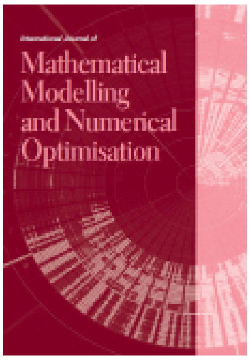

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A review of 0-1 knapsack problem by nature-inspired optimisation algorithms

Ruchi Chauhan, Nirmala Sharma, Harish Sharma

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A review of 0-1 knapsack problem by nature-inspired optimisation algorithms

Ruchi Chauhan*, Nirmala Sharma and Harish Sharma

Department of Computer Science and Engineering,
Rajasthan Technical University,
Kota – 324010, Rajasthan, India
Email: cseruchichauhan@gmail.com
Email: nsharma@rtu.ac.in
Email: hsharma@rtu.ac.in
*Corresponding author

Abstract: Nature is the origin of all knowledge. Researches have built nature-inspired optimisation (NIO) algorithms, that follow natural principles to find solutions, for the real life problems. In the binary knapsack problem (0/1KP), a bag (or a knapsack) has to be filled with articles, where each article has a weight and a profit value, the articles are filled in the knapsack, in whole numbers, up to a weight limit, to attain the optimum profit. The 0/1KP does the optimum sub-structure selection from a given set of articles, i.e., there can be different optimum solutions for a given 0/1KP. The aim of this research is to discuss the NIO algorithms innovated for solving the 0/1KP. The review creates foundation, for future research on optimising the 0/1KP, from meta-heuristic NIO techniques.

Keywords: nature-inspired optimisation; NIO; 0-1 knapsack problem; 0/1KP; NP-hard problems; swarm intelligence.

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Biographical notes: Ruchi Chauhan received her BTech (Honours) from the Government Women Engineering College, Ajmer, Rajasthan, India and MTech (Honours) from the Rajasthan Technical University, Kota, India. She is a research scholar with the Department of Computer Science and Engineering, Rajasthan Technical University, Kota, India. Her research area is swarm intelligence-based algorithms and their applications.

Nirmala Sharma received her BE from the University of Rajasthan, Jaipur, India, MTech from the Rajasthan Technical University, Kota, India and PhD from the Rajasthan Technical University, Kota, India. She is working as an Assistant Professor with the Department of Computer Science and Engineering, Rajasthan Technical University, Kota, India. Her research area is swarm intelligence-based algorithms and their applications.

Harish Sharma received his BE from the University of Rajasthan, Jaipur, India, MTech from the Rajasthan Technical University, Kota, India, and PhD from the ABV-IIITM, Gwalior, Madhya Pradesh, India. He is working as an Associate Professor with the Department of Computer Science and Engineering, Rajasthan Technical University, Kota, India. His research area is swarm intelligence-based algorithms.

1 Introduction

The researchers have devised meta-heuristic techniques to solve NP-hard problems. Meta-heuristic techniques explore the search space, to improve the quality of the solution. The NP-hard problems are those problems that have no fixed solution. Therefore different algorithms when applied to the NP-hard problems yield different results (Da et al., 2016; Gandhi et al., 2013; Sonavane and Bhole, 2020; Bhole and Mastud, 2021). The 0/1KP is an example of NP-hard problem.

The significant work in this area is presented in Table 1 in the form of abbreviations used throughout this review paper.

This paper informs the readers about the different meta-heuristic algorithms that are inspired by the nature to find solutions for the 0/1KP. Informatics is the science of the information. The algorithms find optimised solution based on the informatics of the search space. For example:

- In 2019, Patkar et al. implemented rough set algorithm to design a framework for evaluation of palm oil fruit quality. The framework software can detect disease of the palm tree.
- In 2019, Miqoi et al. implemented perturb and observe algorithm. The research aims to optimise the photo-voltaic water pump to operate under different climatic conditions.
- In 2019, Saidi and Naceri implemented fuzzy logic technique, to design controllers for the induction machines. The fuzzy logic technique implements linguistic variables. The control adaptive system along with the fuzzy logic yields the fuzzy adaptive controllers.
- In 2019, Rathore and Singh implemented whale optimisation algorithm. The controllers of the reverse osmosis plant implement WOA algorithm to calculate the optimisation function.
- In 2011, Singh and Sukavanam implemented neural networks, for tracking the robot manipulators. Feed-forward neural network determines the upper bound of the task space. The two-link elbow robot manipulator is taken for consideration for the research.
- In 2010, Solano-Aragon et al. implemented fuzzy logic technique to control the trajectory, of the autonomous mobile robot. Image database is maintained for recognition of images. Sensors, motors, camera provide the data that is further processed, to decide the trajectory of the autonomous mobile robot.

