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# Coupling Soft Computing, Simulation and Optimization in Supply Chain Applications: Review and Taxonomy

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**ABSTRACT** Supply chain networks are typical examples of complex systems. Thereby, making decisions in such systems remains a very hard issue. To assist decision makers in formulating the appropriate strategies, robust tools are needed. Pure optimization models are not appropriate for several reasons. First, an optimization model cannot capture the dynamic behavior of a complex system. Furthermore, most common practical problems are very constrained to be modeled as simple tractable models. To fill in the gap, hybrid optimization/simulation techniques have been applied to improve the decision-making process. In this paper we explore the near-full spectrum of optimization methods and simulation techniques. A review and taxonomy were performed to give an overview of the broad field of optimization/simulation approaches applied to solve supply chain problems. Since the possibilities of coupling them are numerous, we launch a discussion and analysis that aims at determining the appropriate framework for the studied problem depending on its characteristics. Our study may serve as a guide for researchers and practitioners to select the suitable technique to solve a problem and/or to identify the promising issues to be further explored.

**INDEX TERMS** Optimization, review, simulation, supply chain, taxonomy, guide.

## I. INTRODUCTION

Supply chain is a complex network of entities from the upstream to the downstream including supplier, manufacturer, transporter, warehouses, retailers and customers. Nowadays, supply chain management which involves product, service and information flows management plays a key role in the success of company and customer satisfaction. However, due to today's dynamic marketplace, supply chain management becomes heavy for decision makers who face challenges at different levels of Supply Chain (SC), such as the facility location, inventory management, supplier selection, production, distribution planning and transportation. The complexity of decision-making process in supply chain becomes inherent. This is imputable to the large-scale nature of supply chain networks, the high level of uncertainty in SC environment and the dynamic nature of interactions among supply chain elements, the numerous decision variables, as well as the decentralization of decisions and even the contradiction of certain objectives [1]. To deal with such level of complexity, there is a growing need for modelling approaches. Optimization has been widely used in the literature to model the supply chain system as a set of assumptions taking mathematical or logical relationships form. The limitation is that these models can be solved by optimization techniques if only they are simple enough. However, the real-world systems are too complex, thus there is some business issues that cannot be handled by optimization. For example, if the demand forecast changes over the time, then a forecast up will push the chain to produce more in order to fulfil the demand. This can lead to overtime expanses and supplement charges. If the forecast is down, then manufacturing sites should deal with the inventory products that may become obsolete. In this case, only simulation is a

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valuable tool to address the dynamism in supply chain. But one of the disadvantages of simulation is that it's not a proper tool of optimization. For example, while performing Materials Resources Planning (MRP) capacity analysis, simulations cannot deal with limited capacity situations. But if we use optimization instead, alternative sourcing or production can be determined to handle the situation. Hence the interest of coupling simulation and optimization techniques to get the advantages of both. Simulation-Optimization (SO) approaches have been widely used in different areas. Furthermore, the possibilities of combining these two techniques are so various. For that reason, a taxonomy is needed to get an overview of the full spectrum of approaches. Several classifications have been proposed in the literature according to different criteria. Some differentiated simulation-optimization techniques by the underlying structure of decision variables (discrete or continuous) [2]–[4]. Others classify methods by applied technique (statistical methods, heuristics, gradient-based, etc.) [5]. A taxonomy by hierarchical structure of optimization and simulation was proposed by [6]. These classifications did not cover the full spectrum of SO techniques and did not consider some criteria. In [7], authors provide a taxonomy covering the full spectrum of hybrid SO approaches based on four dimensions. Recently, an interesting paper [8] review SO approaches for SC risk management.

To the best of our knowledge, however, no broad overview of the SO Taxonomies has discussed in detail the usage of SO techniques for the SC applications, their characteristics, and giving pertinent research guidelines for selecting a solving approach. To this end, and in light of the taxonomy proposed by [7], we provide a classification of SO approaches applied in the supply chain context. Our classification comprises three dimensions to cover the range of methods used in the literature. By analyzing the taxonomy, we try to match up between the problem characteristics and method properties. The main contributions of the current paper are the following:

- We explore the near-full spectrum of optimization methods and simulation techniques.
- We provide a taxonomy of Hybrid simulation-optimization techniques applied in the supply chain context.
- We analyze the characteristics of the SO techniques and match it with the supply chain problems in order to provide some guidelines for researchers and give insights into promising research issues.

The remainder of this paper is organized as follows: after presenting the research methodology in section 2, an overview of optimization techniques and simulation paradigms are respectively detailed in sections 3 and 4, the published SO approaches in the supply chain context are reviewed in section 5, the taxonomy of these approaches comes next in section 6, analysis and guidelines for future research are detailed in section 7 and we end with conclusion and perspectives.

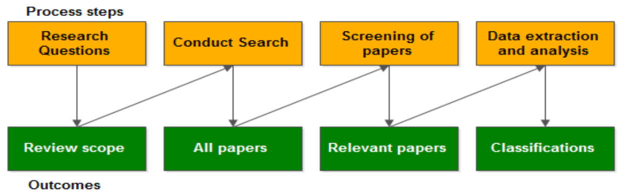


**FIGURE 1.** Research process.

**TABLE 1.** List of databases consulted.

| Databases | |
|---|---|
| Scopus | ProQuest |
| IEEE Xplore | Wiley online library |
| Emerald insight | dblp computer science bibliography |
| EBSCO | Google Scholar |
| ACM Digital library | Mendeley |
| Inspec | Springer |
| Web of science | |

## II. RESEARCH METHODOLOGY

To collect and select the papers to be included in this review, we adopt the process described in Figure 1 inspired from the systematic mapping process [9]. The essential process steps are the definition of research questions, conducting the search, screening of papers to identify relevant ones, and analyses and data extraction. Each process step has an outcome.

### A. RESEARCH QUESTIONS

The overall purpose of our study is to provide an overview of optimization methods and simulation techniques, and to review the literature that uses optimization/simulation in supply chain applications. By the end, guiding researchers and practitioners to choose the appropriate paradigm, to link optimization and simulation for a specific supply chain problem. To gain a detailed view on this topic, the following research questions are addressed:

—What are the main SO techniques?

—What are the possibilities of combining optimization with simulation?

—What are the main supply chain areas that apply SO?

—How to choose the suitable approach for a supply chain application?

### B. CONDUCT SEARCH

As one of our study purposes is to give an overview of optimization methods and simulation techniques, the primary search was conducted using the following combination of keywords: (''Optimization'' OR ''simulation'') Techniques AND (''review'' OR ''survey'' OR ''overview'') on the scientific databases presented in Table 1. We focus only on journal and conference papers. The resulted articles are studied to identify several optimization methods and simulation techniques which are then combined with a set of keywords related to the supply chain field as demonstrated on Table 2.

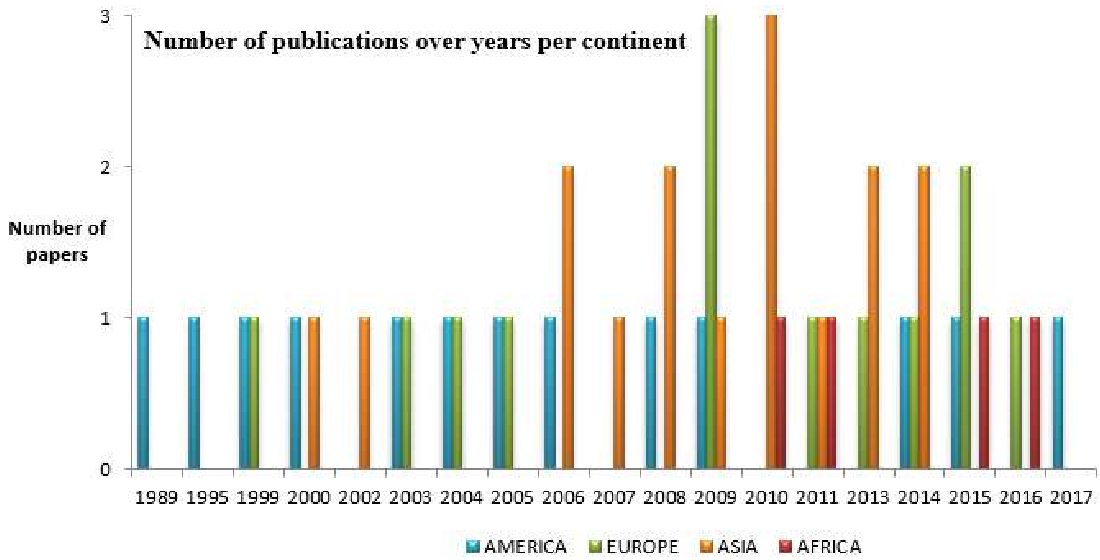


**FIGURE 2.** Number of publications over years per continent.

**TABLE 2.** List of keywords combination for screening papers.

| *Keywords combinations* | | |
|---|---|---|
| 'optimization method' AND 'simulation' | For | 'Inventory management' OR 'production management' OR 'Transportation' OR 'Distribution management' OR 'supply chain design' OR 'Logistics' OR 'sourcing' OR 'procurement' OR 'scheduling' OR 'resource management' OR 'supply chain configuration' OR 'warehousing' OR 'green supply chain' OR 'strategic planning' OR 'demand planning' OR 'Facility Management' OR 'route management' OR 'fleet management' |

### C. SCREENING OF PAPERS

We select the relevant papers based on the title, keywords, and abstract, to identify the contribution of the paper. We try to maintain a diversified literature in terms of application areas and techniques used.

### D. ANALYZES AND DATA EXTRACTION

The final database of papers is analyzed based on content analysis research method. Content analysis is an observational research method that is used to systematically evaluate the literature in terms of various categories, transforming original texts into analyzable representations [10]. The data extracted from each paper is: work methodology, supply chain area. The results of analysis are presented in the subsection E.

### E. CONTENT ANALYSIS

This subsection highlights the content analysis using tables and graphs representing papers classifications. More specifically, subsection 1 shows the classification per continent, subsection 2 shows the classification by application areas, and subsection 3 by work methodology.

#### 1) CLASSIFICATION BASED ON GEOGRAPHICAL REPRESENTATION

In this analysis, we focus only on papers using SO approaches in supply chain applications. Figure 2 shows the results of classification per year and continent. Several inferences could be made from the latter. First, we note that America was the first continent to publish on this area since 1989, and it maintains almost the same number of publications over years. Second, Europe starts interesting on this subject since 1999 followed by Asia with an increasingly number of publications. The main European publishing countries are France, Germany and Netherlands; France represents the country with the highest number of international co-authored papers. Third, it's clearly apparent that the number of publications has increased in the last years with a presence of all continents which demonstrates the relevance of this research area.

