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REVIEW OF ACO ALGORITHM ON NETWORK AND SCHEDULING PROBLEM

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Abstract: The ant colony optimization algorithm is based on the behaviour of real ants. This algorithm was introduced in the 1990s with the aim of finding solutions to problems which simulates the decision-making processes through the use of ants artificial. This paper provides an overview of some of the previous studies and research progress on the traditional and specialized applications of the ACO algorithm towards scheduling and network problems, such as oil pipelines, water distribution system, and natural gas pipelines.

Keywords: ant colony optimization, network problem, scheduling problem, metaheuristic.

I. INTRODUCTION

ACO algorithm was first introduced by an Italian researcher, Marco Dorigo in 1992 in his Ph.D. thesis[1]. He used ACO for the first time to solve the travelling salesman problem (TSP). The algorithm was then developed and applied to solve many other problems such as vehicle routing problem (VRP)[2, 13], quadratic assignment problem (QAP) [3], scheduling problem[4,12], data encoding in telecommunication systems [5], garbage collection[6], mapping problems [7], network model problem [8], graph coloring problems [9], personal placement in airline companies [10] as well as job-shop problem [11]. Besides that, it has been successfully applied in finding the best solution for the complex problem in life such as the design of large communication networks, the scheduling of traffic in major cities and creating the ideal locations and stores of energy plants [12].There are also recent applications such as the development of emerging cells in the design of electronic circuits [13], the design of communication networks [14], and the problems of bioinformatics[9]. In recent years, some researchers have also focused on the application of ACO algorithms on multi-objective problems as well as dynamic or random problems, especially in the field of informatics and the field of biomedical applications such as protein folding [15] and multiple sequence alignment [16].

The ACO algorithm is an evolutionary learning algorithm that relies on observing ants behavior and can be applied to solve combinational optimization problems which categorizes into an NP-Complete problem [17]. The ant colony algorithm is an algorithm for finding optimal paths that are based on the behavior of ants searching for food. At first, the ants wander randomly. When an ant finds a source of food, it walks back to the colony leaving pheromones that shows the path of the food[9]. Ants are naturally able to find the shortest route from food sources to the nest, where they leave the chemical pheromone on the ground which serves as a guide to the rest of the ants to find the food. The choice of the path depends on the density of the pheromone [18], so the behavior of the ants stimulate the emergence of an algorithm which consists of a group of artificial ants as a group of agents. The selection of the path depends on the density of the pheromone[19]. Following from there, this motivates the investigation of developing an algorithm which produces good quality solutions across different instances and problems which do not require extensive parameter tuning. This choice is governed by the following steps, as described in [22]:

(a) Real ants follow a path between the nest and the food source.
(b) An obstacle appears on the path: ants choose whether to turn left or right with equal probability.
(c) Pheromone is deposited more quickly on the shorter path.
(d) All ants have chosen the shorter path.

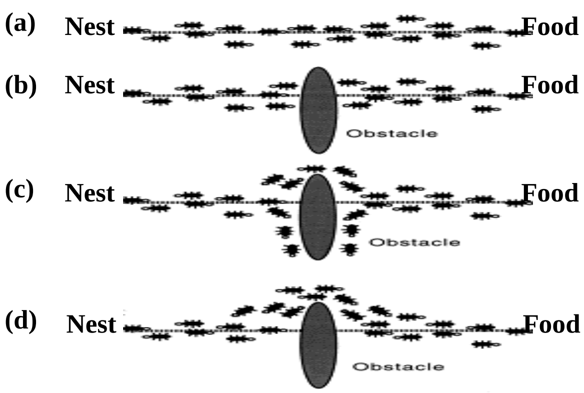

Fig.1: Behavior of ants [20]

Theorem. Let $p*(t)$ be the probability that ACO bs, τ_{min} (the best-so-far solution is used to update pheromones and that a lower limit) finds an optimal solution at least once within the first t iterations. Then, for an arbitrarily small $\varepsilon >$ 0 and for a sufficiently large t it holds that $p*(t) \geq 1-\varepsilon$, and asymptotically

$$lim_{t\to\infty}\, p*(t) = 1. \quad (1)$$

Proof. The proof of this theorem consists in showing that, because of $\tau_{min} > 0$, at each algorithm iteration any generic solution, including any optimal solution, can be generated with a probability greater than zero. Therefore, by choosing a sufficiently large number of iterations, the probability of generating any solution, and in particular an optimal one, can be made arbitrarily close to 1 [21][22].

