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RESEARCH ON SIMULATION-BASED MULTI-OBJECTIVE BUSINESS PROCESS OPTIMIZATION METHODS USING EVOLUTIONARY INTELLIGENCE

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Abstract

Business process optimization (BPO) is the focus of all successful business companies. Various simulation optimization methods, which is understood as simulation-based optimization, are available. Optimization, itself, is known as the process of finding the best solution from all feasible solutions. It is not obviously clear which optimization method or group is most applicable for BPO. Simulation-based business process optimization is an instrument for detailed analysis of processes and further optimization. This paper discusses the simulation optimization methods for BPO.

Keywords: Simulation optimization, business process optimization, simulation software.

Contents

1 Introduction

Business process optimization (BPO) is the focus of all successful business companies. Optimization, itself, is known as the process of finding the best solution from all feasible solutions. Simulation-based BPO is an instrument for detailed analysis of processes and further optimization. Various simulation optimization (SO) methods, which is understood as simulation-based optimization, are available. It is not obviously clear which optimization method or group is most applicable for BPO. This paper discusses the SO methods for BPO. Different simulation optimization approaches have been provided in the related papers, however evolutionary algorithms and in specific genetic algorithms namely are widely used for BPO. Challenging in BPO becomes apparent when solving problems simultaneously against multiple objectives that conflict to each other. Multi-objective optimization involves optimizing a number of objectives simultaneously and evolutionary algorithms are successfully used to solve related problems as well. One of the objectives of the paper is to provide sufficient information about simulation optimization and with which methods is it used for BPO. In the field under discussion, it also is a challenge to understand the relation between different terms, such as, Business process optimization, Business process simulation, Multi-objective optimization, Multi-criteria optimization, Simulation optimization, Evolutionary algorithms, Genetic algorithms and so on. Due to large amount of the terms and in some case with very similar wording, it is highly important to use them in proper and precisely way. For that reason, as next objectives of the paper, the explanations of such relations as well as meanings of terms are provided. In our days, market is suggesting some simulation optimization software and it becomes challenging to choose the best fit. The brief comparison of simulation optimization software is also available in the paper. Some ideas how to prepare and run simulation-based multi-objective optimization method for BPO has been presented in the paper. The experiments with BPO, have been conducted with simulation optimization software, will be done and the results will be described in the paper. In the end of the paper, conclusions are listed and what assumptions might be addressed in the future studies. Nevertheless, it is necessary to continue research in the area of the simulation-based BPO to achieve all research objectives and overcome all challenges.

2 Research problem

Various simulation optimization methods, which is understood as simulation-based optimization, are available. It is not obviously clear which optimization method or group is most applicable for BPO.

2.1Related works

In our research, we point attention to BPO problematic, using simulation optimization methods. Different simulation optimization approaches have been provided in the related papers, however evolutionary algorithms and in specific genetic algorithms are widely used for BPO. Halim R.A. (2011) found that the combination of simulation and optimization has been successfully applied to solve real-world decision making problems. However, there is no formal structure to define the integration between simulation and optimization. Si Y.W. (2018) showed that a Petri Nets based Generic Genetic Algorithm framework can be used to optimize any given business processes. In acceptable way, the systematic review of optimization algorithms is provided in Amaran S. (2016). In addition, it was emphasized the difficulties in simulation optimization. Simulation-based BPO analyses reported in Liu Y. (2015), Yoo T. (2015). Djedović A. (2016) where GA and simulation technology are jointly used to derive optimal resource allocation schemes for business processes. In summary, the work presented in this paper based on previous researches to explore how to apply successfully optimization methods for BPO. While earlier work focused on how to use particular technique for BPO, we focus on systematic review of all available simulation-based multi-objective optimization methods for BPO.

3 Systematic review of the terms of the field

3.1. Research question

In this step, review questions are defined. So, this study was conducted to answer a research question as follows:

RQ1: What is simulation-based optimization?
RQ2: What is multi-objective optimization?
RQ3: What are simulation-based multi-objective optimization methods?
RQ4: What are evolutionary algorithms?
RQ5: What are genetic algorithms?

