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# The application of meta-synthesis in the identification of new combined genetic algorithm methods to solve complex problems

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**Abstract**

The current research aims to identify new combined genetic algorithm methods to solve complex problems. The researcher has analyzed the results and findings of the previous researchers using a systematic reviewing approach and has identified the effective factors by implementing the 7 steps of Sandelowski and Barroso's method. Among 4320 articles, 54 articles were selected based on the CASP method. In this manner, in order to evaluate reliability and quality control, the Kappa index was used, and its value was deemed to be in high compatibility regarding the identified factors. The results of the analysis of the collected data in ATLAS TI software led to the identification of 9 categories and 33 primary codes of new combined genetic algorithm methods to solve complex problems. Based on the coding, 9 categories, and 33 initial codes were identified. The identified categories are layout design, supply network, programming, Anticipation, inventory control, information security, imaging, medical imaging and wireless network.

Keywords: genetic algorithm, complex problems, meta-synthesis
2020 MSC: 68W50

## 1 Introduction

Methods such as mathematical optimization or other precise kinds are very practical in solving such scheduling problems. Nevertheless, in the real world, many researchers use innovative and meta-innovative methods due to the high complexity of these problems and the irrationality of the time it takes to solve them using these methods. In the last few decades, a group of approximate algorithms has been developed trying to find a method for effective and efficient search of solution space by combining the basic principles of heuristic methods. Nowadays, these methods are known as innovative methods. Previously, meta-heuristic methods were called new heuristic methods. Evolutionary algorithms such as genetic algorithms, and optimization algorithms, simulated annealing method, forbidden search and artificial neural networks are instances of these methods. In general, it can be said that meta-heuristic algorithms

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are advanced and general search solutions and suggest steps and criteria that are very effective in escaping the trap of local optima. In general, it can be said that meta-heuristic algorithms are advanced and general search solutions and suggest steps and criteria that are very effective in escaping the trap of local optima. The crucial factor in these methods is the dynamic balance between diversification and strengthening strategies. Diversification refers to an extensive search in the solution space, and strengthening is defined as using the experiences gained in the search process and focusing on the more promising areas of the solution space [39].

Calculating the optimal solution or answer for most of the optimization problems observed in many practical and practical fields is a difficult and even impossible task if the solving opportunity is limited. In this situation, "good" solutions obtained from heuristic or meta-heuristic (meta-heuristic) algorithms are usually sufficient. Meta-heuristics include a set of approximate optimization techniques that have gained popularity mainly during the last four decades. Meta-heuristic methods provide "reasonable" solutions in reasonable time frames for complex and difficult problems in the fields of engineering and science. Unlike exact optimization algorithms, meta-heuristics do not guarantee the optimality of the obtained solutions. The word "initiative" or "heuristic" comes from the Greek word "heuriskein" derived to mean "the art of discovering new rules to solve problems". The prefix "meta" is also derived from a Greek word meaning "high-level methodology". The term "metaheuristic" or "metaheuristic" was first presented by Glover [21]. The meta-heuristic search method can be defined as "high-level general methodologies that can be used as a guiding strategy in designing specific heuristics to solve specialized optimization problems" [1]. Due to the extensivity of the difficult problems in today's world and the importance of solving time and the quality of solving such problems, during the last four decades, a lot of effort has been made by researchers all over the world to develop innovative methods, each of these methods has capabilities and limitations compared to other presented methods. Based on its nature, each method has its unknowns and is proficient in solving specific problems. Some of the most popular problems in the world of science are car routing, scheduling, capital portfolio selection, and project portfolio selection, which have been the focus of researchers' attention. The main focus related to this challenge is the manager's decision-making regarding the problem-solving method. The current research aims to identify new combined genetic algorithm methods to solve totally difficult problems.