Table 1 Abbreviations

Notation	*Full form*
NIO	Nature inspired optimisation
GSO	Galactic swarm optimisation
BinEHO	Binary elephant herding optimisation
ACO	Ant colony optimisation
SOS	Symbiotic organisms search
FPA	Flower pollination algorithm
SSO	Social spider optimisation
BPSO	Binary particle swarm optimisation
WOA	Whale optimisation algorithm
DGSA	Discrete gravitational search algorithm
MBO	Migrating birds optimisation
GBCSO	Greedy binary chick swarm optimisation
CSA	Cuckoo search algorithm
BDA	Binary dragonfly algorithm
BBA	Binary bat algorithm
ABC	Artificial bee colony
CWDO	Complex-valued wind driven optimisation
GHSA	Global harmony search algorithm
WPA	Wolf pack algorithm
CMBO	Chaotic monarch butterfly optimisation
GHSOS	Greedy harmonic symbiotic organisms search
MA	Monkey algorithm
TLO	Teaching-learning optimisation
GA	Genetic algorithm
SFLA	Shuffled frog leaping algorithm
AOA	Amoeboid organism algorithm
S-bAFSA	Simplified binary artificial fish swarm algorithm
CIA	Cohort intelligence algorithm
BBFO	Binary bacteria foraging optimisation
BBO	Binary bio-geography optimisation
CROG	Chemical reaction optimisation with greedy strategy algorithm
AWLA	Ant weight lifting algorithm
QEA	Quantum-inspired evolutionary algorithm
BMBO	Binary monarch butterfly optimisation
I-bAFSA	Improved binary artificial fish swarm algorithm
BBFO-LDCA	Binary bacteria foraging optimisation with linear descending chemo-taxis step length algorithm
MDSFLA	Modified discrete shuffled frog leap algorithm
HSTL	Harmony search-teaching-learning algorithm
CSGHS	Cuckoo search-greedy harmonic search algorithm
BABC-DE	Binary artificial bee colony with differential evolution
IBBA-RSS	Improved binary bat algorithm with rough set system
IABHS	Improved-adaptive binary harmony search

- In 2010, Yang and Luo implemented simulated annealing technique to find a community network within a network. The inferences of this research are: A community network is a sub-network within a network that has high internet connectivity and low intranet connectivity. The community network has high diffusion characteristics.

This review article is designed as follows:

- *second section:* explains the formulation of the 0-1 knapsack problem
- *third section:* gives a review of the opted NIO algorithms for solving the 0-1 KP
- *fourth section:* presents the technical summary of the reviewed algorithms
- *fifth section:* concludes the presented work.

2 The 0-1 knapsack problem

The 0/1KP can be logically understood by the following example: Given a knapsack with a weight limit of 'L' units. The knapsack has to be filled with some articles in 0-1 manner, i.e., each article must be selected in whole quantity or left otherwise, where each article has a weight and a profit.

$$\text{Set A} = \{\text{A1}, \text{A2}, \text{A3}, \text{A4}, \ldots, \text{AN}\}$$
$$\text{Set W} = \{\text{W1}, \text{W2}, \text{W3}, \text{W4}, \ldots, \text{WN}\}$$
$$\text{Set P} = \{\text{P1}, \text{P2}, \text{P3}, \text{P4}, \ldots, \text{PN}\}$$
$$\text{L} = \text{Weight limit of the knapsack}$$

$$\textit{MAXIMUM PROFIT} = \text{A1} * \text{P1} + \text{A2} * \text{P2} + \text{A3} * \text{P3} + \ldots + \text{AN} * \text{PN}$$

SUBJECT TO THE CONSTRAINT:

$$\text{A1} * \text{W1} + \text{A2} * \text{W2} + \text{A3} * \text{W3} + \ldots + \text{AN} * \text{WN} \leq \text{L}$$

where 'N' denotes the dimension of the 0/1KP. Asterisk * denotes multiplication. 'A' refers to the set of the articles, to be added to the knapsack. Values of set A can be 0 or 1. The value of an article is 1 when the article is selected, the value of the article is 0 when the article is not selected. 'W' refers to the set of the corresponding weights of the articles; 'P' refers to the set of the corresponding profits of the articles. The articles are added in the knapsack in a manner that the resulting profit is max and the net weight of the knapsack is within or up to the specified weight limit of the knapsack.

Numerical: Let a trolley carries maximum weight of 30 kg. There are 5 electrical appliances. The weights and profits of the electrical appliances are:

$$\text{Weight in kilograms}, \text{W} = \{10, 15, 5, 20, 25\}$$
$$\text{Profits in thousand rupees}, \text{P} = \{40, 20, 60, 30, 10\}$$

Fill the trolley with electrical appliances, such that the profit is maximum and the weight of the trolley does not exceed the given weight limit i.e., 30 kilogram.

Solution: We have five electrical appliances. Let the set of electrical appliances be E1, E2, E3, E4, E5.

$$E = \{E1, E2, E3, E4, E5\},$$
$$W = \{10, 15, 5, 20, 25\},$$
$$P = \{40, 20, 60, 30, 10\}$$

We can select the following optimum sub-structures to get the maximum profit and satisfy the weight limit.