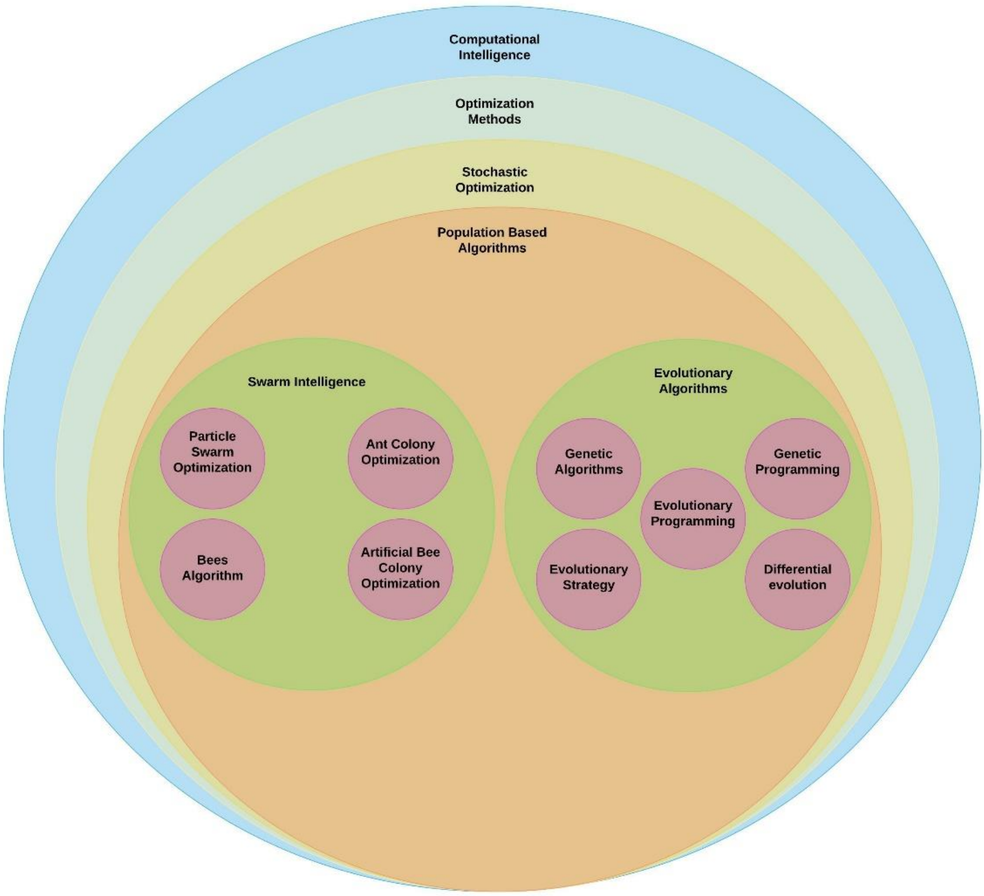


Figure 1. Population-based stochastic optimization algorithms

Computational intelligence (CI) techniques are powerful, efficient, flexible, and reliable. **Swarm Intelligence** (SI) and **Evolutionary Algorithms** (EA) are two very useful components of CI that are primarily used to solve optimization problems. There are many families of algorithms that come under the umbrella of EA such as **Genetic Algorithms** (GA), **Genetic Programming** (GP), **Evolutionary Programming** (EP), and **Evolutionary Strategy** (ES). Except GP, the other members of EA solve optimization problems. On the other hand, GP generally finds programs that can solve a given problem. GA evolve based on Darwinian principle of survival of the fittest and encoding of individuals is usually done as binary vectors while, as mentioned earlier, GP although uses the same principle of survival of the fittest as GA, evolves individuals, that are programs. EP is inspired by the theory of evolution by means of natural selection; on the other hand, ES is a search technique based on the idea of adaptation and evolution, where encoding of individuals is done as a vector of reals. SI is a discipline that deals with natural and artificial systems composed of many individuals that coordinate based on the decentralized, collective and self-organized cooperative behaviour of social entities like flock of birds, or school of fishes, ant colonies, animal herding, bacterial growth, and microbial intelligence. The members of a swarm must be active, dynamic and simple (with no or very little inherent knowledge of the surroundings). Within the swarm, due to this cooperative behaviour, a search strategy, better than random search, emerges. The so obtained intelligent search strategy may be referred to as swarm intelligence, in general Bansal J.C. (2019).

