроблена для покращення можливостей алгоритму для дослідження та використання. По-друге, ми застосували покращений алгоритм, а саме R-NSGA-II, для стохастичного моделювання бізнес-процесів. BPMN надав вхідні дані для цього моделювання, у якому ми змінили розподіл ресурсів, щоб спостерігати вплив на час і вартість процесу.

**Результати.** Наші експериментальні результати продемонстрували, що R-NSGA-II значно перевершив вихідний алгоритм NSGA-II для даної моделі процесу, отриманої з журналу подій. Модифікований алгоритм зміг ідентифікувати ширшу і більш різноманітну оптимальну за критерієм Парето криву, таким чином забезпечивши більш повний набір оптимальних рішень щодо вартості та часу.

**Висновки.** Дослідження підтвердило та підкреслило потенціал інтеграції опорних точок у NSGA-II для оптимізації бізнес-процесів. Покращена продуктивність R-NSGA-II, очевидна з кращою Парето-оптимальною кривою, яку алгоритм ідентифікував, підкреслює його ефективність у задачах багатоцільової оптимізації, а також простоту еталонних підходів у сфері BPM. Наше дослідження визначає напрямком для подальшого вивчення евристик для покращення результатів методів оптимізації або продуктивності їх виконання.

**КЛЮЧОВІ СЛОВА:** бізнес-процес, генетичний алгоритм, опорні точки, багатокритеріальна оптимізація, спейсінг.

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