- E1 (W = 10, P = 40), E2 (W = 15, P = 20), E3 (W = 5, P = 60), the total weight = 30, and total profit = 120.
- E3 (W = 5, P = 60), E5 (W = 25, P = 10), the total weight = 30, and total profit = 70.
- E1 (W = 10, P = 40), E4 (W = 20, P = 30), the total weight = 30, and total profit = 70.

Therefore, we must select E1, E2 and E3 to get the maximum profit and satisfy the weight limit.

$$\textit{MAXIMUM PROFIT} = 1 * 40 + 1 * 20 + 1 * 60 + 0 * 30 + 0 * 10$$

$$\textit{SUBJECT TO THE CONSTRAINT:}$$
$$1 * 10 + 1 * 15 + 1 * 5 + 0 * 20 + 0 * 25 \leq 30$$

The maximum profit obtained is 120 thousand rupees.

The 0/1KP can be used for situations where a choice of selection has to be made. examples of the 0/1KP are:

- *operating systems:* allocating resources to processes for non-preemptive execution
- *real time systems:* multiprocessor process allocation
- *digital electronics:* deciding the number of digital elements for designing the silicon chip
- *telecommunications:* deciding the number of devices that can work on a particular bandwidth
- *network routing:* deciding the number of nodes that can transmit data over the bandwidth with fixed capacity to avoid congestion.

3 Review of the different NIO algorithms for solving the 0/1KP

The following are some of the opted NIO algorithms that are applied to find solutions for the 0/1KP.

3.1 Optimising galactic swarm using data-driven binarisation techniques

In 2020, Vasquez et al. introduced galactic swarm optimisation (GSO) with data-driven binary techniques for the 0/1KP. In this paper, the data-driven binary-making techniques are added to the GSO algorithm to solve the 0/1KP.

- the binary-making techniques can be machine learning or non-machine learning
- the non-machine learning-based binary-making techniques have two stages, the first stage is the normalisation procedure and the second step is the binary-making rule that turns the object into a binary
- the machine learning methods are K-means and data-base scan (DB Scan)
- the average optimum values of the K-means machine learning technique are the highest among the mentioned techniques for each instance tested in the experiment
- the experiment of the GSO algorithm with data-driven binary-making approaches is performed over ten problem instances
- the results tell that the machine learning binary-making techniques are fast and the non-machine learning binary-making techniques are slow.

3.2 Binary elephant herding optimisation

In 2020, Hakli introduced binary elephant herding optimisation (BinEHO) algorithm for the 0/1KP. In this paper, the elephant herding optimisation (EHO) is binarised to optimise 0/1KP.

- the BinEHO algo. is simple since it has one parameter, i.e., dimension rate
- the BinEHO algorithm is performed over 25 different instances of the 0/1KP
- the obtained results tell that the less number of parameters simplify the BinEHO algorithm and improved scatter search algorithm performs better than the BinEHO algorithm.

3.3 Ant system with run-time pheromone update

In 2019, Alzaqebah and Abu-Shareha introduced ant system algo. with run-time pheromone update for the 0/1KP. In this paper, the pheromone on each article is dynamically updated depending on certain constraints.

- in the tour each ant deposits pheromone on the article dynamically depending on certain constraints
- the article that has the maximum pheromone is added to the final result set
- the experiment of ACS algorithm with dynamic pheromone updating algorithm is performed over 100 problem instances.
- the results tell that the convergence of ACS algorithm with dynamic pheromone updating algorithm is faster than its base algorithm which has static pheromone

update and for some instances the static base algorithm gives better results than the dynamic pheromone updating algorithm due to the nature of the problem.

3.4 Binary flower pollination algorithm

In 2018, Abdel-Basset et al. introduced binary flower pollinating (BFP) algorithm for obtaining the solution for 0/1KP.

- A transformation function converts the non-binary numbers into binary, i.e., 0, 1.
- Penalty function produces negative values for inappropriate solutions.
- Flower repair operator is a two-stage repair operator. The flower repair operator improves the quality of the solution.
- The experiment of the BFPA is performed over 52 instances.
- The results tell that the BFPA performs better in time and result-quality than the cohort intelligence algorithm.
- The standard deviation of the BFPA is directly proportional to the problem-scale for weakly correlated instances.
- Note: the standard deviation is inversely proportional to the optimum result.

3.5 Greedy hybrid symbiotic organisms search algorithm

In 2018, Wu et al. introduced greedy hybrid symbiotic organisms search (GHSOS) algorithm for the 0/1KP.