## 2 Literature review

An optimization issue may be defined as a pair $(S, f)$ in which $S$ represents the set of feasible solutions (or configuration space and search space) and the objective function to be $f : S \to \Box$ optimized. The objective function assigns a real number representing its value to each point of the search space. The main goal of solving an optimization issue is to find the global optimal solution. A solution $s^* \in S$ is a globally optimal solution if it has a better objective function value than all solutions in the search space $(\forall s \in S, f(s^*) \leq f(s))$. There may be several global optimal solutions for an issue, and in some cases, the issue may be defined as finding all the global optimal solutions. In practice, different branches of optimization models can be used to formulate and solve decision problems. One of the common models in mathematical programming is linear programming (LP), which can be formulated as follows:

$$\begin{aligned} &\min\ c.x \\ &St: \\ &Ax \geq b \\ &x \geq 0 \end{aligned} \tag{2.1}$$

where $x$ is the vector of continuous variables of decision and $c, b$ and $A$ are vectors and matrix of fixed coefficients. The purpose and constraints of a linear programming challenge are all linear. To solve this model, there are exact methods to find the optimal solution, such as the simplex method. In this model, the feasible region and the objective function are convex and as a result, the global optimal solution is located in one of the corners of the solution space. Moreover, the local optimal solution is the same as the global optimal solution. In general, there is no reason to use meta-heuristics to solve continuous LP problems. A local optimal solution is a solution that is optimal towards its surrounding area, or in other words, it is optimal in a range of the solution space of the issue, but it does not have the condition of optimality in the entire solution space (Figure 1).

Nonlinear programming models (NLP) are mathematical programming models in which the objective function or a number of constraints are nonlinear. Some modeling methods can linearize some non-linear correlations. In this case, many variables and constraints are added to the model and some degree of approximation may be also used. Regarding NLP optimization models, some heuristics inspired by the simplex method similar to Nelder and Mead's algorithm may be utilized. Although many optimization algorithms have been developed for continuous problems compared to

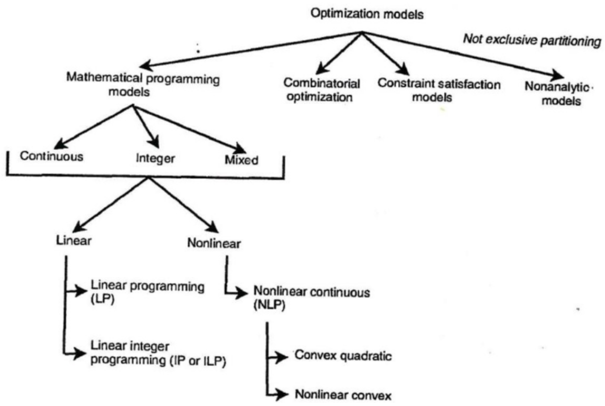


Figure 1: Different branches of optimization models

discrete problems, there are many problems in the real world where discrete variables should be used to model them. When the decision variables of a model consist of both continuous and discrete variables, the issue is included in the group of mixed integer programming (MIP) problems. MIP models are generalizations of LP and integer programming (IP) models. Enumerative methods such as branch and bound methods can be utilized to solve MIP and IP models in small sizes. Meta-heuristics are one of the suitable algorithms for solving these problems, in sizes that solving them using exact methods deems to be very complex, and they produce good answers for them. Also, meta-heuristics can be used to generate upper and lower bounds for accurate algorithms and increase their efficiency. It should be noted that for some issues, such as network flow issues, the linear programming method automatically produces the integer values and the use of integer or meta-heuristic programming to solve them is not useful. Optimization problems can be found anywhere, and given that most optimization problems are complex, meta-heuristics are present everywhere as a result. Figure 2 indicates the taxonomy of some metaheuristics. The simplex algorithm (LS), which was presented in 1947, can be considered a local search algorithm for linear programming problems. Harisane's heuristic was presented in 1971. The rest of the algorithms mentioned in this figure are as follows: Ant colony optimization (1ACO1), artificial immune system (AIS), bee colony (BC), cultural algorithms (CA), co-evolutionary algorithms (2CEA2), the evolutionary strategy of matching with the covariance matrix (3CMA3 - ES), Differential Evolution (DE), estimation of distribution algorithm (EDA), Evolutionary Programming (EP), Evolutionary Strategies (ES), Genetic Algorithm (GA), Gaussian discriminant analysis (GDA), Guided Local Search (GLS), Genetic Programming (GP), greedy randomized adaptive search procedure (GRASP), longest increasing subsequence (LIS), Nelder-Mead algorithm (NM), particle swarm optimization (4P.S.O4), simulated annealing (SA), smoothing method (SM), sparse search (SS), threshold acceptance (TA), forbidden search (TS), variable neighborhood search (VNS).