II. APPLICATION OF ACO ALGORITHM IN NETWORK PROBLEM

This paper focuses on the application of ACO approach in the area of network and scheduling problem. The network problem discussed in this paper involves crude oil pipeline network, gas pipeline network, water pipeline network, travelling salesman problem and vehicle routing problem.

A. Scheduling of Refined Products in a Pipelines

The transfer of refined products is more efficient by using multi-product pipelines which is important in energy supply chain. A nonlinear programming model for a virtual and universal pipeline with one source and multi pumping stations was established to demonstrate the convergence, stability and scientific scope using the simplex methods and ACO algorithm. The latter showed a stable and compatible model in the problem of scheduling the injection of many types of products [23]. Also, the problem of pipeline scheduling of refined products sometime takes a long time to develop a plan for scheduling. Zhigang et al. (2016)[24] introduced a nonlinear programming model using the heuristic algorithms for refined products of single source as well as multiple stations and application on a realistic pipeline which starts from Mao and ends at Da Li in western China, where the time taken for the model is 31.70s and corresponds to the real state of the field.

Crude Oil Pipelines Network

The pipeline industry grew rapidly following the development of the electrically welded electrode tube in the 1920s. This tube is stronger than the previous species, and can transport materials at higher pressures and, therefore, in larger quantities. The pipeline helped gas and oil companies to build economically viable pipelines with a length of more than 1,600 km. At present, these pipelines transport oil and gas from major production areas to refineries and distribution centers.

The most common arrangement is finding the briefest way from a fixed origin Vi to a specified vertex Vj in a graph. As a rule, the total cost in the life expectancy for pipelines is the main issue for optimal design to the pipelines problem, hence the briefest way from the source vertex to the terminal vertex compares to the base total cost for the pipeline system. At the same time, the planner hopes to get a little of the process programs, which could be utilized in decision making. This is the reason why researchers see the design of the oil and gas pipelines as a complex engineering task. These pipelines span long distances, transports large quantities of oil and gas, and that any improvement in the design even if minor, will result in substantial savings in total cost [25].

Oil pipelines extend may be of short distances, for example one mile or may be extended to a distance of more than 1,000 miles. The transmission and distribution pipelines range in a diameter of between 8-24 inches or up to 48 inches. These pipelines may be of simple connecting from one source to one destination or complex connecting from multiple sources to multiple destinations. All the major oil pipelines, which represent the transmission and distribution pipelines, are buried underground except for the gathering pipelines that remains above the ground [26].

Distribution networks consist of pipelines, tankers, ships and railways that transport refined petroleum products such as liquid gas, gasoline, jet fuel and heating oil, as well as large storage tanks for these products. These pipelines have several entry and exit points. The main objective is to ensure that the product is delivered to the customer in a timely manner, where they considered pipelines as the safest and least expensive method.

Cafaro and Cerda, (2010) [27] proposed the formula of Mixed Integer Linear Programming (MILP) which is a continuous operational scheduling of one-way pipes that allows simultaneous injection of payments to provide warehouse requirements at the lowest total cost including backorder expenses. It has been selected as a problem target through an optimal schedule of all product pumping and delivery operations at one time. The results showed the best capacity of the transport pipelines which reduces the time acquired to inject the required payments to the warehouse and thus the MINLP model often achieves the best pipelines schedules.

Diverse kinds of methodologies were proposed to handle the single-source pipeline scheduling issues such as knowledge-based heuristic techniques including rigorous optimization models [28], decomposition frameworks [29], as well as discrete event simulation tools [30]. Rigorous optimization methods generally consist of solving a single MILP or MINLP mathematical model and are usually grouped into two classes: discrete or continuous, depending on the way the volume and time domains are handled. Discrete MILP-definitions isolate both pipeline volumes into countless item packs, and the arranging skyline into time interims of equivalent and settled length [31], [32], [33]. As a result, flow-rate variations due to the changes in pipeline diameter cannot be handled.