- in the paper, an amalgam of the harmony search (HS) algorithm, symbiotic organisms search (SOS) algorithm and the greedy strategy for increasing the efficiency of the results and for optimising the computing time
- the SOS algorithm stimulates the behaviour of the swarm elements
- the harmony phase enhances the local search ability
- the greedy strategy is used for repairing the infeasible solution and for optimising the feasible solution
- the GHSOS algorithm experiment is performed over 64 instances
- the results tell that the GHSOS algorithm is good in converging speed and correctness, and is robust
- the GHSOS algorithm is used for optimising large scale problems
- the GHSOS algorithm is not recommended for small scale problems.

3.6 Social-spider optimisation algorithm

In 2018, Zhou et al. introduced social-spider optimisation (SSO) algorithm for the 0/1KP.

- in the article, the SSO algorithm simulates the cooperative nature of the social-spiders
- the experiment of the SSO algorithm is performed over two instances
- the results tell that the SSO algorithm provides optimum result when the problem scale is large
- the SSO algorithm applies for the large problem only.

3.7 Quantum wolf pack technique

In 2018, Gao et al. introduced quantum-based wolf pack (QWP) algo. for optimisation of the 0/1KP.

- the QWP algorithm consists of the quantum rotation operation and the quantum collapse operation
- a quantum rotation operation results in global optima
- a quantum collapse operation avoids local optima
- the experiment of the QWP algorithm is performed over 14 instances
- the results tell that the QWP algo. performed better for high scale problems
- the QWP algorithm obtained the global optimum in 35% of the tests.

3.8 Hybrid BPSO-GA algorithm

In 2017, Wang et al. introduced hybrid BPSO-GA algorithm for the 0/1KP. In this paper, the following actions are performed:

- the algorithm implements PSO operation and GA operation
- the experimentation of hybrid BPSO-GA algo. is performed over 25 instances
- the results tell that the crossover operator converge the hybrid BPSO-GA algorithm to optima
- the hybrid BPSO-GA out performed for six instances than the BPSO-GA.

3.9 Optimisation based on migrating birds

In 2017, Ulker and Tongur introduced migrating birds optimisation (MBO) algorithm for the 0/1KP.

- the MBO algo. is influenced by ‘V’ formation that the migratory birds form during migration
- the MBO uses neighbourhood structure for improving the solutions
- the experiment of the MBO algorithm is done on ten instances
- the results inform that the MBO solves the small-scale problems fast

- the MBO algorithm could not get optimum result for large scale instances.

3.10 Greedy binary chick swarm optimisation

In 2017, Han and Liu introduced greedy binary chick swarm optimisation (GBCSO) for 0/1KP. In this paper, the following actions are performed:

- greedy scheme improves the feasibility of the solution
- experiment of GBCSO algorithm is conducted on ten instances
- the results tell that the GBCSO algorithm has high precision, good stability and low run time
- the computing time for GBCSO algorithm is higher than that of binary PSO algorithm.

3.11 Binary bat algorithm

In 2017, Rizk-Allah and Hassanien introduced the binary bat algo. (BBA) to optimise the 0/1KP. In the paper, the following actions are performed:

- the BBA implements two important procedures
- the first procedure is binary bat algorithm procedure
- the second procedure is local search scheme procedure
- binary bat algo. procedure improves the global optima
- the local search scheme prevents the algo. from the getting trapped in the local optima
- experiment of the BBA is performed over 32 instances
- the results tell that the Improved BBA with rough set system does away with the shortcomings of the BBA
- the standard deviation of IABHS algo. is lesser than V-BBA.

3.12 Binary-version of artificial bees colony optimisation with differential evolution

In 2017, Cao et al. introduced binary-based artificial bees colony optimisation along with differential evolution (BABC-DE) for solving the 0/1KP. In this paper, the following actions are performed:

- a binary search operator searches the search space of the memory
- neighbour memory is built by employed bee
- the mutation and crossover of the differential evolution is done by onlooker bee
- the experiment of the BABC-DE algorithm is performed over 30 instances

- the results tell that the BABC-DE algorithm has high fitness value and convergence speed
- the complex-valued wind driven optimisation algorithm performs better than BABC-DE algorithm for small-dimension problems.

3.13 Binary dragonfly algorithm

In 2017, Abdel-Basset et al. (2017b) introduced binary dragonfly algorithm (BDA) for the 0/1KP. In this paper, the following actions are performed:

- transfer functions are used to convert non-binary numbers into binary numbers
- experiment of BDA is done on 34 instances
- the results tell that the BDA has high stability and convergence
- the standard deviation increases for large-scale instances for the BDA.

3.14 Opposite learning-based monarch butterfly optimisation with Gaussian perturbation

In 2017, Feng et al. introduced opposite learning-based monarch butterflies optimisation (OMBO) supported by Gaussian perturbation for feasibility optimisation of the 0/1KP. In this paper, the following actions are performed:

- the defects of the monarch butterfly algorithm are mitigated by the OMBO algorithm
- the experiment of the OMBO is performed over 15 instances
- the results tell that the OMBO algorithm has higher convergence speed and avoids the local optima
- the shuffled frog leaping algorithm performs better than the OMBO algorithm.