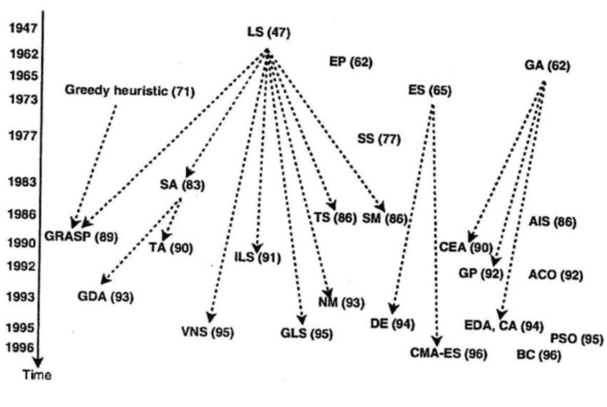


Figure 2: The taxonomy of meta-heuristics

Exact methods are algorithms that find optimal solutions and guarantee the optimality condition. Some of these algorithms include dynamic programming and branch-and-bound family algorithms. Exact methods can also be utilized for small dimensions of some difficult optimization problems. The dimensions of the issue are not of single indicators to describe the difficulty of an issue. For an issue, some dimensions of the issue may not be solvable by exact methods while its larger dimensions can be solved using those exact methods. In approximation algorithms, there is a guarantee for the bounds of the global optimal solution. An approximation algorithm $\varepsilon$ produces an approximate solution in such a way that the factor load size $\varepsilon$ is not less than the global solution $\varepsilon$.

**Definition 2.1.** Approximation algorithms: an algorithm includes an approximation factor if its time complexity is polynomial and produces a solution for each input in a way that (for a minimization challenge):

$$\begin{aligned} a \leq \varepsilon.s \quad if \quad \varepsilon > 1 \\ \varepsilon.s \leq a \quad if \quad \varepsilon > 1 \end{aligned} \tag{2.2}$$

The purpose of approximation algorithms is to find pessimistic bounds for the algorithm. Unlike exact methods, meta-heuristics are used for large-scale issues and provide a satisfactory solution in a reasonable amount of time. In these algorithms, there is no guarantee to find the global optimal solution or its thereabouts. Meta-heuristics have been growing in popularity over the past twenty years. Their application and usage in many problems indicate their efficiency and effectiveness to solve complex and extensive problems. Metaheuristics are used in various fields such as the following:

- Engineering design, topology optimization, optimization of electronics, aerodynamics, fluid dynamics, telecommunications, robotics, etc.
- Machine learning and data mining
- Systems modeling, simulation and research in chemistry, physics, biology, control, signal and image processing
- Robat routing and planning issues, production and scheduling issues, transportation and logistics, supply chain management, etc.

Therefore, the development of innovative, meta-innovative and combined meta-innovative methods is one of the requirements of technical and applied sciences today, and the current research aims to develop a combined meta-innovative method based on the dominant and popular genetic algorithm.

## 3 Methodology

Since the current research seeks to identify new combined genetic algorithm methods to solve totally difficult problems in the studies based on the meta-synthesis approach, it includes a qualitative study approach and is conducted using the library research method and meta-synthesis technique in the field of genetic algorithms. Meta-study is one of the methods that is introduced for reviewing, combining and analyzing previous research in the past few years. Meta-study consists of four main parts, which are: meta-analysis (Quantitative elementary content analysis), meta-method (Methodological analysis of primary studies), meta-theory (analysis of the theories of primary studies) and meta-synthesis (qualitative analysis of the content of primary studies.) Meta-synthesis is one of the types of meta-study subcategory methods that deals with the systematic review of sources to extract, evaluate, combine and, if necessary, summarize research that is already conducted surrounding a specific subject area. In this context, the collected data from these studies are qualitative and not quantitative. As a result, the desired sample for meta-synthesis is selected and formed based on their relationship with the research question. Meta-synthesis is not only an integrated review of the qualitative principles of the case or the analysis of secondary data and primary data from the selected studies but also it is the analysis of the findings of these studies. In other words, meta-synthesis is the integration of the interpretations of the selected studies' primary data. ATLAS TI software was utilized for analysis purposes. According to Sandelowski and Barroso [47], the main stages of meta-synthesis are as follows:

## 4 Findings

As mentioned, the analysis of meta-synthesis consists of seven steps. In this section, the results related to each step of this analysis are presented separately.

