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A nature-inspired meta-heuristic knowledge-based algorithm for solving multiobjective optimization problems

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Abstract
The effectiveness of meta-heuristics has recently been well demonstrated. However, there will be a need for reliable algorithms that can handle problems in the real world. The multiobjective nature-inspired meta-heuristic knowledge-based (NMHK) algorithm is an advanced version of the gaining-sharing knowledge optimization (GSK) algorithm, which is available in the literature. NMHK is designed specifically for tackling multiobjective optimization problems (MOPs). Knowledge-sharing algorithms are essential for easing the transfer of knowledge and expertise between people and groups. It is possible to significantly improve organizational learning, problem-solving, and decision-making by utilizing the collective knowledge and abilities of individuals. The NMHK algorithm, which is described in this paper, intends to improve the process of obtaining and spreading of knowledge. Moreover, the experimental results highlight the proposed NMHK algorithm's overall speedy performance, particularly when applied to realistic optimization problems.

Keywords Gaining-sharing knowledge-based algorithm · Meta-heuristics · Multiobjective optimization problems (MOPs) · Nature-inspired meta-heuristic knowledge-based algorithm (NMHK)

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1 Introduction

Over the past years, various research have been carried out to investigate methods and algorithms designed to successfully handle multiobjective optimization problems (MOPs) [1]. The algorithms commonly applied for tackling such problems (MOPs) are Multiobjective Evolutionary Algorithms (MOEAs) [2]. Within the framework of Multiobjective Optimization Problems (MOPs), an abundance of Pareto-optimal solutions emerges instead of a single one. The Genetic Algorithm (GA) [3, 4], Non-dominated Sorting Genetic Algorithm-II (NSGA-II) [5], etc. and other MOEAs provide a variety of potential solutions, situated either on the Pareto-optimal front or in close proximity, throughout every simulation iteration. Following the rise of evolutionary algorithms, a human-based technique [6] named "Gaining-Sharing Knowledge based algorithm," was introduced. GSK is an optimization algorithm which is based upon the ability to obtain, share, and apply knowledge efficiently. Based upon GSK algorithm, this study proposed Nature-inspired Meta-Heuristic Knowledge-based (NMHK) algorithm, which is a comprehensive approach that promotes obtaining and spreading of knowledge. This algorithm is created to tackle MOPs while allowing the gathering and sharing of knowledge within a network or community. By handling competing objectives and various optimization criteria, this method expands the capabilities of the standard GSK algorithm. The NMHK algorithm is divided into two distinct phases: firstly, the junior (child) phase, which involves the obtaining and spreading of knowledge from the trusted and closest individuals; and secondly, the senior (adult) phase, which focuses on the obtaining and spreading of knowledge from different categories of the individuals within specific population. Initially, all members of the population were considered juniors, similar to newborns with no prior knowledge. This notion reflects the natural state of newborns. Then, these individuals take the initiative to interact with close peers like family members or larger groups like those they meet at school or work. These interactions operate as a stimulant for knowledge accumulation, allowing individuals to eventually share their obtained information with others in the population. With the progression of interactions and collaborative efforts, the obtained knowledge intensifies, leading individuals to transition toward a senior level throughout the optimization process. This procedure showed the good example of nature-inspired algorithm which is capable of solving real-life multiobjective optimization problems. The multiobjective NMHK algorithm is applied to real-world scenarios where conflicting objectives are common. It deals with problems where identifying a single optimal solution is difficult and various trade-offs must be taken into account. Overall, the multiobjective NMHK algorithm offers a sophisticated method for resolving complex problems by balancing numerous objectives simultaneously and utilizing the strength of knowledge sharing within a community.