3.15 Whale optimisation algorithm

In 2017, Abdel-Basset et al. (2017a) introduced improved whale-based optimisation algorithm (WOA) to optimise the 0/1KP. In this paper, the following actions are performed:

- The improved WOA, apply a penalty function to the evaluation function for optimising the fitness of the feasible solutions.
- The sigmoid function can take the real-valued solutions as input and produces the binary solutions as output.
- A repair operator handles the infeasible solutions.
- Improved WOA implements two procedures. The first procedure is local search strategy and another procedure considers the levy flight walks.

- Experiment of the Improved WOA is performed over 117 instances.
- The results inform that the penalty function assigns negative values for the infeasible solutions.
- Local optima is exempted in WOA.
- The standard deviation from the optimum solution increases when the problem-scale increases for the WOA.

3.16 Discrete gravitational search algorithm

In 2016, Sajedi and Razavi (2016) introduced discrete gravity-based search algo. (DGSA) for solving the 0/1KP. In this paper, the following actions are performed:

- the search agents are a collection of entities that communicate with each other
- the Newtonian gravity and the laws of motion are adhered during the search for the feasible solution
- in DGSA the position of the agents can be considered as the solutions
- experiment of DSG algorithm is performed over 18 instances
- the results tell that the DGSA has better results than the binary gravitational search algorithm
- with the increment in the scale of the problem, the number of search agents have to be increased, in the DGS.

3.17 Chaos-based monarch butterfly optimisation

In 2016, Feng et al. (2016b) introduced chaos monarch butterfly optimised (CMBO) algorithm for finding the feasible output of the 0/1KP. In this paper, the following actions are performed:

- the chaos theory is implemented to enhance level of the global optima
- the CMBO algorithm experiment is performed over 15 instances
- the results tell that the chaotic map supported with Gaussian perturbation in the CMBO algorithm, amplifies the solution quality
- shuffled frog leaping algorithm gives higher optimum values than CMBO algorithm.

3.18 Complex-number encoded wind driven optimisation algorithm

In 2016, Zhou et al. introduced complex-number encoded wind driven optimisation (CWDO) algorithm for finding the feasible result of the 0/1KP. In this paper, the following actions are performed:

- the CWDO algorithm uses a complex-value encoding methodology to find the global optimum solution

- the local search ability of the CWDO algorithm is efficient
- experiment of CWDO algorithm is performed with 30 instances
- the results tell that the CWDO algorithm is stable and highly accurate.
- the overall deviation from standard result is high, for f19 test instance of the CWDO algorithm.

3.19 Hybridised cuckoo search and global harmony search

In 2016, Feng et al. (2016a) introduced hybrid cuckoo search and global harmony search (CSGHS) algorithm for optimising the 0/1KP. In this paper, the following actions are performed:

- the global optimum is reached with harmony search
- hybrid encoding scheme and repair operator, improve the efficiency of the algorithm
- the hybrid CSGHS experiment is performed over 36 instances
- the results tell that the hybrid CSGHS algorithm has high search accuracy as well as high convergence speed
- the shuffle frog leap algorithm is more stable than hybrid CSGHS algorithm.

3.20 Binary monarch butterfly optimisation

In 2015, Feng et al. introduced binary monarch butterfly optimised (BMBO) algorithm to find the feasible output for the 0/1KP.

- the repair operator revises the infeasible solutions and optimises the feasible solutions
- the experiment of the BMBO algorithm is performed over 28 instances
- the results indicate that BMBO algorithm has higher stability than the genetic algorithm
- the binary cuckoo search algorithm gives higher optimum values than BMBO algorithm.

3.21 Improved monkey algorithm

In 2015, Zhou et al. introduced improvised monkey algorithm (IMA) for finding the optimised feasible solution of the 0/1KP. In this paper, the following actions are performed:

- the IMA is inspired by the somersaulting behaviour of the monkeys
- the IMA mitigates the defects of the monkey algorithm by modifying the somersault process to avoid falling into local optimal solutions

- the cooperating process is added for optimising the rate of convergence of the algorithm
- control parameter maintains the population diversity
- the IMA experiment is performed over 69 instances
- the results tell that the S-bAFSA performs better than IMA.

3.22 Hybrid of teaching learning-based optimisation-genetic algorithm

In 2015, Umbarkar et al. introduced hybrid teaching learning-based optimisation-genetic algorithm (TLBO-GA) for the 0/1KP. In this paper, the following actions are performed:

- the evolutionary process and binary chromosome techniques are added to make hybrid algorithm
- evolutionary process is contributed by the TLBO and binary chromosome technique is contributed by the GA
- the experiment of the hybrid TLBO-GA is performed over three instances
- the results tell that the hybrid TLBO-GA did better in one instance than simple genetic algorithm
- the hybrid TLBO-GA performed sub-optimum in two instances than simple genetic algorithm.