Evolutionary intelligence (EI) is the capacity to transcend and include the intelligences we currently demonstrate, in order to allow new intelligences to emerge. EI looks backward at our evolutionary history and forward to our evolutionary future. It assumes that life conditions will continue to change and the human species will change and adapt and evolve with such changes (https://integralcity.com/voices-intelligences/evolutionary- intelligence/). CI was first proposed by Bezdek and the term was first used by the Institute of Electrical and Electronics Engineers (IEEE) Neural Networks Council in 1990 Bezdek J.C. (1998). There is no commonly accepted definition of computational intelligence in the literature Siddique N. and Adeli H. (2013). Siddique N. and Adeli H. (2013) defined CI system as a system which deals with low-level data such as numerical data, has a pattern recognition component and does not use knowledge in the artificial intelligence (AI) sense, and additionally when it begins to exhibit computationally adaptivity, fault tolerance, speed approaching human-like turnaround and error rates that approximate human performance. CI is a rapidly advancing research field and includes a collection of various computation techniques Ahmad M.W. (2016). Formally, CI is a set of nature-inspired computational methodologies and approaches to solve complex real world problems Bansal J.C. (2019). EA are **population-based** on **stochastic optimization algorithms**, and the operations are based biological evolution. Recombination, mutation, and selection operations are the example for biological evolution Dash S.S. (2018).

Broadly, the field of CI encompasses three main branches of research and application: neural networks, which model aspects of how brains function, fuzzy systems, which model aspects of how people describe the world around them, and EA, which models aspects of variation and natural selection in the biosphere. These three approaches are often synergistic, working together to supplement each other and provide superior solutions to vexing problems Keller J. M. (2016).

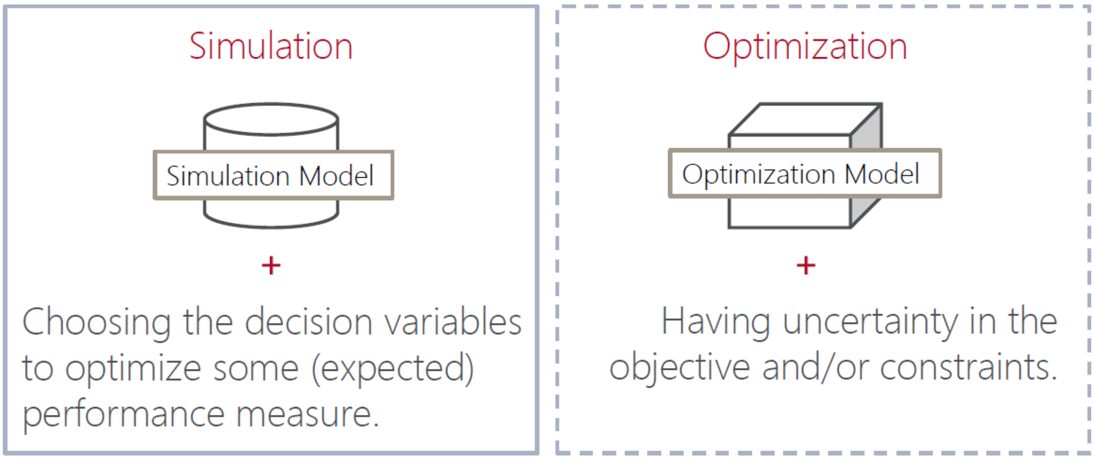
Meta-heuristics, in turn, can be defined as an iterative generation process which guides a subordinate heuristic by combining intelligently different concepts for exploring and exploiting the search space, using strategies to structure information in order to find efficiently near-optimal solutions. Usually, heuristics are specialized in solving problems for one particular domain, while meta-heuristics are more generic and adaptive in several domains. One of the most used meta-heuristics are classified as **Evolutionary Computation** (EC) algorithms. It is the general term for several optimization algorithms that are inspired by the Darwinian principles of nature's capability to evolve living beings well adapted to their environment. These algorithms are also called as EA, and they all share a common underlying idea of simulating the evolution of individual (or solution) structures via processes of selection, recombination, and mutation reproduction, thereby producing better solutions. In a GA, individuals from the population compete and generate offspring using crossover and mutation. GP employs more complex data representation than GA, such as a tree, to represent individuals. Thus, allowing individuals to have different lengths. Both algorithms are focused on mono-objective optimization, that means, one single value to represent the quality of a given solution. However, several real-world problems considerate more than one fitness value in order to properly evaluate an individual quality. In this scenario, **Multi-objective Evolutionary Algorithms** (MOEAs) are able to find good solutions for this kind of problems (AC06502486, A. ed., 2007). **Evolution** – That process of change which is assured given a reproductive population in which there are varieties of individuals, with some varieties being heritable, of which some varieties differ in fitness (reproductive success). **EA** – a collective term for all variants of (probabilistic) optimization and approximation algorithms that are inspired by Darwinian evolution. Optimal states are approximated by successive improvements based on the variation-selection-paradigm. Thereby, the variation operators produce genetic diversity and the selection directs the evolutionary search. **EC** – computation based on evolutionary algorithms. EC encompasses methods of simulating evolution on a computer. The term is relatively new and represents an effort bring together researchers who have been working in closely related fields but following different paradigms. The field is now seen as including research in genetic algorithms, evolution strategies, evolutionary programming, artificial life. **ES** – a type of evolutionary algorithm developed in the early 1960s in Germany. It employs real-coded parameters, and in its original form, it relied on mutation as the search operator, and a population size of one. Since then it has evolved to share many features with genetic algorithms. ES is a variant of EA, which generally operates on the "natural" problem representation (no genotype-phenotype mapping for object parameters). An individual consists of a set of object parameters, the corresponding value of the objective function and a set of (endogenous) strategy parameters. The ES employs mutation and recombination as variation operators. **EP** – it is a stochastic optimization strategy, which is similar to GA, but dispenses with both "genomic" representations and with crossover as a reproduction operator. It is a variant of EA, which, like ES, operates on the "natural" problem representation. Only mutation is used as the variation operator together with tournament selection; recombination is not employed Sumathi, S. (2008).