#### 2) CLASSIFICATION BASED ON APPLICATION AREA

Papers are classified based on their application in the supply chain to identify the most relevant ones. As shown in figure 3, production, inventory management and supply chain design are the 3 mainstream areas, with more emphasis on production, due to the numerous decisions that need to be taken, and the variety of problems encountered at this level, such as scheduling, lot sizing, capacity planning, etc.

#### 3) CLASSIFICATION BASED ON WORK METHODOLOGY

The relevant papers are classified to five categories based on research methodology: mathematical, conceptual, survey,

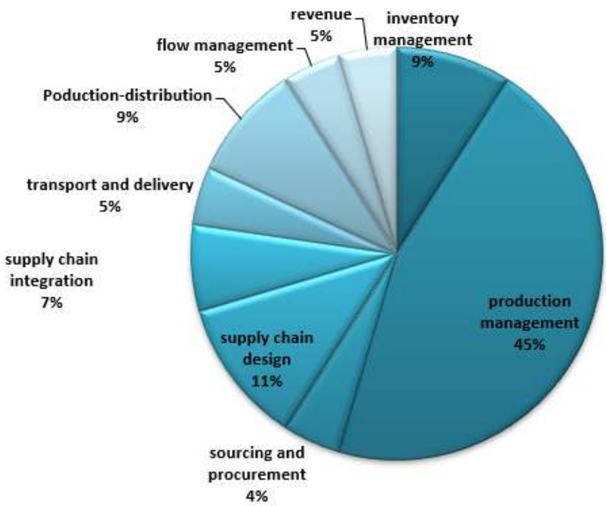


**FIGURE 3.** Publications by supply chain area.

review, and case study Table 3. A research work is classified as mathematical if analytical models, simulation, and mathematical formulas are used, and as a conceptual work if it focuses only on theory and there is no practical applications, to be classified as a case study if the work develops a theory verified through a practical problem.

A survey where research carried out a questionnaire to make analysis on a specific field, and the so-famous review. Surveys and reviews on optimization techniques and simulation in general or in supply chains are considered.

We note that mathematical/case study works represent 66% of total papers, due to their relevance; they will be detailed in the next section by research areas. Surveys and reviews represent 24% and they study only optimization methods or simulation technique, to the best of our knowledge there is no survey or review carrying out simulation/optimization in supply chain, there is only few works on simulation optimization approaches and their application on general.

## III. OPTIMIZATION TECHNIQUES

### A. STOCHASTIC GRADIENT ESTIMATION

The goal of stochastic gradient estimation approaches is to estimate the gradient of the performance measure when input parameters are continuous. They can be classified to gradient-based and non-gradient based methods.

#### 1) GRADIENT-BASED METHODS (GM)

Gradient-based methods are used to solve deterministic optimization problems. These methods require a mathematical expression of the objective function. To solve a SO problem the gradients of the simulation responses to the variables should be estimated first, and then the gradient search methods developed for non-linear programming problems are employed to determine the optimum [2].

An enormous amount of research has focused on techniques for estimating gradients. The four mean approaches used are described below:

- **Perturbation analysis (PA):** Finite Perturbation Analysis (FPA) and Infinitesimal Perturbation Analysis (IPA) are the two principal types of perturbation analysis, FPA estimates the derivatives of discrete variables and IPA can estimate from a single run all gradients of the objective function [11]. In the latter, if the decision variable is perturbed by an infinitesimal amount, the sensitivity of the response of the objective function can be estimated by tracing related statistics of certain events during a simulation run [2].
- **The Likelihood Ratio (LR):** allow to estimate both, the sensitivities and the performance measure through the same simulation. Details about this method are discussed in [12].
- **Frequency Domain Method (FDM):** A method that estimates the sensitivity and gradients of the performance values or responses of simulation models to the variables is proposed. The idea behind FDM is to oscillate the value of a variable according to a sinusoidal function during simulation. This technique is detailed in [13] and [14], [15].
- **Harmonic Analysis (HA):** a methodology which consists of varying input parameters during the simulation rather than holding them constant. This technique was studied by [16].
- **Finite Difference (FD):** which determines partial derivatives of the output variable [5].

#### 2) NON–GRADIENT METHODS (N-GM)

- **Sample path optimization (SPO):** also known as stochastic counterpart method, or sample average approximation method. This method needs some simulation replications to be performed first and the expected value of the objective function is approximated by the average of the observations. This method can effectively deal with difficulties faced by stochastic approximation such as low convergence rates, absence of robust stopping rules and complicated constraints. This method can effectively deal with difficulties faced by stochastic approximation such as low convergence rates, absence of robust stopping rules and complicated constraints. The sample path method converges under conditions presented in [17].
- **Nelder mead simplex:** is a direct search method that was originally dedicated to unconstrained optimization of deterministic functions and then has been frequently applied to the optimization of stochastic simulation models. This method presents an advantage for simulation optimization due to its insensitiveness to stochastic perturbations in function values. For further details see [18].
- **Hook and Jeves:** also called pattern search method is a sequential technique in which each step consists of two moves, an exploratory move to explore the local behavior of the objective function and a pattern move to take advantage of the pattern direction [19].

**TABLE 3.** Classification of papers by work methodology.

| Review | survey | Case study | conceptual | mathematical | Publications number | % | articles |
|---|---|---|---|---|---|---|---|
| x | | | | | 10 | 17 | [2][3] [4][6] [7] [8] [22][27] [33] [63] |
| | | | | x | 39 | 66 | [12] [75] [77] [78] [79] [80] [81] [83] [84][87] [88] [89] [90] [91] [92] [93] [95] [96][97][98] [99] [113] [114] [115] [116] [117] [118] [100] [101][102][103] [106] [108][109] [110][111] [119][123] [124] |
| | | | x | | 1 | 2 | [5] |
| | | x | | | 39 | 66 | [12] [75] [77] [78] [79] [80] [81] [83] [84][87] [88] [89] [90] [91] [92] [93] [95] [96][97][98] [99] [113] [114] [115] [116] [117] [118] [100] [101][102][103] [106] [108][109] [110][111] [119][123] [124] |
| | x | | | | 4 | 7 | [44] [58] [60] [95] |
| | | x | | | 5 | 8 | [38] [112][105] [84] [85] |

### *B. STATISTICAL SELECTION METHODS*

#### 1) RANKING AND SELECTION METHODS (R&S)

R&S methods are frequently used in practical problems such as finding the best facilities location to minimize costs. This technique consists of selecting the best set from a given set of alternatives by estimating the performance of alternatives and comparing them [20]. The goal behind is to minimize the number of simulation runs while ensuring certain probability of getting the best solution. However, to achieve these, there is a restriction; simulation runs should be conducted independently to ensure that the outputs from each run are independent. A review of ranking and selection methods is provided by [21].

#### 2) MULTIPLE COMPARISON

Multiple comparison is alternative to ranking and selection methods, they can efficiently find the optimal alternative from a finite set. A number of simulation replications are performed on all the potential designs, and conclusions are made by constructing confidence intervals on the performance metric [22]. Three main types of multiple comparison procedures can be used: all pairwise Multiple Comparisons (MCA), Multiple Comparisons with the Best (MCB), and Multiple Comparisons with a Control (MCC). Further details about this technique are presented in [23], [24].

#### 3) ORDINAL OPTIMIZATION (OO)

Ordinal Optimization (OO) is suitable when the number of alternatives is very large, thus it can effectively deal with such a difficulty faced by ranking and selection. This method was first proposed by [11]. Ordinal optimization aims at finding the good solution rather than searching the very best one which is computationally expensive. This idea is called ''goal soften'', further explanations are given in [25], [26].

### *C. RANDOM SEARCH (RS)*

Random Search (RS) is very close to meta-heuristics where a neighborhood can be defined for each incumbent solution. However, the next move is probabilistically chosen, based on a given probability distribution [7], RS can work on an infinite parameter space, it was originally developed for deterministic problems and then extended to the stochastic setting. More details about RS are presented in [27].

### *D. NESTED PARTITIONS (NP)*

Nested Partitions method (NP) is a randomized method attempt to solve complex system optimization problems. The idea behind this method is that some parts of the feasible region may be most likely to contain the global optima. Hence, it is efficient to concentrate the computational effort in these regions. The advantages of the NP method include flexibility, convergence to a global optimum, high compatibility with parallel computer structures and so on [2]. NP combines global search through global sampling of the feasible region, and local search that is used to guide where the search should be concentrated. For further explanations see [28].

### *E. META-MODEL-BASED METHODS*

#### 1) RESPONSE SURFACE METHODOLOGY (RSM)

Response Surface Methodology (RSM) consists of a group of mathematical and statistical techniques used in the development of an adequate functional relationship between a response of interest, y, and a number of associated control (or input) variables denoted by $x_1, x_2, \ldots, x_k$ [29]. RSM were originally developed to analyze the results of physical experiments to create empirically based models of the observed response values [30].

#### 2) KRIGING MODELS (KM)

Kriging Models (KM) were first used in mining and geostatistical applications involving spatially and temporally correlated data. These metamodels offer a wide range of spatial correlation functions for building the approximation. KM can approximate linear and non-linear functions equally well [30].

#### 3) ARTIFICIAL NEURAL NETWORK (ANN)

Artificial Neural Network (ANN) is a biologically inspired computer program designed to simulate the way in which the human brain processes information. ANNs gather their knowledge by detecting the patterns and relationships in data and learn through experience, not from programming. The applications of ANNs are various such a classification or pattern recognition, prediction and modeling. For further details see [31].

### F. META-HEURISTICS

#### 1) POPULATION BASED META-HEURISTICS

***-Swarm intelligence:*** also known under the name 'Ant Colony Optimization (ACO)' was first introduced by Dorigo [32] to solve hard combinatorial optimization problems in a reasonable computation time. ACO approach is inspired from the foraging behavior of real ants. This technique was applied to different problems such as vehicle routing problems, scheduling problems. See [32] for further details.

***-Estimation of Distribution Algorithms (EDA):*** are powerful stochastic optimization techniques that explore the space of potential solutions by building and sampling a variety of probabilistic models of promising candidate solutions, which allows solving a variety of problems. Furthermore, the ability of the EDA to provide useful information about the problem landscape makes this technique desirable compared to other optimization techniques, see [33] for more details.