3.23 Harmony search and teaching-learning algorithm

In 2014, Tuo et al. introduced harmony search and teaching-learning (HSTL) algorithm for the 0/1KP.

- the harmony vector dimension is adjusted at run-time
- the run-time-based modifications add stability to the algorithm
- the parameters of the algorithm are changed at run-time
- the experiment of the HSTL algorithm is performed over 13 instances
- the results tell that the HSTL algorithm is constant to optimise the solutions
- the HSTL algorithm has more parameters.

3.24 Improved hybrid encoding cuckoo search algorithm

In 2014, Feng et al. (2014a) introduced improved hybrid encoding cuckoo search (ICS) algorithm for the optimisation of 0/1KP.

- the cuckoo search over a continuous space is transformed into the synchronous evolution search over discrete space
- position updating of the population results in global best or global optima

- genetic mutation keeps away from local optimum
- the ICS algorithm is experimented over 20 instances
- the results tell that the HS algorithm gives better solutions than the ICS algorithm
- the harmonic search algorithm gives better solutions than the ICS algorithm.

3.25 Modified discrete shuffle frog leap algorithm

In 2014, Bhattacharjee and Sarmah introduced modified discrete shuffle frog leaping (MDSFL) algorithm to find the optimised output of the 0/1KP. In this paper, the following actions are performed:

- the experiment of the MDSFL algorithm is performed over 35 instances
- the results tell that the MDSFL algorithm results in mature convergence of discrete SFLA
- the MDSFL algorithm sometimes gets trapped in local optimum.

3.26 Hybridised cuckoo search along with improved shuffle frog leap optimisation

In 2014, Feng et al. introduced hybrid cuckoo search algorithm with improved shuffled frog leaping algorithm (ISFLA) for the 0/1KP. In this paper, the following actions are performed:

- the biased transform procedure optimises feasible solutions and repairs infeasible solutions
- the experiment of the ISFLA performed over 34 instances
- the results tell that the ISFLA has a biased transform procedure is providing feasible solutions
- differential evolution performs better than the ISFLA in solving the weakly correlated KPs.

3.27 Cohort intelligence algorithm

In 2014, Kulkarni and Shabir introduced cohort intelligence (CI) optimisation for the 0/1KP. In this paper, the following actions are performed:

- the natural tendency of a being, to learn from its environment, forms the inspiration of CI algorithm
- infeasible solutions repair themselves by learning from the feasible solutions
- the experiment of the CI algorithm is performed over 20 instances
- the results tell that for all the CI methodology produced satisfactory results with reasonable computational cost

- standard deviation and the computational cost increases with the increase in the problem size.

3.28 Binary bacterial foraging optimisation algorithm

In 2014, Niu and Bi introduced binary bacterial foraging optimisation (BBFO) algorithm for the 0/1KP. In this paper, the following actions are performed:

- the mapping function, transforms non-binary values into binary values
- the experiment of the BBFO and BBFO-LDC algorithms are performed over six instances
- the results tell that the performance of BBFO-LDC algorithm is better than BFO algorithm
- the limiting transformation parameter has to be applied with different values to reach the optimum solution for the BBFO algorithm.

3.29 Improved binary artificial fish swarm algorithm

In 2014, Azad et al. introduced improved binary artificial fish swarm algorithm (improved b-AFSA) for the 0/1KP. In this paper, the following actions are performed:

- the improved b-AFSA is works by simulating the behaviour of a fish school inside the water
- the experiment of improved b-AFSA is performed over 55 instances
- the results tell that a periodic re-initialisation of the population improves the level accuracy of the solutions
- the selection of an inappropriate penalty parameter produces unsatisfactory results.

3.30 Chemical reaction optimised with greedy search

In 2014, Truong et al. introduced improved chemical reaction optimised with greedy strategy (CROG) algorithm for the 0/1KP. In this paper, the following actions are performed:

- the nature of the chemical reactions forms the basis of the chemical reaction optimisation
- the repair operator turns infeasible results into feasible results
- the CROG experiment is performed over three problem instances
- the results tell that the new repair function of the CROG algorithm yields fast convergence and avoids the local optima
- the standard deviation from the optimum solution increases when the number of knapsack articles increase in the CROG algorithm.

3.31 Ant weight lifting algorithm

In 2013, Samanta et al. introduced ant weight lift (AWL) optimisation algorithm to find feasible solution for the 0/1KP. In this paper, the following actions are performed:

- the ants are assigned some weight capacity individually and each ant can lift weight up to the weight capacity assigned to it
- once the ant has reached the threshold of its weight capacity it can no longer collect more articles.
- the articles are collected such that the weight limit of the knapsack is satisfied
- the experiment of the AWL algorithm is performed over three problem instances
- the results tell that the increase in the number of iterations improves the performance of the AWL algorithm
- the solution produced by the AWL algorithm is a valid solution, but might not be an optimised solution.