Wang, (2015) [34] used an ant colony algorithm and genetic algorithm to establish a multi-objective programming model to improve the transmission networks of China's crude oil imports. The result showed that the very large crude carrier (VLCC) is less secure than the pipeline transport but is superior in long-haul crude oil transport. Taking this into consideration, multilayered networks should be established to transport crude oil imports, and to enhance land transport to reduce the environmental damage that may arise from seaborne transportation.

Razavi, (2010) [35] used improved ACO algorithm, known as continuous ant colony algorithm (CACO), for multidimensional optimization. This algorithm has been successfully applied on three examples with different degrees of complexities in improving the petroleum engineering and estimating continuous parameters to solve process improvement regarding problems in petroleum engineering. The objectives are as follows: to determine an optimum number of phase separators and separators pressure in the oil industry, parameter estimation in history matching problem in petroleum reservoirs, as well as maximizing cumulative oil production. The results show the ability of the ACO algorithm in providing accurate and fast solutions.

B. *Gas Pipelines Network*

Rothfarb and Goldstein (1970) [36]ponders the ideal plan of seaward flammable gas pipeline frameworks where three issues were examined. Firstly, the choice of ideal distances across a given pipeline; second is the structure of an ideal pipeline framework given the gas-field areas and conveyance prerequisites; while the third is the ideal extension of a current pipeline arrangement. The system is expected to have a tree (or arborescence). Stream of gas in a pipe is represented by the nonlinear weight drop requirements, with most extreme and least weights applying. The expense of a blower relies upon the way from the conveyance hub to the point of most prominent weight.

In the previous study by Arya & Honwad, (2017)[37] in solving the multiobjective gas pipeline transportation problem, a multi-objective ACO technique for pipeline optimization has been developed. The multi-objective of the problem is to minimize fuel consumption in compressors as well as to maximize the production. For validation of the technique used, it has been applied on some test problems reported in the literature. After validation, the technique has then been implemented in the gas pipeline transportation problem where an eighteen-node gas pipeline networks has been taken for analysis. The result obtained supports the industrial practice of maximizing the cost of an increase in fuel consumption in compressors.

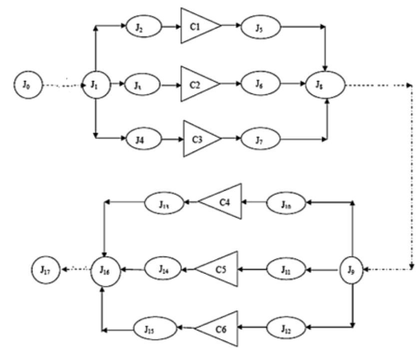

Fig. 2: Gas pipeline network [37]

Another study by Mikolajkova (2018)[38], proposed a mixed integer linear programming model with the aim to improve the regional natural gas chains for those areas that cannot be supplied with natural gas through transport pipelines. The results show the role of the cost of the local and alternative fuels and the price margins at which it is achievable to fabricate a pipeline organize as opposed to providing the fuel by trucks to stockpiles associated with pipeline islands. The findings also give support to the decision maker in the energy sector leading to the optimal design of the gas supply chain.

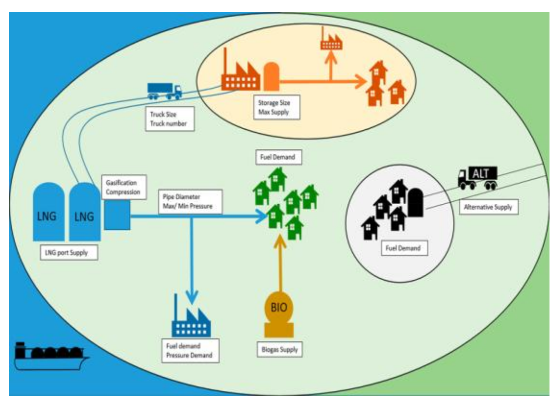

Fig. 3: Scheme of the pipeline and truck transportation of the gas in a local network [38].

Chebouba, (2006)[39]improved the ant colony optimization algorithm by hybridizing it with the genetic algorithm to run the natural gas pipeline efficiently and stable as well as to compare the results with the dynamic programming technique to reduce the amount of gas consumed as fuel to run the pressure stations located on the natural gas pipeline which connects two cities in Algeria. The results showed a remarkable performance of the hybrid algorithm compared to the linear programming with a shorter computation of time.