Differential evolution (DE), on the other hand, differs from GA in the reproduction mechanism. While DE sharesmany similarities with other evolutionary algorithms, it differs significantly in the sense that in DE distance and direction information from the current population is used to guide the search process. Mutation is applied first to generate a trial vector, which is then used within the crossover operator to produce one offspring, while in a general EA, the crossover operator is applied first and then the mutation operator. Also DE mutation step sizes are influenced by differences between individuals of the current population while EA mutations are sampled from some probability distribution Bansal J. C. (2019). Pham et al. (2006a) proposed an optimization algorithm inspired by the natural foraging behavior of honey bees, called **Bees Algorithm** (BA). The proposed algorithm is also applicable to both combinatorial and functional optimization problems. In real life, foraging process begins by scout bees being sent to search for promising flower patches. When they return to the hive, unload their nectar and go to the dance floor to perform a dance known as the waggle dance which is essential for colony communication. After waggle dancing, the dancer goes back to the flower patch with follower bees that were waiting inside the hive. More follower bees are sent to more promising patches. This allows the colony to gather food quickly and efficiently. Similarly BA starts with scout bees being placed randomly on the search space. The main steps of the algorithm are: 1) initialize population with random solutions; 2) evaluate fitness of the population; 3) determine a certain number of fittest bees and select their sites for neighborhood search; 4) recruit a certain number of bees for selected sites, evaluate their fitness; 5) select the fittest bee from each site to form the new population; 6) assign remaining bees to search randomly and evaluate their fitness. The BA is applied to two standard functional optimization problems with two and six dimensions, respectively. The results showed that the BA is able to find solutions very close to the optimum. The algorithm is also applied to eight benchmark functions and the results were compared with deterministic simplex method, stochastic simulated annealing optimization procedure, genetic algorithm and ant colony system. BA generally outperformed other techniques in terms of speed of optimization and accuracy of results. On the other hand BA has too many tuneable parameters.

Artificial Bee Colony (ABC) is a relatively new member of SI. ABC tries to model natural behavior of real honey bees in food foraging. Honey bees use several mechanisms like waggle dance to optimally locate food sources and to search new ones. This makes them a good candidate for developing new intelligent search algorithms. In this chapter an extensive review of work on artificial bee algorithms is given. Afterwards, development of an ABC algorithm for solving generalized assignment problem which is known as NP-hard problem is presented in detail along with some comparisons Baykasoğlu A. (2007).

Discrete optimization via simulation is concerned with finding optimal settings for variables that can only take discrete values. Integer-ordered variables are allowed to take on integer or discrete values within a finite interval, where the order of these values translates to some physical interpretation. For example, this could be the number of trucks available for vehicle routing, or the set of standard pipe diameters that are available for the construction of a manufacturing plant. Categorical variables refer to more general kinds of discrete decisions, ranging from conventional on–off (0–1 or binary) variables to more abstract decisions such as the sequence of actions to take given a finite set of actions. It should be noted that though integer-ordered variables, for instance, may be logically represented using binary variables, it may be beneficial to retain them as integer-ordered to exploit correlations in objective function values between adjacent integer values Amaran S. (2016).

What is Simulation Optimization?



Other names: “Simulation-based Optimization” or “Optimization via Simulation”.

4 Applications

The most simulation software vendors are providing similar functionalities to each other. However, the answer which simulation software is more applicable is depends on what is actually will be simulated and further optimized. For the business process optimization – very sophisticated simulation software must be chosen. It is because the human resources must be simulated in such processes. For the industry processes any of representing simulation software could be selected.