3.32 Amoeboid organism algorithm

In 2013, Zhang et al. introduced amoeboid organism algorithm (AOA) for the 0/1KP. In this paper, the following actions are performed:

- The AOA has three main steps namely:

  Step 1 the 0/1KP is converted into a directed graph by the network converting algorithm

  Step 2 the directed graph is changed to shortest path problem

  Step 3 the AOA solves the shortest path problem and finds solution for the 0/1KP.

- The AOA experiment is performed over six problem instances.
- The shortest path problems can be solved by the AOA and the longest path problems cannot be solved by the AOA.

3.33 Binary bio-geography optimisation

In 2012, Zhao et al. introduced binary bio-geography optimisation (BBO) algorithm to yield feasible solution of the 0/1KP.

- the high habitat suitability index solutions share their features with other solutions
- the low habitat suitability index solutions accept the shared features from the other solutions
- the greedy mutation operator repairs the infeasible solutions
- the experiment of the BBO algorithm is performed over four problem instances

- the results tell that the binary mutation operator improves the global optima of the BBO algorithm
- the BBO algorithm gives higher standard deviation from the optimal solution than the genetic algorithm for one problem instance of the given experiment.

4 Technical summary of the reviewed NIO algorithms applied for solving the 0/1KP

The different NIO algorithms applied to optimise the 0/1KP are studied. The main features that are learned from this study are:

- *binarisation techniques:* the algorithms are converted into binary to solve the 0/1KP
- *local optima:* the algorithms aim to avoid trapping in the local optima
- *global optima:* the algorithms aim to attain the global optima
- *stability:* the algorithms aim to gain consistency in the optimised results
- *computation time:* the algorithms effort to decrease the computation time.
- *clustering functions:* the clustering functions are grouping methods to get the optimum solution.

Table 2 demonstrate the summary, merits, and limitations of the studied NIO algorithms.

Table 2 A summary of the instances, merits and limitations of the NIO algorithms for solving the 0/1KP

Authors	*Year*	*Instances*	*Merits*	*Limitations*
Vasquez et al.	2020	10	Machine learning binarisation techniques are fast.	Non-machine learning binarisation techniques are slow.
Hakli	2020	25	The less number of parameters simplify the BinEHO algorithm.	Improved scatter search algorithm performs better than the BinEHO algorithm.
Alzaqebah and Abu-Shareha	2019	100	The convergence of ACS algorithm with dynamic pheromone updating algorithm is faster than its base algorithm which has static pheromone update.	For some instances the static base algorithm gives better results than the dynamic pheromone updating algorithm due to the nature of the problem.
Abdel-Basset et al.	2018	52	The BFPA performs better in time and result-quality than the cohort intelligence algorithm.	The standard deviation of the BFPA is directly proportional to the problem-scale for weakly correlated instances.

Table 2 A summary of the instances, merits and limitations of the NIO algorithms for solving the 0/1KP (continued)

Authors	*Year*	*Instances*	*Merits*	*Limitations*
Wu et al.	2018	64	The GHSOS algorithm is highly recommended when the scale is very large.	The GHSOS algorithm is not recommended for small scale problems.
Zhou et al.	2018	2	The SSO algorithm provides optimum result when the problem scale is large.	The SSO algorithm applies for the large problem only.
Gao et al.	2018	14	The QWP algorithm performed better in high-dimension problems.	The QWP algorithm only obtained the global optimum 7 times out of 20 attempts.
Wang et al.	2017	25	The crossover operator converge the hybrid BPSO-GA algorithm to optima.	The hybrid BPSO-GA algorithm performed better on six instances than BPSO-GA algorithm.
Ulker and Tongur	2017	10	The MBO algorithm solves the small-scale problems fast.	The MBO algorithm could not get optimum result for large scale instances.
Han and Liu	2017	10	The GBCSO algorithm has high precision, good stability and low run time.	The time consumed by the GBCSO algorithm is greater than that of the binary particle swarm optimisation algorithm.
Rizk-Allah and Hassanien	2017	32	The improved BBA with rough set scheme algorithm has a desirable performance and the immature convergence inaccuracies of the BBA phase are mitigated, efficiently.	The standard deviation of the improved adaptive binary harmony search algorithm is lesser than V-BBA algorithm.
Cao et al.	2017	30	The BABC-DE algorithm has high fitness value and convergence speed.	The compex-valued wind driven optimisation algorithm performs better than BABC-DE algorithm for small-dimension problems.
Abdel-Basset et al.	2017b	34	The BDA has high stability and convergence.	The standard deviation increases for large-scale instances for the BDA.