**First stage: Developing the fundamental questions of the research**

Developing research questions is the first step in Sandelowski and Barroso's method. These questions are generally based on four parameters: what, who, when and how; It can be adjusted. After the research questions are developed

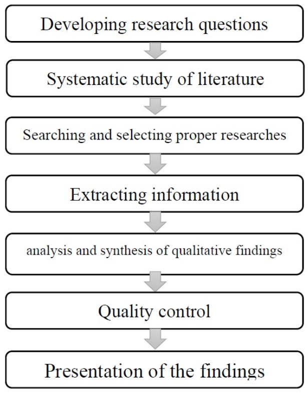


Figure 3: Main stages of meta-synthesis

Table 1: Fundamental questions of the research

| Parameter | Research Question |
|---|---|
| What | Identifying new combined genetic algorithm methods to solve totally difficult problems based on the specific keyword |
| Who | Various works including books, articles, and reports in the field of the identification of new combined genetic algorithm methods to solve totally difficult problems |
| When | Including all the works between 2000 to 2023 |
| How | Case study, identification and note-taking, key points, analysis of the concepts |

based on the purpose of the research, the stage of a systematic review of the texts begins. Table 1 shows the answers to these fundamental questions related to the meta-synthesis method:

**Second stage: Systematic study of literature**

To collect research data, secondary data defined as past documents are used. As stated earlier, the research databases of interest are the two popular databases of Scopus and Web of Science, and in these two databases, the following publishing databases were focused on:

Emerald insight- Springer Link- Science Direct- Taylor & Francis Online- SAGE journals- Wiley Online Library

Moreover, in the field of Persian articles, the database of the Academic Jihad Scientific Information Center and the comprehensive portal of humanities were also taken into consideration.

**Third stage: Searching and selecting texts**

Table 2 shows the steps taken to refine the extracted articles. Based on this table, in order to refine the articles extracted from the literature, four steps were taken, the last step was based on the opinions of 5 experts observing this research. To evaluate the final quality of the articles based on the approach introduced in the following, these experts presented their opinions for each final isolated article, and the articles that had a lower score than the applied quota, were excluded from the process.

In this stage, the 4340 studies found in the previous stage are carefully reviewed in several steps so that the studies that do not fit in the research questions are excluded and finally the most relevant studies are identified to extract the answers to the questions. The reviewing process includes the reviewing of the title, abstract and content of the studies along with their research method. The steps of the reviewing process in this research are as follows:

1. At this stage, the titles of the reviewed studies and the studies that were irrelevant to the research questions were excluded. By examining the titles of the studies, 4050 studies were excluded due to their title's irrelevance to the research questions.
2. At this stage, the abstracts of the reviewed studies and the studies that were irrelevant to the research questions were excluded. By studying the abstract of the studies, 220 studies were excluded due to the lack of connection between the abstract and the research questions.
3. At this stage, the contents of the studies were studied, in other words, the entire research was studied and the studies that were not irrelevant to the research questions were excluded. By examining the content of the studies, 30 studies that were irrelevant to the research questions were excluded.

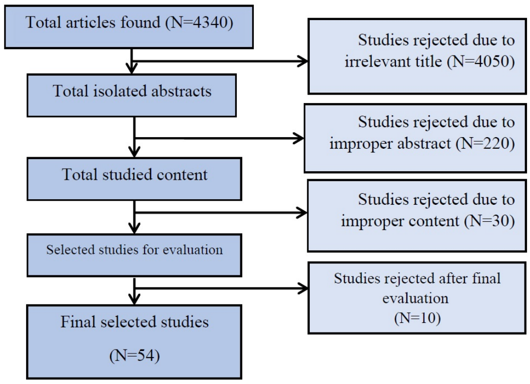


Figure 4: Selection and reviewing stage

4. 4. Since this research aims to extract the research framework based on the combination of past studies, according to the opinion of the experts, a meta-synthesis of the studies through qualitative and quantitative research methods were conducted. Thus, at this stage, no study was excluded due to the methodology. After excluding the studies that are irrelevant to the objectives and questions of the research, the researcher must evaluate the methodological quality of the research. The purpose of this step is to discard researches and their presented findings that the researcher does not trust. Tools that are usually utilized to evaluate the quality of the primary qualitative research studies is the "Critical Evaluation Skills Program" which helps to determine the accuracy, validity and importance of the qualitative research studies by proposing ten questions. These questions concentrate on the following: 1. Objectives of the research 2. Methodological logic 3. Research plan 4. Sampling method 5. Data collection 6. Reflexivity (which refers to the relationship between the researcher and the participants) 7. Ethical considerations 8. Accuracy of the data analysis 9. Clear presentation of the findings 10. Research value.