***-Cross-Entropy Method (CE):*** is an efficient technique for probabilities estimation of rare event, as well as for combinatorial problems. The CE method involves an iterative procedure where each iteration can be broken down into two phases (1) generating a random data sample (2) Updating the parameters of the random mechanism to get a "better" sample in the next iteration. The method has been successfully applied for diverse problems such as assignment problems, travel salesman problems, scheduling problems, and buffer allocation problems. For much detail about the CE procedure, see [34].

***-Model Reference Adaptive Search:*** is a randomize search method for solving both continuous and combinatorial optimization problems. As in EDAs, this approach updates a parameterized probability distribution, and like the CE method, it also uses the cross-entropy measure to project a parameterized distribution [35], for further details see [36].

***-Genetic Algorithm (GA):*** is a stochastic search procedure based on the mechanism of natural selection and natural genetics, developed by John Holland 1975. GA has three main operators, selection, crossover, and mutation. It is used to search large, non-linear search spaces where expert knowledge is lacking or difficult to encode and where traditional optimization techniques fall short [37], [38]. For much detail about GA procedure you can see [39].

***- Evolution Strategies (ES):*** a robust method similar to GA, which imitate the principle of natural evolution as an optimization technique to solve deterministic problems. ES was introduced by Rechenberg in 1964 at the Technical University of Berlin to optimize the shape of a pipe and nozzle. Further details about ES are given in [5].

***- Evolutionary programming:*** techniques developed by Lawrence Fogel, they aimed at evolution of artificial intelligence in the sense of developing ability to predict changes in an environment. For further details about these techniques, the interested reader can see [40].

***- Scatter Search (SS):*** Scatter Search (SS) is an evolutionary algorithm that proved its effectiveness to solve hard optimization problems. The SS algorithm operates on a set of reference points. That constitutes good solutions obtained thought previous solving efforts. For defining "good" includes special criteria such as diversity that purposefully go beyond the objective function value [35]. The implementation of SS is based on five methods: diversification generation method, improvement method, a reference set update method, subset generation method, and solution combination method. For further details on the SS method see [41].

#### 2) TRAJECTORY BASED METHODS

-***Tabu Search (TS):*** first introduced by Glover and McMillan [42], Tabu search uses special memory structures (short-term and long-term) during the search process that allows the method to go beyond local optimality to explore promising regions of the search space. The basic form of Tabu search consists of a modified neighborhood search procedure that employs adaptive memory to keep track of relevant solution history, together with strategies for exploiting this memory [22].

-***Simulated Annealing (SA):*** was first proposed by [43]. SA is inspired by the annealing technique used by the metallurgist to obtain a "well-ordered," solid state of minimal energy (while avoiding the" metastable" structures, characteristic of the local minima of energy). This technique consists in carrying a material at high temperature, then in lowering this temperature slowly [44].

### G. GRADIENT SURFACE METHOD (GSM)

A technique that combines the advantages of Response Surface Methodology (RSM) and estimation techniques like

Perturbation Analysis (PA) or Likelihood Ratio method (LR). In GSM, the gradient estimation is obtained by PA (or LR), and the performance gradient surface is obtained from observations at various points in a fashion similar to the RSM. Zero points of the successive approximating gradient surface are then taken as the estimates of the optimal solution. Compared to RSM, GSM is more efficient indeed it's a single run method [45].

### H. BAYESIAN/SAMPLING ALGORITHMS

The Bayesian/Sampling (B/S) methodology is an iterative search strategy, where at each iteration; the next guess is chosen to be the point that maximizes the probability of not exceeding the previous value by some positive constant [3], [46].

### I. MATHEMATICAL PROGRAMMING METHODS

#### 1) LINEAR PROGRAMMING

Linear Programming (LP) was developed to solve linear programs. A LP is an optimization problem characterized by linear objective functions of the unknowns, and the constraints are linear equalities or linear inequalities in the unknowns. Linear programming problems are structured into the following form:

$$\begin{aligned}
&\text{Minimize } Z = c_1x_1 + c_2x_2 + \ldots.. + c_nx_n \\
&\text{Subject to } a_{11}x_1 + a_{12}x_2 + \ldots. + a_{1n}x_n = b_1 \\
&\qquad a_{21}x_1 + a_{22}x_2 + \ldots. + a_{2n}x_n = b_2 \\
&\qquad . \\
&\qquad . \\
&\qquad a_{m1}x_1 + a_{m2}x_2 + \ldots. + a_{mn}x_n = b_m \\
&\qquad x_1 \geq 0, x_2 \geq 0, \ldots\ldots.x_n \geq 0,
\end{aligned}$$

where Z is called the objective function, the variable $x_1 \ldots. x_n$ the decision variables to be determined, and $c_1$, $c_2, \ldots, c_n, b_1, b_2, \ldots, b_n, a_{11}, a_{12}, \ldots, a_{nm}$ are fixed real constants.

Linear programming arises in different areas. The most reasons of his popularity are the simpler computation, as well as, it's less difficult to define. In the supply chain context linear programming was used for planning production, distribution and inventory operations [47] to solve integrated supply, production and distribution planning [48]. Simplex is the most popular method for solving LP problems.

- **Simplex:** developed by George Dantzig, a member of the U.S. Air Force, in 1947 in order to solve linear programming problems. The idea behind simplex is to start from one basic feasible solution rather than checking the entire extreme. Then, each iteration of the algorithm takes the system to the adjacent extreme point with the best objective function value. These iterations are repeated until there are no more points with better objective function values, thus the optimality is reached [49]. Simplex can converge to an exact solution in a finite number of steps.
- **Interior point method:** was introduced first by Ho man (1953) [50] and Frisch [51] to solve LP. However, it was weak compared to simplex due to the expensive computational steps, numerical instability in calculation. Reference [52] has presented then a novel interior point method faster than simplex and does not require a feasible starting point. The interior-point is appropriate when the problems are large and convex. In addition, this approach has the advantage that the system of linear equations to be solved at each iteration has the same dimension and structure throughout the algorithm, making it possible to exploit any structure inherent in the problem [53].

#### 2) MIXED INTEGER PROGRAMMING

Mixed-Integer Linear Programming (MILP) problems are problems where some or all variables are integer-valued and the objective function and the constraints are linear. Techniques for solving MILP differ from those used for LP. Indeed, the solution of an entire LP problem is required at each step of the algorithm. The most popular techniques to solve MILP are branch and bound and cutting plane. MILP have been widely used in the supply chain context for production, transport, and distribution planning

- **Branch and bound:** the idea behind this technique is that since the initial problem is hard to solve, it's subdivided to sub-problems. A search strategy is used at each stage of the algorithm to select an unsolved problem. A bounding strategy is used to compute a lower bound on the objective value of a solution available from this sub-problem. If this lower bound exceeds a known incumbent solution value, then this sub problem is eliminated. Otherwise, the sub-problem is further partitioned using the branching strategy, and the process continues until all sub problems are fathomed. For further details see [54], [55].
- **Cutting plane:** the fundamental idea is to start with the integer linear program and solve its LP relaxation. If the solution is integral, it's the optimal for the original problem, otherwise find a linear constraint that excludes the LP solution but does not exclude any integer Points called the CUT. Then, add the CUT constraint to the problem and return to the first step.

#### 3) NON-LINEAR PROGRAMMING

Non-linear Programming (NLP) deals with problems characterized by a non-linearity of the objective function and/or the non-linearity of any of the constraints. A NLP problem is structured as follows:

$$\begin{aligned}
&\text{Minimize } f(x) \\
&\text{Subject to } \; g_i(x) \leq 0 \quad \text{for i} = 1, \ldots, \text{m} \\
&\qquad h_i(x) = 0 \quad \text{for i} = 1, \ldots, \text{p} \\
&\qquad x \in X
\end{aligned}$$

where $f(x)$ is the objective function, $g_i(x) \leq 0$ is the inequality constraints and $h_i(x) = 0$ is the equality constraints. Branch and bound is most used for NLP.

## IV. SIMULATION TECHNIQUES

### A. DISCRETE-EVENT SIMULATION

Discrete-Event Simulation (DES) is the kind of simulation that models the operation of a system as a discrete sequence of events in time. Each event occurs at a particular instant in time and marks a change of state in the system. Between consecutive events, no change is assumed to occur [56]. DES models are generally stochastic in nature, where randomness is generated using statistical Distributions [57].

DES is suitable for modeling problems at operational/tactical level.

### B. AGENT BASED SIMULATION

Agent Based Simulation (ABS) is a relatively new method compared to system dynamics and discrete event modeling. In ABS, active entities known as agents must be identified and their behavior defined. ABS has been adopted to solve complex problems, form logistics optimization, to traffic, to urban planning, and an example of the latter is presented in [58]. ABS can be used in different purposes: (1) Understanding observed dynamics, processes and systems (2) Designing or engineering of processes or systems (3) Managing a system or process (4) Formulating theory and explanatory models (5) Prediction (6) Optimizing resources, capabilities and processes. For further details refer to [59].

### C. MONTE CARLO SIMULATION

Monte Carlo simulation is a simulation technique used to incorporate the uncertainty of valuation parameters that has been largely used in manufacturing and business: for investments and cash flow forecasting and so on. It's a technique specially dedicated to static problems and numerical problems with a stochastic nature. For further details the reader can refer to [60].

### D. SYSTEM DYNAMICS SIMULATION

The System Dynamics (SD) method was created in 1950s by MIT Professor Jay Forrester. Drawing on his science and engineering background, Forrester sought to use the laws of physics, in particular the laws of electrical circuits, to investigate economic and social systems. SD views companies as systems with six types of flows, namely materials, goods, personnel, money, orders and information [61]. SD models are generally deterministic and typically used to solve problems at the strategic level. In SD individual entities are not specifically modeled, but instead they are represented as a continuous quantity in a stock [57].

### E. PETRI NETS

Graphical and mathematical tool that can be implemented using hardware (or micro programed, and software) to model and study processes. Because of the graphical nature of net models, they are mostly self-documented specifications, making easier the communication among designers and users. For its application in manufacturing systems see [62].

### F. INTELLIGENT SIMULATION

Integrates simulation and artificial intelligence techniques to tackle the volatility of real-life, or the over-complexity of some problems such as scheduling, making the solution approach quicker, sometimes real-time, as well as more manageable [63].

### G. TRAFFIC SIMULATION

A group of techniques aimed to tackle traffic management problems. The applications of traffic simulation programs can be classified into; microscopic, mesoscopic and macroscopic, or depending on time into continuous and discrete time approach. Some of these areas are the traffic signal control, traffic safety and simulation of travel demand. An overview is provided by [64] and an example is reported in [65].