C. Water Pipelines Network

The first historic pipeline was built as part of the water distribution network (WDN) in ancient Rome. It was more than 612 km long and probably transported about 1,200,000,000 liters of water per day. This pipeline was built in such a way to allow gravity to transfer water in the distribution system. In 1582, the first pumps for pipelines were installed in the London City water system, while in the 19th century, pipelines began to become an important part of water distribution systems in many industrialized countries.

In the past century, the use of algorithms as an evolutionary method of operation and optimization of WDN such as genetic algorithm has been observed[40]. The ACO algorithm was developed for the optimal design of WDN and its results were compared with the results of the genetic algorithm. The ACO algorithm was considered an alternative to the GA algorithm in terms of finding optimal solutions and computational efficiency [41].

Improvement of the water distribution network using the ACO algorithm were achieved since this algorithm has a good research capability and can meet the engineering requirements by avoiding the appearance of the pipeline diameter that does not meet the purpose. The results show that the ACO algorithm is capable of meeting the engineering requirements of the optimal design of the water distribution system[42]. Note that, the water distribution network plays an important role in improving people's livelihood and ensuring the economic construction. Because of the longer period and higher investment to pay for the investment in the WDN, the reasonable design and operation of the WDN directly affects the project’s investment, operating and management costs, as well as the system’s stability. The optimal design of the water distribution system is vital to provide investment, reduce energy consumption, as well as to enhance monetary and social advantages[43].

Besides that, Holger (2004)[44]used ACO algorithm to improve the water distribution system (WDS) of a 14-pipes network used by Simpson et al. (1994), and compared the results with the GA algorithm. The results indicated that the ACO algorithm is better in reaching the optimal solution in terms of the number of appropriate assessments for the optimal design of the water distribution network.

Apart from that, Maroua (2018)[45] proposed hybridization of the ACO algorithm with the K-means algorithm, called K-ACO algorithm to improve water distribution networks. The aim was to ensure that water distribution networks increase its life-span, as well as detecting hydraulic faults that can occur through industrial wireless sensor networks (IWDN) systems.

The work of the hybrid algorithm is divided into two parts. Firstly, a WDN is divided into five groups of 80 sensors, while secondly, the ACO algorithm defines the shortest distance between the sensors and ensures the least amount of energy consumption to improve the WDN.

In the past decade, numerous researchers have completed broad perspectives into the planning issue of water distribution network. One of these evolutionary algorithms was the particle swarm optimization (PSO) that was applied to the WDN which regulates the variation of the speed round to fit the discrete pipe diameter for Hanoi water distribution network and the New York City water supply tunnel system [46].

D. Travelling Salesman Problems

The travelling salesman problem is one of the best-known NP-hard problems. The best known exact methods for solving TSP are dynamic programming, branch and bound method, implicit enumeration, explicit enumeration, and cutting plane method. These methods provide the best optimal solutions when the numbers of the nodes are between 40-80 nodes. As for the heuristic methods, particle swarm optimization, ant colony optimization, genetic algorithms, differential evolution, etc. are the evolutionary algorithms inspired by nature[47].

Dorigo and colleagues developed an ant colony system for solving the travelling salesman problem in 1991[48]. Ant colony optimization algorithms have been used to produce near-optimal solutions to the traveling salesman problem. The first ACO algorithm known as the Ant system, aimed to solve the travelling salesman problem where Dorigo developed a relatively simple algorithm to find the shortest path in a series of cities. The general algorithm is relatively simple and based on a set of ants, each making one of the possible round-trips along the cities. At each stage, the ant chooses to move from one city to another according to some rules given by:

1. It must visit each city exactly once;
2. A distant city has less chance of being chosen (the visibility);
3. The more intense the pheromone trail laid out on an edge between two cities; the greater the probability that that edge will be chosen;
4. Having completed its journey, the ant deposits more pheromones on all edges it traversed, if the journey is short;
5. After each iteration, trails of pheromones evaporate.

One of the exploratory methods of the ACO algorithm is Max-Min ant system (MMAS). It was used as an application to solve the 3D travelling salesman problem on a sphere to find the optimized time-cost. The result shows that ACO’s average results were better than the Discrete Cuckoo Search Algorithm (DCS) and GA’s average results [49].