**Fourth stage: Extracting information**

This stage includes reviewing the remaining articles and extracting texts for coding in the next stage. This stage is focused on separating the results and outputs and the interpretations of these outputs along with the discussion and the final conclusion of the researchers. At this stage, 54 articles were entered into the ATLAS TI software, and for preliminary review, parts of the study articles were randomly studied and coded in order to familiarize the researcher with the available data. Thus, the researcher became familiar with the generalities of the discussion and its prevailing atmosphere. In Table 3, an instance of the coding conducted on the articles is studied. In the first column, the basic descriptions of the article and in the last column, the main keywords that were converted into primary codes are presented:

**Fifth stage: Analysis of qualitative findings**

During the analysis, the researcher searches for topics that are emerged among the existing studies in the meta-synthesis. This is known as (thematic analysis). As soon as the themes are identified and defined, the examiner forms a classification and places similar and related classifications into a theme that best describes it. Topics provide the basis for creating explanations, models and theories or hypotheses. In this research, first, all the factors extracted from the studies were considered as identifiers, and then, by considering the meaning of each of them, the identifiers were defined in a similar concept; Then, similar concepts were classified into explanatory categories so that the explanatory features of the research indicators were identified in the form of primary and secondary variables of the research.

**Sixth stage: Quality control of outputs**

In this research, the researchers made use of the comparison of their opinions with another expert to control the extractive concepts of the studied research. For this purpose, a 33-question questionnaire consisting of identified variables was designed. Subsequently, the obtained data were analyzed through SPSS software's version 23 and transcript index. The results of the calculations are presented below, the transcript index value equal to 0.711 was obtained, which is at the level of valid accordance.

**Seventh stage: Final Presentation**

At this stage of the meta-synthesis method, the findings of the previous stages are presented. In the following, the research variables are identified. 9 categories and 33 codes were obtained from the variables extracted from the texts