### H. SIMULATION GAMING

Have appeared in the policy analyst toolkit since the 1960s in response to the need for human-centered approaches that incorporate the socio-political complexity of public policy issues [66]. It's an interactive simulation, where managers can operate within the simulation worlds. This technique is applied in different areas such as: resource management [67]–[69], urban planning [70], and peri-urban conflicts [71]. Gaming simulation has got much interest from education and training sector. An example of their usage is education training as well as production scheduling.

### I. DISTRIBUTED SIMULATION

Is concerned with execution of simulations on geographically distributed computers interconnected via a network, local or wide [72]. This kind of simulation is mostly applied in transportation and supply chain management.

### J. HYBRID TECHNIQUES

Simulation techniques presented above can be combined to solve problems. The well-known hybridization is DES with SD. An example of its application in manufacturing field is presented in [73] to evaluate production decisions, where SD is used to measure the long-term effects of these decisions and DES provides detailed analyses of the shorter-term decisions.

## V. SUPPLY CHAIN APPLICATIONS

SO approaches have been widely used in supply chain management to support the decision-making process. In this section we review the published contributions in the field following a classification into three broad categories (i) Strategic (ii) Tactical and (ii) Operational.

### A. STRATEGIC DECISION PLANNING

-**Supplier selection:** is an important issue in supply chain management, where a best supplier is selected fulfilling a set of criteria. [38] Studied supplier selection under uncertainties (demand fluctuation, supply lead-time variability) using an optimization-based simulation methodology. The approach includes three modules developed in C++, a GA optimizer, a discrete-event simulator and a supply chain modeling framework. The GA search for possible configurations that will be tested during the simulation by using KPI such as purchasing costs, transportation costs, inventory costs and total backlogged demands; the results of a real-life case study of a multinational textile supply chain, validate the efficiency of the solution proposed.

-**Sourcing strategy design** in supply chain is crucial to gain competitive advantages. It involves the selection of suppliers, design of supplier contracts, product design collaboration, procurement of materials, and evaluation of supplier performance [74].

Supply chain risks have grown in recent years, and supplier failure is considered as one of the most risks encountered. A hybrid optimization and simulation approach is proposed by [75] to evaluate the performance of various sourcing strategies under different settings and two supply risk profiles. The problem is modeled as a dynamic program and solved by an Approximate Dynamic Programming (ADP) approach. Simulation was performed with a C++ program. Experimental results proved the ability of ADP to provide an optimal solution in less time.

–**Supply chain design:** Supply Chain (SC) design plays a key role in meeting corporate and supply chain strategy as establish a framework in which operation could be realized [76]. Therefore it highly influences customer satisfaction and SC efficiency. The selection of the optimal Facility location is one of the most critical and difficult decisions needed to gain in efficiency.

To solve the facility location problem, [77] proposed a general iterative solution approach that incorporates a generalized MIP and a simulation model. The optimal deterministic solution suggested by the MIP model is then simulated while integrating uncertainties to measures their impact, and based on the MIP formulation is updated in each iteration to generate a new optimal deterministic solution, until a previously simulated solution is obtained as the optimal solution from the MIP. The methodology was applied to a multi-product, Multi-Period Facility Location Problem (MPP-FLP) using the ILOG CEPLEX to solve the MIP model and AUTOMOD to run the simulation model. Experimental results demonstrate that proposed approach outperform the deterministic model in case of a high level of uncertainty, indeed the cost saving increase as the uncertainty increase.

SC design awarded a great interest from several researchers, [78] present a simulation based robust optimization for supply chain network design. A model is established which aims to minimize total costs under uncertainty. The model is solved by a hybrid intelligent algorithm which consists combining the genetic algorithm with fuzzy simulation to calculate value of object function; the proposed supply chain structure is then simulated to evaluate its performance. The proposed approach is compared to stochastic optimization models throughout computational study and results proved the efficiency of the approach to design supply chain structure with a minimum of market risk.

To handle the Supply Chain Configuration Design, authors in [79] developed a hybrid approach with the objective of minimizing the overall system-wide cost while maintaining a good customer service. The approach combines the genetic algorithm to optimize qualitative and policy variables, and incorporates decisions of suppliers/company selection, production policy selection, and transportation mode selection. The MIP model which undertakes decisions related to location selection, facility capacity and distribution decision. And finally, simulation is used to evaluate performance of each supply chain configuration. The proposed approach is compared to random sampling and pure GA approaches through an empirical study, and results showed its efficiency.

As to supply chain collaborative design, authors in [80] developed a three-stage framework that incorporates decision makers taking into account their considerations. The first stage consists of getting a set of efficient designs, it's a multimodal optimization problem solved by the Crowding Clustering Genetic Algorithm (CCGA) combined with simulation. The designs are then analyzed by decision makers in the second stage in terms of their preferences, the best one is chosen in stage 3. The problem in the 2$^{nd}$ and 3$^{rd}$ stage is handled as a preference aggregation problem in the social choice theory by using Analytic Hierarchy Process (AHP) methodology.

The Sample Average Approximation (SAA) scheme was combined with an accelerated Benders decomposition algorithm also known as the L-shaped decomposition method by [81], to get high quality solutions to supply chain design problems with infinite scenarios. The proposed methodology was tested in two realistic supply chain design problems and the algorithmic scheme was developed in C++ with CPLEX 7. Computational results highlighted the efficacy of the proposed solution strategy, which can be considered as a viable strategic planning tool.

-**Supply chain integration:** Supply Chain Integration (SCI), which is the degree to which a manufacturer strategically collaborates with its supply chain partners and collaboratively manages intra- and inter-organizational processes, in order to achieve effective and efficient flows of products and services, information, money and decisions, to provide maximum value to the customer [82].

To ensure a cooperative integration on a generic supply chain between 3 systems: suppliers, logistics, and distributors. Reference [83] presents a methodology consists of describing each of these systems as a distributed optimization problem solved by an ant colony algorithm, which allows the exchange of information between different optimization problems through a pheromone matrix. Simulation was performed for a real case of supply chain management at Fujitsu-Siemens computers. And results showed that the proposed strategy can effectively improve the global supply chain performance.

In [84] authors addressed the problem of aggregating procurement, production, and distribution planning for a multi-echelon supply chain using the particle swarm intelligence and the artificial bee colony optimization.

-**Revenue:** for maximizing the profit of a small automated manufacturing system, authors in [85] studied the integration of SA and simulation. ASIMAN simulation model was developed to evaluate system profit so that the algorithm can find the global optimum of the input variable combinations.

To maximize profit in a distribution system consisting of multiple manufactures and one retailer, authors in [86] present a methodology based on optimization and simulation. A simulation was done to this system under both, non-cooperation and cooperation situations based on Q-learning algorithm. The experimentation results showed the importance of cooperation between manufacturers to improve their profits. However, the profit of retailers is damaged. Authors in [87] integrate ordering and pricing planning problem by developing a multi-objective model intending to maximize the profit and the service level. The model is solved using the weighting method, the genetic algorithm as well as the L-P metric method.

**-Production capacity planning:** in capacity planning, decisions about how resources will be allocated to meet customers' demand are made. However, the demand uncertainties make this task difficult. To handle a multiple-period capacity planning problem in semiconductor manufacturing, authors in [88] have developed a new framework based on sample path method. Authors use min-max regret as an objective function and model the demand uncertainty as a continuous stochastic process. The framework decomposes the problem into several small problems, and gradually improves the quality of the optimal solution. A computational study demonstrates its efficiency in computing time compared to the traditional mathematical programming.

### B. TACTICAL DECISION PLANNING

- Inventory management can be defined as the process of planning, controlling inventory levels at different stages of supply chain. This process is challenging for decision makers due to the uncertain supply chain environment. Henceforward, analytical models don't hold in solving such complex problems. Thereupon, simulation/optimization approaches come into use to deal with such complex problems.

Determining optimal stock levels is challenging under demand uncertainties, to cope with the later, authors in [89] have proposed a simulation-based optimization framework to determine the optimal safety stock level for maintaining a good customer service under demand uncertainty. The problem is formulated as a multi-stage stochastic problem and solved in rolling-horizon within an approximation strategy using a deterministic supply chain planning and scheduling models, which is built based on demands generated by Monte Carlo. The production and scheduling plans obtained are implemented in a discrete event simulation model. A refinement of the model is performed using the antithetic variants technique to reduce the computation load. Approach efficiency was proved through a case study. However, the large computing time required still a limitation key of this approach.

Regarding the inventory policy, two decisions variables (s,S) need to be specified. The order is placed when the inventory level is below s units; the order amount is the difference between the maximum inventory level S and the current inventory.

To find the optimal (s,S) values, authors in [90] combines simulated annealing with ranking and selection, with the objective of minimizing holding and ordering costs. In another typical work, [91] combines a particle swarm optimization tool and a simulation model to design a three echelon network inventory system to satisfy customers' demand and set (R,s) inventory policy at each location, under uncertainty while minimizing the total cost of the system.

Customer service level is one of Key Performance Indicators (KPI) in supply chain management. This KPI can be computed as the percentage of times that received customer orders are fulfilled by on-hand inventory. Hence, improving customer service levels require an efficient inventory control. In this regard, authors in [92] have proposed a regional surrogate-based framework for inventory control and optimization problems in a supply chain network under demand uncertainty, with the objective of minimizing total operation costs while keeping a good service level. The optimization problem is formulated as an aggregation of regional surrogate models which is constructed via the Design and Analysis of Computer Experiment (DACE) approach and optimized by a trust-region framework.

-**Production panning:** In [93] authors proposed a two-level Hierarchical Production Planning (HPP) Method for semiconductor wafer manufacturing where production plans are generated in the aggregated level by solving a LP model and operations are scheduled in the disaggregated level with a priority-rule-based scheduling method. Feasibility of production and scheduling plan is evaluated through a discrete-event simulation model. In case of undesirable plans, parameters of LP models are updated, and another plan is generated. HPP was compared to the method developed in [94]. The LP model was solved using CPLEX solver and simulation was performed on a real data of a Korean semiconductor manufacturer. Results showed that HPP is better than HL in terms of total costs and tardiness and computation time. However, the convergence of the proposed iterative approach cannot be guaranteed.

A simulation study was conducted in [95] for a production planning model to specify the non-linear relationship between the expected work-in-progress and the expected throughput. This relationship is presented as a clear function, which can be estimated from empirical data using a simulation model as a surrogate for observation of the production system under study.

Sensitivity of the estimated function to different dispatching algorithms, demand patterns and production planning was examined. A scaled-down model of a semiconductor wafer fabrication is used as a test bed to show the potential of clearing function compared to LP models.