2 Literature survey

Mohamed et al. [6] present "Gaining-Sharing Knowledge-based Algorithm (GSK)," which is a nature-inspired algorithm, for addressing optimization problems within a continuous space. The GSK algorithm imitates how people acquire and share information throughout every phase of their lives. The “junior gaining and sharing phase” and “the senior gaining and sharing phase” serve as its foundation. These two phases are mathematically formulated in their study to solve single objective optimization problems. In an effort to enhance the performance of the recently introduced GSK algorithm, Mohamed et al. [7] made modifications to the algorithm. The core objective of their work is to refine and expand upon the original GSK algorithm by proposing an innovative approach to adaptively determine the values of the knowledge factor and knowledge ratio, both critical control parameters within the GSK framework. Agarwal et al. [8] presented a novel binary version of the recently established GSK algorithm. This binary adaptation, known as the innovative “Binary Gaining-Sharing Knowledge-based optimization method (NBGSK),” focuses on two essential binary stages with a knowledge factor of one: the “binary junior gaining-sharing stage” and “the binary senior gaining-sharing stage.” These phases allow NBGSK to successfully explore and exploit the binary search space, enabling it to efficiently address binary domain problems. Furthermore, the work presents NBGSK with population size reduction (PR-NBGSK) to improve NBGSK’s performance and avoid solutions from being caught in local optima. Xiong et al. [9] introduced an improved form of the “Binary Gaining-Sharing Knowledge-based algorithm (IBGSK)” that uses mutation to solve the challenges of binary optimization. IBGSK encodes individuals as binary vectors rather than real vectors to modify the original GSK for binary search spaces. Mohamed et al. [10] introduced APGSK-IMODE, an integrated strategy that combines the GSK algorithm with adaptive parameters and the improved multi-operator differential evolution (IMODE) algorithm. This integration improves the performance of the adaptive gaining-sharing knowledge-based algorithms. The effectiveness of APGSK-IMODE is examined using CEC2021 benchmark problems that include 10 test functions of varying dimensions (10 and 20). Mohamed et al. [11] have further improved and modified the original GSK method by introducing adaptive settings for two critical control parameters: the knowledge factor and knowledge ratio. During the optimization process, these parameters regulate the dynamics of junior and senior gaining and sharing phases. The performance of this algorithm, termed AGSK, was evaluated using the IEEE-CEC2020 benchmark suite, which encompasses diverse and challenging optimization problems with varying dimensions. Chalabi et al. [12] proposed a novel application of the GSK algorithm, introducing the “multiobjective gaining-sharing knowledge optimization (MOGSK)” approach for addressing multiobjective optimization problems [12]. An external archive population is implemented to retain the non-dominated solutions generated throughout the optimization process. This archive population serves as a guiding mechanism to steer solutions during exploration. To uphold the diversity of the solution and drive convergence toward the Pareto-optimal set, the technique integrates fast non-dominated sorting alongside crowding distance calculations. Furthermore, the ϵ-dominance relation is employed to update the solutions within the archive population. Therefore, as we have stated, there is a great demand for a tool that can assist in solving the growing number of real-world optimization problems. Therefore, to handle real-world multiobjective optimization problems, this study provides an advanced version of the recently implemented GSK algorithm called the Nature-inspired Meta-Heuristic Knowledge-based Algorithm (NMHK).

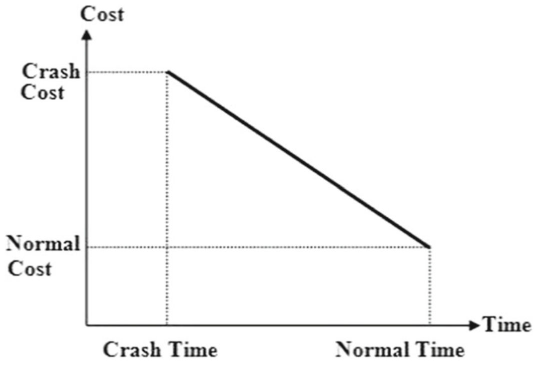

Fig. 1 Linear TCT relationship of the project activity

3 Problem description

In a multiobjective optimization method, competing objective functions are simultaneously optimized. Multiobjective optimization can minimize or maximize, depending on the problem being addressed. The primary objective of this section is to provide an effective optimization model for dealing with a real-world Time–Cost Trade-off (TCT) problems often termed as MOPs [13–15]. The major purpose of this model is to minimize project duration and cost while adhering to any applicable constraint requirements. The terms "normal cost" and "normal time" in this context refer to the minimum costs and maximum times, respectively, required to execute a project activity. In contrast, "crash time" denotes the shortest amount of time that can be used to finish a project activity, accompanied by its corresponding "crash cost." Figure 1 [15] shows the linear model used in this paper to determine the relation between cost and time.