Table 2: Selected articles

| Article ID | Title | Year | Author | Total Scores |
|---|---|---|---|---|
| S01 | Meta-heuristics, from design to implementation | 2009 | [52] | 40 |
| S02 | A multi objective genetic algorithm for the facility layout problem based upon slicing structure encoding | 2012 | [4] | 35 |
| S03 | Single row facility layout problem using a permutation-based genetic algorithm | 2011 | [13] | 39 |
| S04 | Solving a multi-floor layout design model of a dynamic cellular manufacturing system by an efficient genetic algorithm | 2011 | [32] | 40 |
| S05 | A review of applications of genetic algorithms in operations management | 2018 | [33] | 39 |
| S06 | Dynamic facility layout problem based on flexible bay structure and solving by genetic algorithm. | 2013 | [36] | 44 |
| S07 | An island model genetic algorithm for unequal area facility layout problems | 2017 | [41] | 34 |
| S08 | A genetic algorithm with the heuristic procedure to solve the multi-line layout problem | 2012 | [46] | 32 |
| S09 | Presentation of a meta-heuristic algorithm based on refrigeration simulation for the group scheduling problem in a flexible workshop flow environment with sequence-dependent preparation times | 2019 | [44] | 33 |
| S10 | A tool for solving stochastic dynamic facility layout problems with stochastic demand using either a genetic algorithm or modified backtracking search algorithm | 2016 | [54] | 37 |
| S11 | A genetic algorithm for cellular manufacturing design and layout | 2007 | [55] | 37 |
| S12 | A genetic algorithm for supply chain configuration with new product development | 2016 | [3] | 33 |
| S13 | A hybrid genetic algorithm based heuristic for an integrated supply chain problem | 2016 | [16] | 35 |
| S14 | A novel hybrid genetic algorithm to solve the sequence dependent permutation flow-shop scheduling problem | 2014 | [37] | 33 |
| S15 | An Effective Hybrid Ant Colony Optimization for Permutation Flow-Shop Scheduling | 2014 | [58] | 38 |
| S16 | A genetic algorithm to optimize the total cost and service level for just-in-time distribution in a supply chain | 2008 | [17] | 39 |
| S17 | An effective combined genetic algorithm to solve the vehicle routing problem | 2009 | [57] | 37 |
| S18 | A new heuristic for the multi-depot vehicle routing problem that improves upon best known solutions | 1993 | [7] | 44 |
| S19 | Multi-objective optimization for a closed-loop network design problem using an improved genetic algorithm | 2017 | [50] | 40 |
| S20 | A variable neighborhood search heuristic for periodic routing problems | 2009 | [23] | 37 |
| S21 | Solving the vehicle routing problem with soft time windows using a meta-innovative combined algorithm | 2005 | [53] | 38 |
| S22 | Fuzzy multi-objective sustainable and green closed-loop supply chain network design | 2017 | [51] | 35 |
| S23 | Forecasting holiday daily tourist flow based on seasonal support vector regression with adaptive genetic algorithm | 2015 | [8] | 45 |
| S24 | Particle group optimization algorithm to determine the cumulative size and integrated scheduling in the workshop flow production environment | 2013 | [43] | 33 |
| S25 | SVR with hybrid chaotic genetic algorithms for tourism demand forecasting | 2011 | [26] | 39 |
| S26 | Modified genetic algorithm-based feature selection combined with pre-trained deep neural network for demand forecasting in outpatient department | 2017 | [27] | 35 |
| S27 | A Fast and Effective Insertion Algorithm for MDVRP with Fixed Distribution of Vehicles and A new Simulated Annealing Approach | 2006 | [34] | 33 |
| S28 | A general heuristic for the vehicle routing problems | 2007 | [42] | 44 |
| S29 | A hybrid genetic algorithm for the multi-depot vehicle routing problem | 2008 | [25] | 45 |
| S30 | New assignment algorithms for the multi-depot vehicle routing problem | 2002 | [20] | 43 |
| S31 | The multi-depot vehicle routing problem with inter-depot routes | 2007 | [11] | 43 |
| S32 | A novel hybrid genetic algorithm for the multidepot periodic vehicle routing problem | 2017 | [38] | 35 |
| S33 | An ant colony algorithm for the multi-compartment vehicle routing problem | 2014 | [45] | 39 |
| S34 | Modeling, forecasting and trading the EUR exchange rates with hybrid rolling genetic algorithms–support vector regression forecast combinations | 2015 | [49] | 41 |
| S35 | Beta chaotic map based image encryption using genetic algorithm | 2018 | [28] | 33 |
| S36 | Parallel non-dominated sorting genetic algorithm-II-based image encryption technique | 2018 | [30] | 35 |
| S37 | Fourier–Mellin moment-based intertwining map for image encryption | 2018 | [29] | 37 |
| S38 | Effective hybrid genetic algorithm for removing salt and pepper noise | 2020 | [5] | 40 |
| S39 | Soft computing approaches for image segmentation: a survey | 2018 | [10] | 41 |
| S40 | A survey on nature-inspired optimization algorithms and their application in image enhancement domain | 2018 | [14] | 38 |
| S41 | Comparative analysis of evolutionary algorithms for image enhancement | 2012 | [22] | 35 |
| S42 | Color image segmentation using genetic algorithm with aggregation-based clustering validity index (CVI) | 2019 | [31] | 45 |
| S43 | An approach based on hybrid genetic algorithm applied to image denoising problem | 2016 | [40] | 33 |
| S44 | A genetic algorithm-Taguchi based approach to inventory routing problem of a single perishable product with transshipment | 2017 | [6] | 39 |

| | | | | |
|---|---|---|---|---|
| S45 | A genetic algorithm approach for location-inventory-routing problem with perishable products | 2017 | [24] | 35 |
| S46 | Discovering interesting rules from biological data using parallel genetic algorithm | 2013 | [12] | 34 |
| S47 | The applications of genetic algorithms in medicine | 2015 | [18] | 44 |
| S48 | A data-driven understanding of COVID-19 dynamics using sequential genetic algorithm based probabilistic cellular automata | 2020 | [19] | 46 |
| S49 | Prediction of pathological subjects using genetic algorithms | 2018 | [48] | 43 |
| S50 | Multi-population genetic algorithms with immigrants scheme for dynamic shortest path routing problems in mobile ad hoc networks | 2010 | [9] | 43 |
| S51 | Optimal routing and traffic scheduling for multihop cellular networks using genetic algorithm | 2013 | [35] | 36 |
| S52 | Genetic algorithms with immigrants and memory schemes for dynamic shortest path routing problems in mobile ad hoc networks | 2010 | [56] | 39 |
| S53 | Multiobjectives ga-based QoS routing protocol for mobile ad hoc network | 2010 | [2] | 42 |
| S54 | A genetic algorithm for the design of a fuzzy controller for active queue management | 2003 | [15] | 44 |