The iterative optimization simulation approach is criticized in [96] where authors attempt to demonstrate that convergence poses a problem, by examining the convergence behavior of the Hung-Leachman (HL) procedure opposed in [94]. It's an iterative approach that combine a LP model with a simulation model, for production planning in semiconductor manufacturing. Experimental results showed that the convergence of iterative approaches is quite complex and it's difficult to propose a stopping criterion.

A hybrid mathematical-simulation model is used by [97] to solve the production—distribution planning problem for a multi-site multi-product supply chain. The problem is modeled as a MILP and firstly solved without considering stochastic parameters. The solution is then used as input to the simulation model that calculates stochastic variables. The mathematical model is then adjusted by the results of simulation.

Most models for supply chain planning problems under uncertainties are based on analytical approaches, simulation, or hybrid approaches. In [98] authors use the fuzzy set theory to develop a tactical SC planning model which considers integrally uncertainties in supply, demand, and processes. The proposed fuzzy mixed-integer linear programming model jointly considers the possible lack of knowledge in data and existing fuzziness. The model was tested using a real data of automobile supply chain. Results clearly identified the effectiveness of fuzzy formulation compared to deterministic methods

**-lot sizing:** For the lot sizing problem in make to order supply chain, authors in [99] proposed an approach using a DES model built on arena to evaluate the Order Mean Flow Time (OMFT) performance for a case study. Based on simulation outputs a multi-objective desirability optimization is achieved by using a Response surface methodology to minimize the number of runs. In another work [100], they developed a reverse simulation metamodels based ANN. The paradigm was tested in practical application, furthermore, ANN proved to be viable tool for stochastic simulation metamodeling.

To solve the joint pricing and lot-sizing problem under fluctuations in demand and unit purchasing costs, authors in [101] propose a mathematical model and solve it by the PSO in order to find the optimal replenishment number, time scheduling and periodic selling price.

The authors in [102] considered the pricing, marketing, and lot-sizing decisions simultaneously by formulating the problem as a fuzzy non-linear multi-objective. To deal with uncertainty, the fuzzy goal programming and the possibilistic flexible programming methods are used. The model is the in solved using the PSO. For the same target, authors propose in [103] a hybrid bi-objective credibility-based fuzzy optimization model. After defuzzification the model is solved using fuzzy goal programming and the PSO.

**- Manufacturing process**: A methodology that can optimize qualitative variables in a manufacturing system by using a simulation-optimization approach is developed in [104]. The proposed methodology uses a GA connected to a simulation-model generator for flexible manufacturers system design. This approach has been implemented in the language Modsim 11, tested in 3 problems to minimize the work in process and compared to simple random sampling. Results show that the developed methodology outperforms random sampling especially when a lot of simulations run is required.

To optimize the performance and profitability of manufacturing systems, [105] proposes a two-stage approach aims at determining the best sitting of operational variable for a uniform parallel machine production system while minimizing manufacturing costs. Settings are picked at the first stage based on Ordinal Optimization (OO) and PSO with the crude model. At the second stage, a discrete event simulation model is designed to identify the best setting. To save in computational time, authors combine simulation models with Optimal Computing Budget Allocation (OCBA) to allocate several simulations to each setting. Experimental results demonstrate that OO-PSO outperforms PSO-exact in the large scale and prove its effectiveness. Sensitivity analysis was also conducted.

In [106], authors developed a reach-based methodology, combining random search, adaptive random search, hill climbing and simulated annealing algorithms for testing continuous controllers. To identify worst-case test scenarios, the approach was implemented on a tool called coco TEST and applied to a real case study in the automotive industry. Experimental results demonstrate the efficiency of the approach in identifying potential errors in controllers that cannot be found by manual testing and in a short time.

The sensitivity estimation problem of the throughput for flexible manufacturing system was carried out by [107], with respect to the routing mix by using a simulation-based perturbation analyses approach. Simulation was conducted using the SIMAN IV simulation language. Computational results proved the feasibility of the proposed approach.

**-Vehicle routing problem:** Regarding logistics distribution, [108] used a simulation optimization approach for solving a practical Vehicle Routing Problem with Time Windows (VRPTW) for a distribution center in Michigan, USA. The problem is modeled as a multi-objective optimization problem and solved by the non-dominated sorting genetic algorithm II (NSGA-II). VRPTW is simulated using Anylogic software to analyze the effects of factors such as the crowding level and time windows on distribution. So, we can improve a range of parameters related to the vehicle routing problems.

**-Distribution system:** to optimize the supply chain of a distribution network, [109] has proposed a simulation-based optimization approach by unifying the Modal-Shift Transportation Problem (MSTP) algorithm that makes a multi-modal transportation schedule and the Warehouse Location Problem (WLP) that locate facilities. The model resulted called Warehouse Location and Transportation Problem (WLTP). The system optimizes gradually the supply chain through a series of optimization simulation while changing the boundary conditions, or warehouse locations, that connect the two Algorithms. An experiment study shows the ability of the system to find a solution near to the optimal.

**-Production-distribution:** To determine the optimal production distribution planning for multi-facility multi-products, multi-period supply chain, authors in [110] employed a simulation/optimization approach. First, a mathematical model is solved to obtain capacity of facilities that minimize relevant costs, which is then used to feed the simulation model. This latter generates feasible production-distribution plan and performance measures, taking into consideration replenishment policies. A computational study was performed using the IBM Supply Chain Analyzer (SCA) simulation optimizer tool.

In another work, [111] authors combine linear programming and simulation to solve production distribution planning problems in supply chains, subject to capacity and inventory balance constraints. Machine capacity and distribution capacity are considered as a stochastic factor adjusted based on the simulation outputs. The proposed hybrid approach was tested through a case study, the problem was modeled as a linear programming and solved by GAMS and simulation run was perfumed in ARENA software. Results proved the ability of the approach to provide more realistic optimal solutions.

### C. STRATEGIC-TACTICAL DECISION PLANNING

Regarding the decision on qualitative variables, [112] proposes a simulation-based optimization approach to make decision in production strategies and safety stock at the same time in semi-conductor supply chain. The authors determine the partition of the products in Make To Order (MTO), Make To Stock (MTS), and Assemble To Order (ATO). And the safety stock levels for each product and storage location to maximize the profit by using a genetic algorithm called GA-I. A simulation model of semi-conductor supply chain is used to evaluate the performance of GA-I in comparison with 2 other heuristics that doesn't integrate safety stock. Experiment proves that the GA-I outperform the other heuristic when the demand is highly variable.

### D. OPERATIONAL DECISION PLANNING

**-Scheduling:** For production scheduling, [113] used a simulation-based optimization by combining a Monte Carlo simulation with SPO method. The proposed approach attempts to set release time for jobs and due date, while minimizing costs of tardiness and cycle time, and maximizing flexibility in manufacturing. The model incorporates machines breakdowns and provides sensitivity analysis with respect to capacity and due dates. A numerical study shows that the proposed methodology is suitable for small samples and computations are intensive.

In flow shop scheduling, authors in [114] proposed a simulation-based optimization algorithm to solve a multi-objective hybrid flow shop scheduling problem that consists on reducing the make span and the total tardiness. The approach combines a Fuzzy Logic Controller (FLC) with the traditional non-dominated Sorting Genetic Algorithm (NSGA-II) to enhance its ability. The proposed FLC-NSGA-II is then coupled with the ARENA environment. The efficiency of the proposed methodology is compared with the industrial solution and the classical NSGA-II. Results show that the FLC can enhance the search ability of the genetic algorithm.

In [115] authors used a SA algorithm in conjunction with a simulation model to schedule a hybrid flow shop under maintenance constraints.

For the job shop scheduling, [116] identify the optimal number of kanbans' in a Just-In-Time (JIT) system by randomly generating kanban combination used as an input value for the simulation, and obtaining the cycle time to get the optimal objective function value. The performance of TS in SO is compared with a random search algorithm and numerical results show the high efficiency of TS in searching solution space. Two methods are proposed by [117] for scheduling Engineer-To-Order (ETO) products under stochastic durations and finite capacity resources. A two phases method which consists of optimizing the operations sequence by using a heuristic at the first phase and then further optimize timing using perturbation analysis. The other method optimizes the time directly through random search method with a simulation of schedules suggested for evaluation. Proposed methods were tested and validated based on several examples from a real ETO manufacturer.

In [118], authors have developed an Iterative Optimization Simulation (IOS) framework where optimization is embedded into a simulation system. The framework integrates a simulation manager, optimization manager, and a database manager to transfer data between the latter. The simulation manager continues run, and the model status is stored in the database until a trigger event (planned or unplanned) occurs. Hence, the simulation model is paused, and the optimizer is launched, the latter retrieves the data stored to feed the analytical model and re-optimize the system. IOS was compared to Simulation-Based Optimization (SBO) thought a case study in scheduling problems of a manufacturing system. Simulation runs was performed, and once an event occurs such as machine failure or the arrival of new batch of jobs, simulation is paused, and optimization called to obtain a new schedule. Results indicate that IOS slightly outperform SBO when problem is small and less complex and strongly outperform (dominate) SBO when the problem is hard and large.

**-Flow management and resource allocation:** Authors have proposed in [119] and [120] a strategy for the transfer of containers between the maritime Atlantic Terminal and the multimodal terminal of the Havre Port at a lower cost based on a simulation optimization coupling approach, composed of 2 modules: an optimization module, which consists in determining an optimized planning of the transfers by resolving a linear program under CPLEX. The solutions are then used to power the simulation model which evaluates the performance of the chosen strategy. Authors in [121] have highlighted the drawbacks of the model proposed by [119] and propose a new one to overcome the issues, applied in rail-rail transshipment for minimizing unproductive situations of cranes in Le Havre Port. And they have proposed another typical work inspired by the ant colony [122].

Regarding resource allocation problems in supply chain, [123] presents a hybrid approach that combines the nested partition method and an efficient technique for simultaneous simulation experiments called optimal computing budget allocation method OCBA, which consists on determining the best allocation of simulation samples for each design to improve simulation efficiency. The approach was applied to a stochastic buffer allocation problem, and numerical results proved that the proposed approach can quickly obtain an optimal solution thanks to the OCBA that reduces the computation time by 96%.

## VI. TAXONOMY OF OPTIMIZATION/SIMULATION APPROACHES

The possibilities of linking optimization and simulation are so vast. Selecting the appropriate technique to solve a specific problem is not evident. Hence the need for a taxonomy that provides a good overview of the different approaches. Considering the taxonomy presented in [7], we provide a taxonomy based on three dimensions. The aim is to categorize the well-known methods applied in the literature reviewed and explore their characteristics. To the best of our knowledge, this is the first paper to present this classification in the supply chain field.