Suppose that a project network contains n activities. Each activity i can be performed with k_i; $1 \leq i \leq 2$ options with a corresponding cost c_i and time duration t_i. It is assumed that each activity i in a project has a normal activity completion time NT_i and a crash activity completion time CT_i; CC_i and NC_i are the crash cost and normal cost of i^{th} activity, respectively. The mathematical model mainly refers to minimizing project completion time and minimizing project completion cost of a project according to some constraint conditions if any described as below:

$$T_\theta = \sum_{i=1}^{n} t_i \tag{1}$$

$$\text{s.t.} \quad CT_i \leq t_i \leq NT_i, \tag{2}$$

$$C_\theta = \sum_{i=1}^{n} c_i \tag{3}$$

$$\text{s.t.} \quad c_i = m_i t_i + k_i \tag{4}$$

$$\& \quad NC_i \leq c_i \leq CC_i. \tag{5}$$

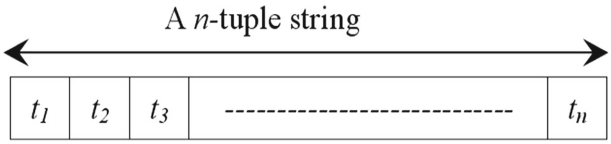

Fig. 2 Time of the project schedule

The relation between time and cost of each activity is defined in equation (3.4). In this equation m_i is the slope with X-axis and k_i is the intercept with Y-axis of a straight line, which are given as

$$m_i = \frac{CC_i - NC_i}{NT_i - CT_i}, \tag{6}$$

$$k_i = CC_i - NC_i. \tag{7}$$

4 Methodology

The methodology of multiobjective NMHK Algorithm is mentioned below:

The multiobjective NMHK algorithm has been developed from the traditional GSK method to achieve multiple objectives. It seeks to optimize a variety of characteristics including knowledge accuracy, diversity, etc. while facilitating the obtaining and sharing of knowledge within a network or community.

Let x_i, where $i = 1, 2, 3, ..., N$, represent the members of a specific population. In this case, N is the overall population size, and x_i is defined as $x_{ij} = (x_{i1}, x_{i2}, ..., x_{iD})$. The total number of disciplines or knowledge domains that have been allocated to a person in this context, determining their dimensions, is denoted by (Dim). For $i = 1, 2, ..., N$, f_i represents their respective fitness values.

4.1 Population initialization

The population contains N solutions initially, whereas the solution is a string (Fig. 2) of type $[t_1, t_2, ..., t_i, ..., t_n]$ such that $CT_i \leq t_i \leq NT_i$ and $i = 1, 2, ..., n$, which represents the time of the project schedule. The project's associated cost (C_θ) and duration (T_θ) for each individual schedule are determined by computing the maximum path time and aggregating the costs for all activities. These solutions are referred to as "parents."

4.2 Non-dominated sort

The multiobjective NMHK algorithm sorts the population using non-dominated sorting [5], and one can choose individuals from these sorted fronts to make up the population of the next generation. This crucial step is focused on striking a balance between preserving diversity and adhering to previous solutions of superior quality. In particular, a fixed number of people are chosen from the non-dominated fronts with the best objective values, which is often the first front. This strategic selection strengthens the algorithm's advancement by ensuring the continuous existence of the best solutions in the next generation.