Table 1. Simulation software analysis

Name / Vendor	Output Analysis support	Optimization	Support of model packaging	Batch run / experimental design	Mixed discrete / continuous modeling (levels, flows, etc.)
ANYLOGIC / AnyLogic North America https://www.anylogic.com/	• Reports • Model execution logs • Charts • Output to the built-in database or any external data storage (databases, spreadsheets, text files)	OptQuest is included, additionally, users can employ any custom optimization algorithms.	Models can be exported as standalone Java applications or shared online via AnyLogic Cloud web service.	Flexible user interface to create the following experiments: Parameter Variation, Compare Runs, Monte Carlo, Sensitivity Analysis, Calibration, and custom.	YES
ARENA / Rockwell Automation https://www.arenasimulation.com/	Arena Output Analyzer and Process Analyzer to review results and users may use external products as well	OptQuest for Arena	Arena Runtime	Process Analyzer to run a series of different model runs in a batch	YES
ENTERPRISE DYNAMICS / INCONTROL Simulation Solutions https://www.incontrolsim.com/software/enterprise-dynamics/	Experiment Wizard – an internal feature	By providing support for various third-party optimizers	By providing a free Viewer License of the software	By providing Experiment Wizard and Scenario Manager	YES
EXTENDSIM PRO / Imagine That Inc https://extendsim.com/	• Output to charts & reports • Integrated Scenario Manager with dialog or database factors and responses, sensitivity analysis, confidence intervals, Gantt charts, and quantile and interval statistical analysis.	Evolutionary Optimizer is included in all versions of ExtendSim.	Trial version runs any model built in ExtendSim. Analysis RunTime version allows for further model analysis.	Users choose to store run results in the internal database or export to an external application. DOE includes manual, full factorial, and two options each for JMP custom design and Minitab optimal design.	YES

Name / Vendor	Output Analysis support	Optimization	Support of model packaging	Batch run / experimental design	Mixed discrete / continuous modeling (levels, flows, etc.)
	• Export to external analysis applications is also available.				
FLEXSIM / FlexSim Software Products, Inc. https://www.flexsim.com/	A full suite of charts and graphs in the Dashboard, as well as extensive Excel output options.	An optimization engine, powered by OptQuest, is available as an add-on.	The free trial version of FlexSim is capable of running any simulation model built with FlexSim.	An experimentation engine is built into the software.	YES
PROMODEL OPTIMIZATION SUITE / ProModel Corporation https://www.promodel.com/products/ProModel	• Output Viewer • Minitab • Excel	SimRunner	N/A	Scenario Manager	YES
SAS SIMULATION STUDIO / SAS https://www.sas.com/en_us/software/simulation-studio.html	Output analysis via SAS software products. Steady state analysis included.	Via data transfer to SAS/OR software; can be embedded in a simulation model via SAS Program block.	N/A	Experimental design; manual in the Simulation Studio interface or automated (with interactive modifications) via JMP or SAS software integration.	NO
SIMUL8 PROFESSIONAL / SIMUL8 Corporation https://www.simul8.com/products/	N/A	OptQuest	SIMUL8 Studio and SIMUL8 Web Technology	Multiple replications and scenario management	YES
SIMIO ENTERPRISE EDITION / Simio LLC https://www.simio.com/software/enterprise.php	SMORE Plots for risk analysis, sensitivity analysis, custom dashboards, comprehensive data in pivot tables, export summary or details to external packages	OptQuest (option) takes full advantage of all processors. Featuring Multi-Objective and Pattern Frontier optimization	Requires Team Edition or above to package model	Run manual scenarios with multiple replications. Concurrent full use of all processors. Built-in ranking and selection	YES

Name / Vendor	Output Analysis support	Optimization	Support of model packaging	Batch run / experimental design	Mixed discrete / continuous modeling (levels, flows, etc.)
PLANT SIMULATION / Siemens Product Lifecycle Management Software Inc. https://www.dex.siemens.com/plm/plant-simulation	• Datafit • Charts • Sankey • Bottleneck analyzer • Energy Analyzer • Neural networks	Genetic Algorithm, Layout Optimizer, Neural networks, Hill Climbing, Dynamic Programming, Branch and Bound	Built-in Pack and Go functionality	Experiment Manager supporting distributed simulation	YES
WITNESS / Lanner https://www.lanner.com/en-gb/technology/witness-simulation-software.html	N/A	N/A	Cloud Deployment, Experimentation, Optimization	N/A	YES

5 Conclusions

Simulation can provide the necessary means to analyze a business process and identify its bottlenecks providing a solid basis for improving the business process. From the review presented here, it can be concluded that interest in the area of simulation optimization is growing. More direct search methods need to be explored for suitability to simulation optimization problems.

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