In the following subsections, we describe categories of each dimension; the methods are classified following the categories pre-defined.

### A. SIMULATION PURPOSE

#### 1) SOLUTION EVALUATION APPROACHES (SE)

Solution evaluation approach consists of developing a simulation model to mimic a system and use it to evaluate the performance of solutions. Hence the nomination solution evaluation since simulation is used for the purpose of evaluation. A wide variety of methods can be used to develop SE. The relevant ones in the literature are detailed in follow:

-Statistical Selection Methods (SSM)**:** These methods compare and select solutions applying statistical analysis. Include multiple comparison and the well know ranking and selection that was combined to SA in [90] for inventory problems, and the OO method to optimize the profitability of a manufacturing system [105].

-Meta-heuristics (MH): metaheuristics is used in a great range of supply chain applications. Specifically genetic algorithms are mainstream, indeed GA was applied in supplier selection [38], supply chain design [78]–[80], and mostly adopted in manufacturing problems to decide in the production strategy [112], schedule operation [114], as well as manufacturing system design [104].

-Random Search (RS): was originally dedicated to deterministic problems and extended then to deal with stochastic one. RS was used by [117] to handle stochastic settings in scheduling operation

-Stochastic Approximation Methods (SAM): including the sample path optimization applied in an Optimization with Simulation-Based Iteration (OSI) approach to find the optimal material release times by [113].

**-** Reverse Simulation Technique (RST): it's a heuristic procedure that starts by specifying target values or range of values and adjusts the system configuration to conform the user-defined values. RST can address both, continuous and discrete decision variables. Was used by [83] to solve the system design problem.

- **Surrogate Model construction (SMC)**

*-Model based methods***:** also called memory-based metaheuristics (MMH), include the so famous swarm intelligence, estimation of distribution method, cross entropy and model reference adaptive search.

*-Metamodel based Methods (MM):* the well-known RSM was used by [99] to solve a lot-sizing problem.

*-Gradient Surface Methods (GSM):* combining RSM with stochastic approximation, proposed in [45] to handle manufacturing and transportation system optimization.

*-Approximate Dynamic Programming (ADP):* known as reinforcement learning in the artificial intelligence community. ADP combines Dynamic Programming (DP) with simulation. The most important dimension of ADP is ''learning what to learn and how to learn it for a better decision making''. ADP is based on learning agent which selects solution according to its knowledge. For much details view [124]. ADP was adopted by [75] for supply risk management and profit maximization [86].

#### 2) SOLUTION GENERATION APPROACHES (SG)

Using simulation to evaluate solutions quality as in method previously mentioned is computationally expensive. In some cases, the feedback from simulation is not even being important to choose the best solution. In SG approaches, the analytical model is solved, and their solutions are then simulated to compute some variables, hence simulation here is a part of solution generation and not an assessor of solutions. The optimization process can be performed either before or during the simulation run. These two schemes are respectively described below.

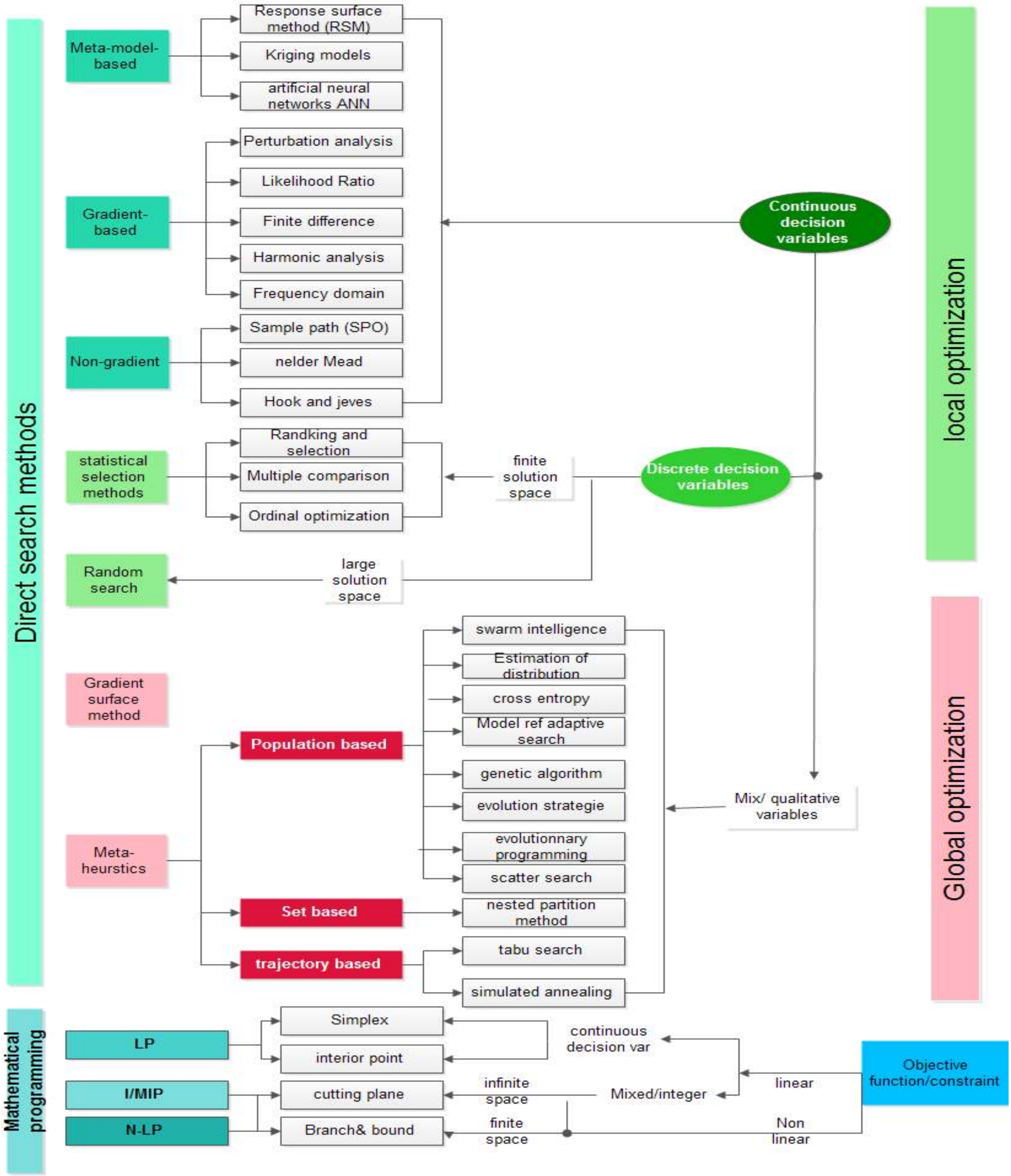


**FIGURE 4.** Optimization methods taxonomy.

—*Solution Completion by Simulation (SCS)*

Simulation is used to compute some variables to complete or correct the solution generated by optimization. SCS can be hybridized with SE approaches, a typical example is presented by [114] to find the optimal production-distribution plan. Furthermore, [79] embed SCS to meta-heuristics to tackle supply chain design problems.

-*Iterative Optimization-Based Simulation (IOS)*

In this approach, optimization may be called during simulation execution in as periodic scheme or in an event-driven

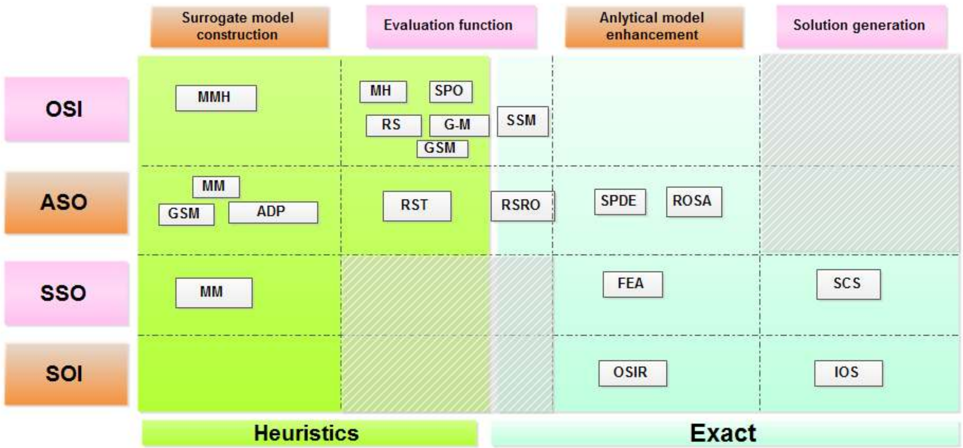


**FIGURE 5.** Taxonomy of Optimization Simulation Approaches-inspired from [7].

basis. This approach is similar to RST. However, they differ by the fact that optimization doesn't need simulation to evaluate the solutions generated. IOS was successfully applied by [118] for scheduling problems.

#### 3) ANALYTICAL MODEL ENHANCEMENT (AME)

-*Stochastic Programming Deterministic Equivalent (SPDE):*

Stochastic programming is an appropriate approach to deal with uncertainties. The concept behind is to use mote Carlo simulation to perform the sampling of scenarios, embedded then in the analytical model. This model is called a large-scale deterministic equivalent. This approach requires some approximations to be made. SPDE is presented by [81] to solve the supply chain network design problem

-*Recursive* Optimization–Simulation Approach (ROSA):

The idea behind this approach is to run alternately optimization model and simulation model. Where simulation uses the analytical model solutions to compute some measures, the outputs are then used to refine parameters of analytical models. A stopping criterion is applied to end this iterative process. ROSA proved its success in production planning [96] and supply chain design [77].

-*Function Estimation based Approach (FEA):*

This approach is an alternative to ROSA; simulation is conducted to specify the relationship between particulate input and output variable. This relationship is then incorporated in the analytical model. An example of FEA application for production planning is presented in [95].

-*Optimization-based Simulation with Iterative Refinement (OSIR):*

This approach is similar to IOS, but it performs refinements to the analytic model. An application in inventory management under uncertainties is presented in [89].

### B. HIERARCHICAL STRUCTURE

Hierarchical structure concerns the dependency and the way optimization module interacts with simulation module. Authors in [7] define four structures:

-Optimization With Simulation-Based Iteration (OSI): in which the overall model of the total system is an optimization model, and in all or part of iterations simulation runs are performed.

-Alternate Simulation—Optimization (ASO): consists of alternating between using independent simulation and analytic models, the simulation part of the model is carried out without intermediate use of the analytic part and vice versa.