Table 3: Examining the information of several articles

| **Field** | **Primary code (concept)** | **Source** |
|---|---|---|
| Layout design | Genetic algorithm, hierarchical genetics, multi-objective genetic algorithm, parallel genetic algorithm | S2, S3, S4, S5, S6, S7, S8, S10, S11 |
| Supply network | Genetic algorithm, NSGA-II, genetic algorithm + particle swarm, multi-objective genetic algorithm, genetic algorithm + fuzzy approach | S12, S13, S16, S19, S22 |
| Programming | branch and bound algorithm + genetic algorithm; Genetic algorithm, optimization algorithm + genetic algorithm, NSGA-II, multi-objective genetic algorithm, parallel genetic algorithm | S1, S9, S14, S15, S17, S18, S19, S20, S21, S24, S27, S28, S29, S30, S31, S32, S33 |

of the related articles, by removing synonymous and frequent variables and finally by categorizing the final variables. At this stage of coding, the primary and secondary categories of the research were identified. After identifying the research indicators based on meta-synthesis analysis and determining the units of analysis (words and themes), Shannon's entropy method will be utilized for data analysis as follows:

First, the frequency of each identified category should be determined based on content analysis.

The frequency matrix should be normalized. For this purpose, the linear normalization method is used:

$$n_{ij} = \frac{x_{ij}}{\sum x_{ij}} \tag{4.1}$$

The information content of each category should be calculated. Accordingly, the following equation is used:

$$k = \frac{1}{Ln(a)}; \quad a = \text{Number of variants} \tag{4.2}$$

$$E_j = -k \sum [n_{ij} LN(n_{ij})] \tag{4.3}$$

Each category's coefficient of significance should be calculated. Any category with more information content is more significant. Accordingly, the following equation is used:

$$W_j = \frac{E_j}{\sum E_j} \tag{4.4}$$

Therefore, in the first step, the decision matrix is formed. The points obtained from the decision matrix regarding the issue are presented in the following table:

Table 4: Primary categories and their corresponding codes

| Algorithm | Thematic domain | The problem under consideration | Source |
|---|---|---|---|
| Genetic algorithm, hierarchical genetics, multi-objective genetic algorithm, parallel genetic algorithm | Layout design | Facility layout design<br>Dynamic layout<br>Flexible layout | S2, S3, S4, S5, S6, S7, S8, S10, S11 |
| Genetic algorithm, NSGA-II, genetic algorithm + particle swarm, multi-objective genetic algorithm, genetic algorithm + fuzzy approach | Supply network | Multi-product, multi-period<br>Multi-product, single period<br>Single product, single period | S12, S13, S16, S19, S22 |
| branch and bound algorithm + genetic algorithm; Genetic algorithm, optimization algorithm + genetic algorithm, NSGA-II, multi-objective genetic algorithm, parallel genetic algorithm | Programming | Vehicle navigation<br>Resource sharing and scheduling<br>Machine programming<br>Airline programming | S1, S9, S14, S15, S17, S18, S19, S20, S21, S24, S27, S28, S29, S30, S31, S32, S33 |
| Genetic algorithm, particle chaos optimization algorithm, self-organization algorithm, genetic algorithm + neural network | Anticipation | Financial planning<br>Tourism planning<br>Care and treatment planning | S23, S25, S26, S34 |
| Genetic Algorithm, NSGA-II | Inventory control | Routing<br>Geolocation<br>Location Routing - Inventory | S43, S44, S45 |
| Genetic Algorithm, NSGA-II, Parallel Genetic Algorithm, NSGA | Information security | Coding<br>Hiding information | S35, S36, S37 |
| Genetic Algorithm, NSGA-II, Hybrid Genetic Algorithm, Self-Organizing Algorithm, Parallel Genetic Algorithm, NSGA | Imaging | Categorization<br>Process improvement<br>Detection<br>noise reduction (transparency)<br>Procedure recognition<br>Video segmentation<br>Motion detection<br>Face recognition | S38, S39, S40, S41, S42, S43 |
| Serial genetic algorithm, combined genetic algorithm, parallel genetic algorithm | Medical imaging | Diagnosis of cancerous tumors<br>Diagnosis of COVID-19<br>Bioinformatics | S46, S47, S48 |
| Serial Genetic Algorithm, Genetic Algorithm, Multi-objective Genetic Algorithm, Fuzzy + Genetic Algorithm, NSG, Distributed Genetic Algorithm | Wireless network | Energy load balancing<br>Localization<br>Bandwidth allocation<br>Bandwidth transfer | S49, S50, S51, S52, S53, S54 |