4.3 Obtaining and spreading of knowledge

Over the course of the year, new optimization techniques are created and released to address real-world problems. As a result, GSK [6] was recently proposed as a new optimization technique. Based on GSK, this work introduces the NMHK algorithm, a human-based algorithm that replicates the gathering and spreading of knowledge over the span of a human lifetime. The primary mechanism of NMHK relies on two crucial stages: junior obtaining and spreading of knowledge, and senior obtaining and spreading of knowledge.

4.4 Junior obtaining and spreading of knowledge phase

In the NMHK Algorithm, the "Junior obtaining and spreading of knowledge phase" refers to a specific aspect that caters to the knowledge obtaining and sharing behaviors of young learners, typically children or adolescents. In this stage, juniors still have the desire to impart their knowledge to those they know and those they do not; they also lack the capacity to judge others as good or bad at this time, so they do so out of curiosity and exploration. This phase acknowledges the unique characteristics of junior learners, including their curiosity, eagerness to learn, and spontaneous sharing tendencies, and aims to create an inclusive and engaging learning environment for them within the algorithm.
According to the fundamental idea of the NMHK algorithm, the dimensionality Dim is calculated using a nonlinear increasing and decreasing formula.
For the Junior phase [6]

$$Dim_{(\text{juniorphase})} = V\left(1 - \frac{g}{g_{\max}}\right)^{k}, \tag{8}$$

where V represents the size of the problem, g indicates generation, $g_{\max}$ represents the maximum number of generations, and k indicates the knowledge rate, a real number greater than or equal to zero. The current stages of people are updated in accordance with the junior scheme [6], where M represents the number of objectives which have to be minimized. Also, Algorithm 1 (Fig. 3) shows the step-by-step process of junior obtaining and spreading of knowledge phase.

The knowledge factor (K_f), where ($K_f \succ 0$), governs how much knowledge (obtained or shared) will be added to the actual person. The knowledge ratio, or K_r, governs how much knowledge (obtained or shared) will be imparted to a recipient and has a range of [0, 1].

Algorithm 1 Junior obtaining and spreading of knowledge phase

for $i = 1 : (N)$ **do**
  for $j = 1 : dim_{junior}$ **do**
$ran = rand; index = i;$
    if $(ran \leq K_r)$ **then**
      if $f(x_{(index,M+V+1)} > f(x_{(r,M+V+1)})$ **then**
$x^{new}_{(index,j)} = x_{(index,j)} + K_f[(x_{(index-1,j)} - x_{(index+1,j)}) + (x_{(r,j)} - x_{(index,j)})];$
      else
$x^{new}_{(index,j)} = x_{(index,j)} + K_f[(x_{(index-1,j)} - x_{(index+1,j)}) + (x_{(index,j)} - x_{(r,j)})];$
      end if
    else
$x^{new}_{(index,j)} = x^{old}_{(index,j)};$
    end if
  end for
end for

Fig. 3 Junior obtaining and spreading of knowledge phase

4.5 Senior obtaining and spreading of knowledge phase

The "Senior obtaining and spreading of knowledge phase" in the NMHK Algorithm pertains to the specific considerations and features for accommodating senior learners, typically older adults, in the knowledge obtaining and sharing process. This phase recognizes the unique characteristics and needs of senior users, such as life experiences, diverse expertise, and preferences for certain learning methods. Incorporating the senior obtaining and spreading of knowledge phase in the NMHK Algorithm helps ensure that older adults can actively engage in the knowledge-sharing ecosystem and contribute their valuable insights. In this stage, adolescents learn from those around them. They also have excellent classification skills at this stage, able to group people into categories like best, better, and worst. As a result, they enhance their talents and impart knowledge to the best candidates.
This phase takes into consideration a person's tendency for classification (such as superior and inferior).

Regarding the senior phase [6]

$$Dim_{(\text{seniorphase})} = V - Dim_{(\text{juniorphase})}. \tag{9}$$

As a result, the number of dimensions for obtaining and sharing for each vector is determined during the initialization phase, taking into account both the junior and senior phases. Algorithm 2 (Fig. 4) shows the step-by-step process of senior obtaining and spreading of knowledge phase.