-Sequential Simulation—Optimization (SSO): both modules run sequentially either optimization first or simulation.

-Simulation with Optimization-based Iterations (SOI): where the overall model is a simulation model, and in all or part of iteration, optimization model is called to compute some parameters.

### C. SEARCH METHOD

For this dimension, we use two categories defined in the first section depending on the characteristic of the problem. Exact algorithms appropriate to problems relatively easy, that guarantee to find the optimal solution, but the larger the problem, the more complex the solution space. In the other hand, heuristic methods can handle complex problems by providing good solutions, in a reasonable time but not necessarily optimal ones.

## VII. ANALYSIS AND DISCUSSION

The taxonomy presented allowed to distinguish between the popular methods used in SO framework and to grasp their characteristics. The aim now is to establish the relationship between these approaches and the supply chain problems characteristics.

To this end we launch a discussion and analysis of typical decision problems at the 3 levels (strategic, tactical and operational), and the methods used by researchers. The objective behind is to understand the main criteria for selecting the proper technique. As an output we propose the following selection process Figure 6.

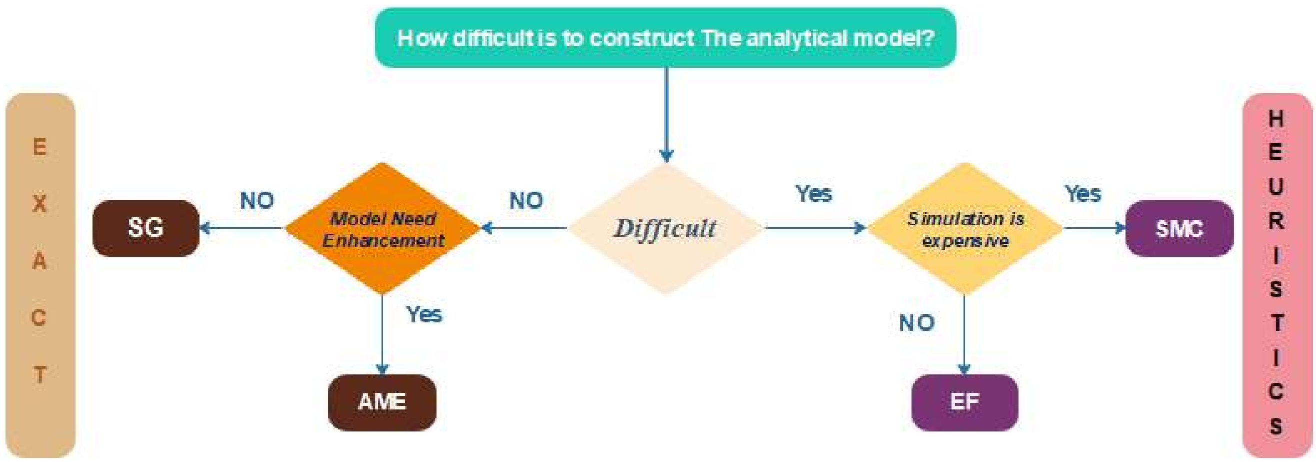


**FIGURE 6.** Steps to choose the appropriate SO paradigm.

The first step is to find out about the complexity of modeling the problem by answering the following question: How difficult is to construct the analytical model?

If it's practicable to model the problem, then the researcher can select between the AME or SG frameworks, which are based on exact search, depending on the problem approached. Precisely, if there are some difficult aspects to incorporate in the analytical model (e.g. dynamic, stochastic parameters), AME can be powerful. Elsewhere, SG approach is appropriate.

In case of a very complex problem that cannot be modeled mathematically, Heuristics methods can be very effective. For this search method, there are two optional approaches, SMC and SE. The choice of one depend on how expensive the simulation is. If the latter is costly either because it's computationally expensive or multiple simulation runs need to be performed, then EF is appropriate. In case of inexpensive simulation, SMC can be very efficient.

Based on this process, we suggest the connections between the problem characteristics and the methods in the following table Table 4. This may serve as guidelines for researchers. Here we do not propose an extensive guide, but we believe that it will be helpful to select the appropriate approach.

***-Strategic decision planning*:**

The time horizon of strategic decisions is between 2 and 5 years. At this level decisions are difficult to change and have a great impact on the overall supply chain management. As examples of the major and the most significant decisions to be made at this level, we cite the sourcing strategy, supplier selection, production strategy and capacity planning, supply chain design and integration. Supplier selection is one of the key activities in the procurement and purchasing process. The process consists of selecting from a set of alternative suppliers following the selection criteria formulated by decisions makers.

At this stage simulation can be used to evaluate the alternative solutions to select a final supplier (EF).

For this type of SO hybridization, a wide range of optimization techniques can be used, as presented in the taxonomy figure 4.

To qualify the suitable alternative the decision maker may use qualitative variables in this case GA is the most suitable technique because of their ability to operate on qualitative variables.

The supplier selection process makes part of the sourcing strategy design which also involves the design of supplier contracts, product design collaboration, procurement of materials, and evaluation of supplier performance. To design the supply chain sourcing strategy, simulation can be used to evaluate and study the performance of alternative sourcing strategies under different risks profiles and uncertainty (price changing, random demand). To evaluate the robustness of strategies under various sittings, multiple simulation runs need to be performed. In this case simulation becomes very expensive and the SMC is the appropriate way to couple optimization and simulation. The strategy design is considered as a complex stochastic optimization problem due to the high level of uncertainty and the large number of parameters. Approximate dynamic programming (ADP) provides an adequate framework to solve such a problem, the technique was successfully used by [75].

An efficient supplier selection and strategy design is essential to meet the current and future business requirement. But the production capacity must be planned correctly. The capacity planning is a complex problem due to the uncertainty in customers' demand and as in most of the real word problem, there is no knowledge about the global optimum. Therefore, it's not evident to decide on the appropriate time to end an optimization run.

To deal with the absence of robust stopping rules and complicated constraints, Sample path optimization may be very effective [88]. Simulation here can serve as a test

**TABLE 4. Connections between SC problems and SO approaches.**

| | Decision Problems | Problem characteristic | examples | How difficult is to construct The analytical model? | | The analytical model Needs to be enhanced? | | How expensive is simulation? | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | Practicable | difficult | yes | no | expensive | inexpensive |
| strategic | ***Supplier selection*** | -Fluctuation in demand<br>-qualitative variables | [38] | | ✓ | | | | (EF,MH) |
| strategic | ***Sourcing strategy design*** | -dynamic aspect<br>-uncertainty<br>- large set decision variables | [75] | | ✓ | | | (SMC, ADP) | |
| strategic | ***Production***<br>-capacity planning | - uncertainty in customer's Demand<br>-no robust stopping criteria | [88] | | ✓ | | | | (EF,SPO) |
| strategic | ***SC Design***<br>-Facility location | High level of Risk and variability | [77] | ✓ | | ROSA | | | |
| strategic | -SC network Design<br>-SC Configuration Design<br>-SC collaborative Design | NP hard optimization problem incorporate multiple decisions | [78]<br>[79]<br>[80] | | ✓ | | | | (EF,MH) |
| strategic | ***SC integration*** | -NP hard optimization problem<br>-Dependencies in decisions variable | [83] | | ✓ | | | | (EF,RST) |
| strategic | ***Profitability maximization*** | NP hard problem<br>large number of decisions variables | [105]<br>[85]<br>[86] | | ✓ | | | | (EF,MH) |
| Strategic tactical | ***Production strategy and safety stock*** | -qualitative variable<br>- High level of uncertainty<br>-dependencies in decision variables | [112] | | ✓ | | | | (EF,MH) |
| Tactical | ***Production distribution Planning*** | -high level of uncertainty<br>-dependencies in decision variables | [110]<br>[111] | ✓ | | | IOS<br>SCS | | |
| Tactical | ***Inventory management***<br>-stock level | -high level of uncertainty | [89] | ✓ | | OSIR | | | |
| Tactical | -inventory policy<br>-inventory control | -select from a set of alternatives Policies | [90] [91]<br>[92] | | ✓ | | | (SMC, GSM) | [(SSM,MH), EF] |
| Tactical | ***Production***<br>-production planning<br>-Lot sizing | -Continuous decision variable Space | [93,94,95]<br>[99,100] | ✓ | ✓ | FEA | | (SMC, MM) | |
| Tactical | ***Transportation and delivery***<br>Small scale problem | Hard combinatorial optimization problem | [109] | ✓ | | FEA<br>OSIR | IOS<br>SCS | | |
| Tactical | Large-scale problem | NP-Hard combinatorial optimization problem | [108] | | ✓ | | | | (EF,MH) |
| Operational | **Production scheduling** | NP-Hard combinatorial optimization Problem<br><br>Disturbance (e.g. Demand Cancelation) | [114]<br>[115]<br>[116] | | ✓ | | | | (EF,MH) |

bed for evaluating the robustness of different planning options (EF).

To save on logistics costs, companies must choose the correct location to their facilities. For so the decision maker can model the problem using mathematical programming. However, the analytical model cannot consider the inherent risk and variability. To fill in this gap, simulation can be applied to incorporate uncertainties and accounts for the risk in the creation or using a facility. The simulation model is used to compute some parameters under uncertainty, and the output is then used to enhance the Model (AME, ROSA).

At the strategic level, making each of the aforementioned decisions is a quite complex task. Therefore, finding the right strategy to manage the whole supply chain network is a huge challenge. The design and configuration of supply chain networks involve several decisions: the facility location, stocking location, production policy, production capacity, assignment of distribution resources and transportation modes. Duly, the problem is characterized by multiple constraints, conflicting objectives and a dynamic aspect (customer's demand and supplier's capacity change over the time). Such a problem belongs to the NP-hard problem. To solve it, metaheuristics are very practicable techniques to find supply chain configurations, and the simulation can be used to evaluate the performance of each configuration (EF, MH). And in order to reduce the computing efforts, EF approaches can be hybridized with SCS approaches, by using an analytical model to manipulate quantitative variables. This technique was successfully used by authors in [79].

A successful supply chain management depends upon the cooperative integration between supplier, logistics and distribution. The successful way is to consider each of the entities in the network as a system to be optimized. This allows the information exchange between them in order to insure the cooperation. The suitable optimization technique for so is the ant colony which allow the information exchange through pheromones. Simulation is then used to evaluate the performance of strategies (centralized, decentralized). RST in another single run methods that can handle both continuous and discrete decision problems was successfully used by authors in [83] to handle the supply chain integration problem.