Table 5: Determining the significance and emphasis of the past research

| Code | Frequency | $\sum P_{ij} \times knP_{ij}$ | Uncertainty $E_j$ | Coefficient of significance $W_j$ | Rank |
|---|---|---|---|---|---|
| Layout design | 9 | −0.31652 | 0.695459 | 0.14487 | 2 |
| Supply network | 5 | −0.23837 | 0.52376 | 0.109103 | 5 |
| Programming | 17 | −0.36783 | 0.808199 | 0.168354 | 1 |
| Anticipation | 4 | −0.20969 | 0.460735 | 0.095975 | 6 |
| Inventory control | 3 | −0.17563 | 0.385989 | 0.080386 | 7 |
| Information security | 3 | −0.17563 | 0.358989 | 0.080386 | 7 |
| Imaging | 6 | −0.26277 | 0.577371 | 0.120271 | 3 |
| Medical imaging | 3 | −0.17563 | 0.385989 | 0.080386 | 8 |
| Wireless network | 6 | −0.26277 | 0.577371 | 0.120271 | 3 |

At last, the extracted codes are shown in a preliminary model based on the analysis.

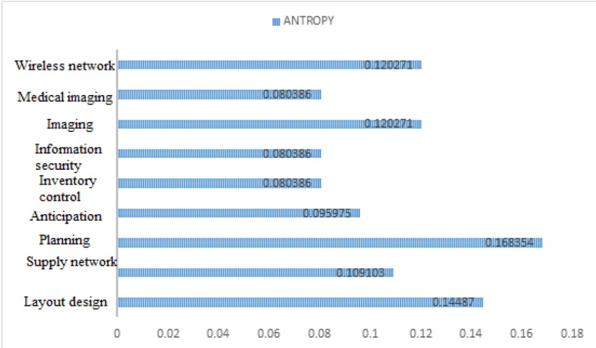


Figure 5: The obtained entropy based on previous research

## 5 Discussion and conclusion

According to calculation theory, problems can be divided into two categories of P and NP based on complexity. The problems that are placed in the P category can be solved through deterministic algorithms and polynomial time complexity and as a result, are also known as simple problems to solve. The shortest path, network maximum flow, minimal spanning tree, maximum bipartite matching problems and problems of linear programming continuum models are placed in the P category. Problems including NP degree of complexity, can only be solved using nondeterministic algorithms and polynomial time complexity. Many real-life development problems including an extensive part of the university's theoretical problems are placed into the NP category. Problems including vehicle routing, timing, workflow and work field environments, backpack, localization, and allocation are placed in this category. There's no effective method to efficiently solve the problems and meta-heuristic methods with different structures (pure and combined) have extensive applications. A meta-heuristic method is a repetitive procedure that seeks to achieve answers that are close to optimal answers by intelligently combining concepts such as production, extraction, search space and learning methods. The current research aims to identify new combined genetic algorithm methods to solve complex problems. Based on the coding, 9 categories, and 33 initial codes were identified. The identified categories are: layout design, supply network, programming, Anticipation, inventory control, information security, imaging, medical imaging and wireless network. Various meta-heuristic methods are presented in the topic's literature, each having particular accuracy and speed. Due to the importance and extensiveness of the difficult problems in the world of science, there is a constant need to develop new algorithms with optimal features. It can be claimed that the use of artificial intelligence methods can be a proper tool to cope with the complexity of many paths and to select the best path based on the current models in the literature. Accordingly, the simulated annealing application procedure used in this research had a beneficial performance in this model. Key results are obtained from studying the output of the algorithm to solve timing and localization problems which can be beneficial for the decision-makers in this field. Since the simulated annealing has a rather simple structure in optimizing different problems, the solving time of this algorithm is very slow. The contrasting tables of the previous chapter indicate this algorithm's speed of action to find optimal answers.

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