4.6 Update the population

In the NMHK algorithm, the population update comprises the fusion of individuals from the existing population with those chosen from the upcoming generation.

Algorithm 2 Senior obtaining and spreading of knowledge phase

for $i = 1 : (N)$ **do**
  for $j = 1 : dim_{senior}$ **do**
$ran = rand; index = i;$
    if $(ran \leq K_r)$ **then**
      if $f(x_{(index,M+V+1)}) > f(x_{(m,M+V+1)})$ **then**
$x^{new}_{(index,j)} = x_{(index,j)} + K_f[(x_{(index-1,j)} - x_{(index+1,j)}) + (x_{(middle,j)} - x_{(index,j)})];$
      else
$x^{new}_{(index,j)} = x_{(index,j)} + K_f[(x_{(index-1,j)} - x_{(index+1,j)}) + (x_{(index,j)} - x_{middle,j)})];$
      end if
    else
$x^{new}_{(index,j)} = x^{old}_{(index,j)};$
    end if
  end for
end for

Fig. 4 Senior obtaining and spreading of knowledge phase

This dynamic procedure drives the iterative progress of the algorithm and aspires to better solutions that successfully balance multiple objectives. The NMHK algorithm relies on this population update mechanism to refine the population over time, bringing it closer to the complex trade-off between the several objectives. This complex procedure combines obtained and shared operators, fitness evaluations, and selection procedures, collectively guiding the algorithm toward a gradually improving set of solutions throughout successive iterations.

5 Results and discussion

To establish a linear and continuous relation between activity time and cost in the experimental case study, modifications have been made to the real-world project network depicted in Fig. 5 [14]. Table 1 provides a list of alternatives for each activity within this project network. The proposed approach, namely the NMHK algorithm, is subsequently employed to address this problem.

To solve this experimental case study through the proposed NMHK algorithm, several factors must be taken into account, including the initial population, knowledge rate, knowledge factor, knowledge ratio, and maximum number of generations, as detailed out in Table 2. Furthermore, the search process is designed to terminate after 15,000 consecutive iterations, as the trade-off points have been observed to remain constant beyond this point. Figure 6 visually presents the trade-off points attained over these 15,000 generations, depicting both project completion time and cost. To provide a comprehensive overview of the obtained results, a statistical analysis has been compiled and is presented in Table 3.

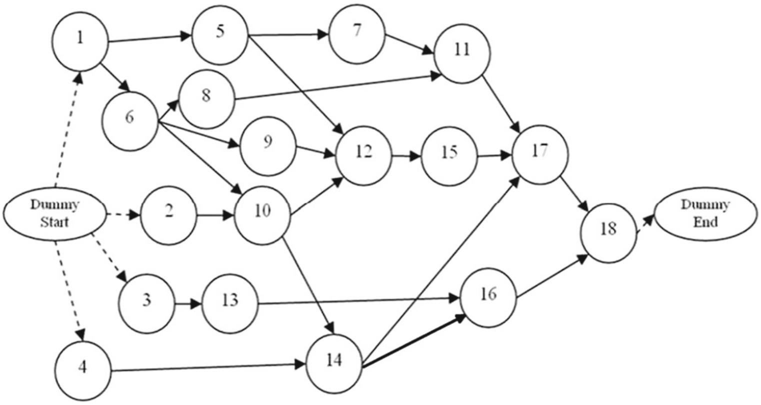

Fig. 5 Network of experimental case study

Table 1 Alternatives of case study

Activity No.	Crash time	Normal time	Crash cost	Normal cost
1	14	24	2400	1200
2	15	25	3000	1000
3	15	33	4500	3200
4	12	20	45000	30000
5	22	30	20000	10000
6	14	24	40000	18000
7	09	18	30000	20000
8	14	24	220	120
9	15	25	300	100
10	15	33	450	320
11	12	20	450	300
12	22	30	2000	1000
13	14	24	4000	1800
14	09	18	3000	2200
15	16	16	3500	3500
16	20	30	3000	1000
17	14	24	4000	1800
18	09	18	3000	2200