Developing an integrated plan for supply chain (strategic, tactical and operational) is essential but not enough. These plans must also ensure a maximum profit. The profit maximization is a complex linear and non-linear combinatorial problem that can be solved using hybrid simulation—heuristics approach. The latter is suitable for large scale linear and non-linear problems and have been successfully used by researchers, we can cite for example [85], [86], [105].

***-Tactical decision planning:***

An effective production planning plays a key role for the manufacturing system. Draw up a production plan for an actual workshop production is a complex problem. Drawing a production plan is usually a multi-constraint, multi-objective, stochastic and uncertainty optimization problem. At this stage of planification, simulation is valuable to evaluate the feasibility of production plans considering stochastic events. The most relevant approach for this purpose is OSIR which allows the refinement of the analytical model and parameter update in case of undesirable plans.

In the production planning, the planner needs also to determine the actions necessary to achieve the desired output, work in process, and manufacturing lead time objectives. For such a purpose the FEA approach is the most helpful thanks to its ability to establish the relationship between input/output.

Determining the optimal lot size is a cornerstone in production planning. The lot sizing problem is characterized by a continuous decision variable space. For such a problem, Metamodel-based methods, gradient and non-gradient based methods are appropriate (see figure 4). An example of implementation is presented in [99] and [100] applying the well-known RSM.

The production-distribution planning can be modeled as a mixed integer program, the resolution of the program using exact methods is not sufficient. To obtain more realistic plans, simulation is practicable. The most suitable common approaches to solve such a problem are IOS and SCS. Since the problem is a highly dimension combinatorial problem, it's advisable to hybridize these approaches with heuristics to reduce the computational efforts.

Inventory system serves as a buffer between production and demand. In order to determine the stock level to avoid shortage and prevent random changes caused by demand uncertainty, OSIR is a proper approach where the problem is modeled using analytical models, and simulation runs are performed to consider the uncertainty. And based on the simulation output the parameters of the model are updated to determine the optimal stock level.

The inventory policy decision is also a part of the inventory management with only discrete decision variable. Statistical selection methods are suited. Ranking and selection approach is adopted by [90] to decide in the inventory policy. Certainly R&S can minimize the number of simulation replications. However, SSM are powerful only if the solution space is finite, and hence they cannot solve large scale problems characterize by a large number of decision variables. In such case the one can opt for PSO [91], another alternative is Ordinal Optimization (OO) that can be used to fill in this gap with the idea of finding a subset designed by sampling from a large set of solutions and evaluating a smaller number of designs. To reduce simulations efforts and converge quickly, OO can be integrated with other algorithms, [105] apply OO through the OCBA technique fed into PSO.

GSM is another efficient single run method, applicable for discrete variable space. It's found to be more effective than RSM, that combine the advantages of the latter with stochastic approximation method such as PA or LR. A key advantage of GSM is its ability to quickly reach the vicinity of the optimal solution because of its global orientation.

The distribution of products known as the vehicle routing problem is one of the most crucial parts in the supply chain. The distribution constitutes the major part in the logistics costs. The VRP is a hard-combinatorial problem that has been solved using a variety of optimization techniques. If the researcher is dealing with a small-scale problem (in terms of decision variables and constraints), an analytical model may be constructed and solved using exact algorithms such as the branch and bound, simplex. Different hybrid SO approaches may be adopted, SCS, IOS. Furthermore, the one can opt for ROSA, OSIR approaches in order to revise decision after being made. For example, simulation can be helpful to consider traffic congestion and then update the generated routes.

For a large-scale problem, metaheuristics are very effective. A typical example of techniques that can be used includes but not limited to SA, TS, and GA, PSO [91]. PSO is easily implemented and it is computationally inexpensive, and TS can converge quickly as well as find the optimal solution in a limited number of runs. The generated routes can be then evaluated using simulation (EF, MH).

***-Strategic-tactical decision planning:***

The production strategies such as MTO and MTS are interrelated to the inventory level. For example, a MTS strategy may result in excess inventory. To overcome this, these decisions must be taken in an integrated way. The production strategy decision is among the NP-hard combinatorial problems due to the variety of decision variable type (quantitative and qualitative). It has been shown in the literature that GA is the most popular. Such popularity comes from their ability to operate on qualitative variables. Whereas traditional GA is time consuming, and not adequate for multi-objective optimization, such in scheduling problems, hence it's advisable to use some derivatives such as CCGA and NSGAII.

***-Operational decision planning:***

The Scheduling of operations is among the hardest combinatorial problems. They are varied and difficult to solve to optimality. In this case, metaheuristics methods provide good quality and robust solutions in a short time. GA's derivative is one of the successful metaheuristics used by [114] to deal with disturbance, during operation scheduling such as demand cancelation. Simulated annealing is another strong algorithm employed by authors in [115]. However, numerous simulation-runs need to be performed. Hence in all, metaheuristics are appropriate if simulation run is inexpensive.

## VIII. CONCLUSION AND PERSPECTIVES

Supply chain decision-making process is quite complex. A stand-alone optimization models cannot overcome the complexity because they are usually built on a very abstract level, neglecting the dynamic behavior of real-world supply chain systems. To fill in this gap hybrid optimization simulation have been applied. After exploring the near-full spectrum of optimization methods and simulation techniques, we present a review of SO approaches applied in the supply chain context. Applications are classified by decision level (strategic, tactical and operational). Moreover, a taxonomy of optimization/simulation paradigms is provided which combine three dimensions (simulation purpose, hierarchical structure and search method), in an attempt to grasp the appropriate methods for use in each simulation optimization approach and discover the gaps and opportunities to explore new approaches. The discussion and analysis of the problems approached in the literature and the characteristics of the methods used has greatly contributed to construct a guide for practitioners and researchers to select the appropriate simulation/optimization approach for a given supply chain problem. The variety of papers reviewed reveal a wide range of possibilities to link optimization and simulation, and a set of powerful optimization methods that can be used. Even though, there are many gaps in this research field. As for future studies, we identify some promising and important issues:

-Using Retrospective Simulation Response Optimization (RSRO) [7] in SE approaches that can work by using either exact methods or heuristics, hence it's powerful for simple combinatorial problems and NP-hard also.

-For SMC, surrogate management framework [7] is another efficient technique, which has never been used before in the supply chain field. This technique is like model-based methods and consists of using a surrogate model to guide the search.

-Filling the gaps identified from the taxonomy: AME-OSI, run simulation models in part or all of optimization iteration to enhance the analytical model. SMC-SOI is another combination that can be explored.

-Regarding the supply chain areas, we have not found enough paper that applies SO approaches to solve sustainability problems. Further research can be undertaken in this field.

## APPENDIX
## LIST OF ACRONYMS
### GENERAL

| | |
|---|---|
| SC | Supply Chain |
| SO | Simulation Optimization |
| MRP | Materials Resources Planning |
| KPI | Key Performance Indicators |
| DACE | Design and Analysis of Computer Experiment |
| HPP | Hierarchical Production Planning |
| JIT | Just-In-Time |
| ETO | Engineer-To-Order |
| HL | Hung-Leachman |
| OMFT | Order Mean Flow Time |
| MTO | Make To Order |
| MTS | Make To Stock |
| ATO | Assemble To Order |
| MPP-FLP | Multi-Period Facility Location Problem |
| AHP | Analytic Hierarchy Process |
| SCI | Supply Chain Integration |
| VRPTW | Vehicle Routing Problem with Time Windows |
| MSTP | Modal-Shift Transportation Problem |
| WLP | Warehouse Location Problem |
| WLTP | Warehouse Location and Transportation Problem |
| SCA | Supply Chain Analyzer |

### OPTIMIZATION/ SIMULATION METHODS

| | |
|---|---|
| MH | Metaheuristics |
| GM | Gradient-Based Methods |
| PA | Perturbation Analysis |
| FPA | Finite Perturbation Analysis |
| IPA | Infinitesimal Perturbation Analysis |
| LR | The Likelihood Ratio |
| FDM | Frequency Domain Method |
| HA | Harmonic Analysis |
| FD | Finite Difference |
| N-GM | Non—Gradient Methods |
| SPO | Sample path optimization |
| R&S | Ranking And Selection |
| MCA | all pair wise Multiple Comparisons |

| | |
|---|---|
| MCB | Multiple Comparisons with the Best |
| MCC | Multiple Comparisons with a Control |
| OO | Ordinal Optimization |
| RS | Random Search |
| NP | Nested Partitions |
| RSM | Response Surface Methodology |
| GSM | Gradient Surface Method |
| KM | Kriging Models |
| ANN | Artificial Neural Network |
| ACO | Ant Colony Optimization |
| EDA | Estimation of Distribution Algorithms |
| CE | Cross-Entropy Method |
| GA | Genetic Algorithm |
| ES | Evolution Strategies |
| SS | Scatter Search |
| TS | Tabu Search |
| SA | Simulated Annealing |
| B/S | Bayesian/Sampling |
| LP | Linear Programming |
| MILP | Mixed-Integer Linear Programming |
| NLP | Nonlinear Programming |
| FLC | Fuzzy Logic Controller |
| NSGA-II | Non-dominated Sorting Genetic Algorithm |
| OCBA | Optimal Computing Budget Allocation |
| CCGA | Crowding Clustering Genetic Algorithm |
| DP | Dynamic Programming |
| ADP | Approximate Dynamic Programming |
| IOS | Iterative Optimization Simulation |
| SBO | Simulation-Based Optimization |
| SAA | Sample Average Approximation |
| SAM | Stochastic Approximation Methods |
| RST | Reverse Simulation Technique |
| MMH | Memory-Based Metaheuristics |
| MM | Metamodel based Methods |
| GSM | Gradient Surface Methods |
| SCS | Solution Completion by Simulation |
| IOS | Iterative Optimization-based Simulation |
| SPDE | Stochastic Programming Deterministic Equivalent |
| ROSA | Recursive Optimization—Simulation Approach |
| FEA | Function Estimation based Approach |
| OSIR | Optimization-based Simulation with Iterative Refinement |
| SSM | Statistical Selection Methods |

### SIMULATIONS PURPOSES

| | |
|---|---|
| SG | Solution Generation |
| AME | Analytical Model Enhancement |
| SE | Solution Evaluation |
| EF | Evaluation Function |
| SMC | Surrogate Model Construction |

### HIERARCHICAL STRUCTURES

| | |
|---|---|
| OSI | Optimization with Simulation-Based Iteration |
| ASO | Alternate Simulation—Optimization |
| SSO | Sequential Simulation—Optimization |
| SOI | Simulation with Optimization-based Iterations |

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