Table 2 A summary of the instances, merits and limitations of the NIO algorithms for solving the 0/1KP (continued)

Authors	*Year*	*Instances*	*Merits*	*Limitations*
Feng et al.	2017	15	The OMBO algorithm has higher convergence speed and avoids the local optima.	The shuffled frog leaping algorithm performs better than the OMBO algorithm.
Abdel-Basset et al.	2017a	117	The WOA avoids local optima.	The standard deviation from the optimum solution increases when the problem-scale increases for the WOA.
Sajedi and Razavi	2016	18	The results tell that the DGSA has better results than the binary gravitational search algorithm.	The size of the population and the iteration number must be proportional to the size of the problem in the DGSA.
Feng et al.	2016b	15	The results tell that the chaotic map and Gaussian perturbation significantly improve the solution quality in the CMBO algorithm.	The shuffled frog leaping algorithm gives higher optimum values than CMBO algorithm.
Zhou et al.	2016	30	The results tell that the CWDO algorithm is stable and highly accurate.	The standard deviation of the CWDO algorithm is more for the test instance f19.
Feng et al.	2016a	36	The results tell that the hybrid CSGHS algorithm has high search accuracy and convergence speed.	The shuffled frog leaping algorithm is more stable than hybrid CSGHS algorithm.
Feng et al.	2015	28	The results tell that the BMBO algorithm has better stability than genetic algorithm.	The binary cuckoo search algorithm gives higher optimum values than BMBO algorithm.
Zhou et al.	2015	69	The somersault process is modified to avoid falling into local search, the cooperation process increases the convergence rate and the control parameter maintains population diversity.	The simplified binary-artificial fish swarm algorithm performs better than IMA.
Umbarkar et al.	2015	3	The hybrid TLBO-GA did better in one instance than simple genetic algorithm.	The hybrid TLBO-GA performed sub-optimum in two instances than simple genetic algorithm.

Table 2 A summary of the instances, merits and limitations of the NIO algorithms for solving the 0/1KP (continued)

Authors	*Year*	*Instances*	*Merits*	*Limitations*
Tuo et al.	2014	13	The HSTL algorithm is constant to optimise the solutions.	The HSTL algorithm has more parameters.
Feng et al.	2014a	20	The HS algorithm gives better solutions than the ICS algorithm.	The harmonic search algorithm gives better solutions than the ICS algorithm.
Bhattacharjee and Sarmah	2014	35	The MDSFL algorithm has strong capability of preventing premature convergence of the discrete SFLA.	The MDSFL algorithm traps within a local optimum point for some time.
Feng et al.	2014b	34	The ISFLA uses a greedy transform method to assure the feasibility of the solutions.	The differential evolution performs better than the ISFLA in solving the weakly correlated KP.
Kulkarni and Shabir	2014	20	The CI methodology produced satisfactory result with reasonable computing cost.	With the increase in the problem size, the standard deviation cum the computing cost increases.
Niu and Bi	2014	6	The BBFO-LDC algorithm is better than the BFO algorithm.	The limiting transformation parameter has to be applied with different values to reach the optimum solution for the BBFO algorithm.
Azad et al.	2014	55	A periodic re-initialisation of the population optimises the solutions and improved b-AFSA consistency.	An inappropriate penalty parameter results in non-optimised performance of the improved b-AFSA.
Truong et al.	2013	3	The new repair function of the CROG algorithm yields fast convergence and avoids the local optima.	The standard deviation from the optimum solution increases when the number of knapsack articles increase in the CROG algorithm.
Samanta et al.	2013	3	The increment in the number of iterations improves the quality of the result for the AWL algorithm.	A solution produced by the AWL algorithm is a valid solution but may not be an optimised solution.

Table 2 A summary of the instances, merits and limitations of the NIO algorithms for solving the 0/1KP (continued)

Authors	*Year*	*Instances*	*Merits*	*Limitations*
Zhang et al.	2013	6	The shortest path problems can be solved by the AOA.	The longest path problems cannot be solved by the AOA.
Zhao et al.	2012	4	The binary mutation operator improves the exploration ability of the binary BBO algorithm.	The binary BBO algorithm gives higher standard deviation from the optimal solution than the genetic algorithm for one problem instance of the given experiment.

5 Conclusions

The researchers have devised meta-heuristic techniques, to solve NP-hard problems. Meta-heuristic techniques, explore the search space, to improve the feasibility of the solution. The NP-hard problems are those problems that have no fixed solution. Therefore different algorithms when applied to the NP-hard problems, yield different results. The 0/1 knapsack problem is NP-hard, it can be used for situations where, a choice of selection has to be made. The review informs the readers about the various nature-inspired optimisation algorithms (NIOs) that are meta-heuristic and easy to implement, for optimising the 0/1KP. The review also presents the number of solved instances, merits and limitations of the NIOs for optimising the 0/1KP. It is concluded from this study that still there is requirement of better approaches for solving the 0/1KP. In future, various other recent strategies may be applied to solve 0/1KP.

This review creates a base for further research and provides a direction to the future researchers. In future, the optimisation of the 0/1KP using untouched NIOs and the available significant modifications of the NIOs may be experimented. Further, a modified 0/1KP may also be designed for the better execution.

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