Table 2 NMHK parameters

Initial population (N)	200
Knowledge rate (k)	10
Knowledge ratio (K_r)	0.9
Knowledge factor (K_f)	0.5
Maximum number of generations ($g_{\max}$)	15000

Table 3 Statistical analysis

Statistics	Min	Max	Mean	Median	Std	Range
Project time	115.9	149.4	130.1	127.7	10.93	33.48
Project cost	1.143e+05	1.287e+05	1.21e+05	1.202e+05	6292	1.441e+04

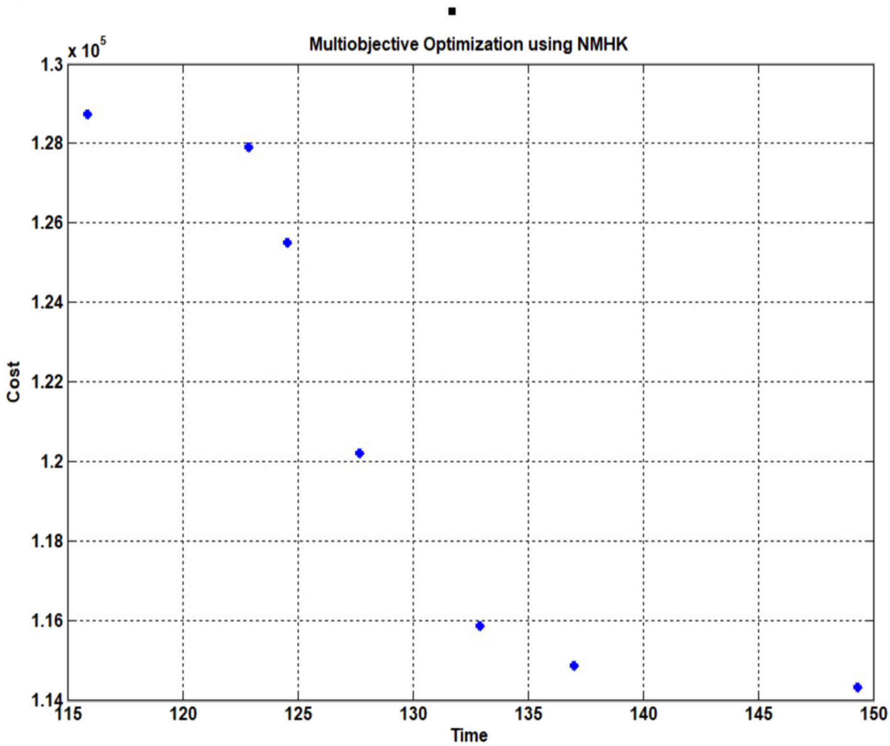

Fig. 6 Trade-off points using NMHK

6 Conclusion

In this paper, the multiobjective Nature-inspired Meta-Heuristic Knowledge-based Algorithm has been shown a promising and successful approach for dealing with multiobjective optimization problems. NMHK extends the GSK algorithm by introducing refinements that empower it to effectively address the complex trade-offs and challenges inherent in real-world multiobjective optimization problems. Its capability to maintain diversity and converge toward meaningful Pareto-optimal solutions demonstrates its strength in dealing with real-world situations with competing aims. As a result, NMHK has the potential to be a useful tool in the field of multiobjective optimization, providing a path to better decision-making and improved solutions for complicated and diverse problems.

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Data availability Sharing of data is not applicable to this article, as no datasets were generated or analyzed during the present study.

Code availability Sharing of data is not applicable to this article, as no datasets were generated or analyzed during the present study.

Declarations

Conflict of interest The authors affirm that they have no competing interests.

Consent to participate All authors have provided their consent to participate in this research.

Consent for publication The authors have granted consent for the publication of identifiable details, including figures, graphs, tables, and case studies, in the specified journal.

Ethical approval This research is an original work of the authors and has not been previously published elsewhere.

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