Apart from that, in 2008, Bountoux and Feillet[50]proposed a hybrid algorithm consisting of an ACO algorithm and local search to solve TSP problem called the dynamic multi-dimensional anamorphic travelling ant (DMD-ATA).Results show the efficiency of the algorithm, which allows the finding of a large set of new best known solutions.

In addition, in 2006, Pasti and Castro[51], used a meta-heuristics for solving TSP based on a neutral network trained using ideas from the immune system. The network was self-organized and the learning algorithm aims at locating one network cell at each position of a city to be solved. This algorithm is known as the real-valued antibody network (RABNET).The results refer to the exponential growth of the processing time and a number of iterations for convergence in relation to the number of cities which requires further investigation; and modifies the algorithm to solve other types of combinatorial optimization problems such as the multiple travelling salesman problem and capacitated vehicle-routing, etc.

Apart from that, in 2007, Cheng and Mao[52]developed a modified ant algorithm known as the ant colony system travelling salesman problem with time windows (ACS-TSPTW) based on the ACO technique to solve the TSP. The results showed that ACS-Time failed to determine feasible solutions for five cases of this problem, while ACS-TSPTW found feasible solutions for four of the five cases. In addition, ACS-TSPTW outperforms ACS-Time in six problems and obtains an equivalent performance as ACS-Time in seven problems. The overall performance of ACS-TSPTW is better than ACS-Time in seventeen out of the thirty-one problem instances. The lower bound results have shown that ACS-TSPTW obtains the optimum solution in three of the problem instances.

Also, Dong et al., (2012) [53] proposed a new hierarchic model of swarm intelligence algorithms to solve TSP, which combines both GA and ACO together in a cooperative manner called Cooperative Genetic Ant System (CGAS) to improve the performance of ACO. The results of simulation shows that CGAS has a better performance from other GA and ACO algorithms for solving TSP in terms of consistency and capability of achieving the optimal solution, and quality of average optimal solutions, particularly with respect to TSP problems.

Meanwhile, Gunduz and Kiran, (2015) [54]proposed a new hierarchic model of swarm intelligence algorithm to solve the TSP problem. The swarm intelligence algorithm used in their study was divided into two types as path improvement and path construction based method. The path construction based on ACO algorithm produced better solutions but took more time to achieve a good solution. Meanwhile, the path improvement based on artificial bee colony technique quickly produced results but did not achieve a good solution in a reasonable time. Therefore, their hierarchic method which consists of ant colony optimization - artificial bee colony (ACO-ABC) was proposed to achieve a good solution in a reasonable time. ACO was used to provide better initial solution for ABC that uses path improvement technique in order to achieve optimal or near optimal solution.

E. Vehicle Routing Problem (VRP)

The VRP formulation was first introduced by Dantzig and Ramser in 1959 as a generalization of the Travelling Salesman Problem (TSP) presented by Flood [55]. Pillac, et al., [2] believed that dynamic routing offers other concepts such as productivity and service or profit. Other important concepts were such as the response time. Customers may request for services with as little time as possible. Dynamic routing is designed to reduce the delay between the time of the demand and the arrival time.

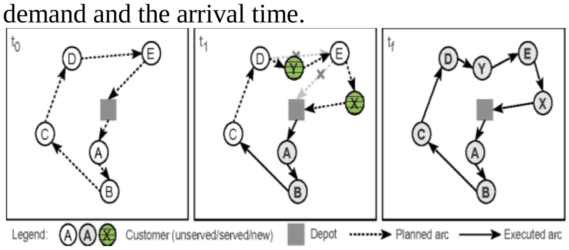

Fig. 4: Example of dynamic vehicle routing [2].

Previous studies of the VRP focused on creating a multi-objective model with a time window including the cost of fixed vehicles, operating cost, loss of lifespan and default cost. This was mentioned by researchers in their study where they applied generation of ACO with ABC customers' classification strategy to solve the problem. The computational results show that the ACO with targeted customer classification is 20.8 % faster and with 5.9% cost reduction [56].

The VRP is a kind of NP-hard problem applied in many areas of communication, logistics, manufacturing, transportation, and others. The traditional VRP problem consists of using a group of vehicles in a single warehouse to meet the client's request for a particular commodity in delivering the goods to customers [57].Different heuristic algorithms have been proposed for achieving great solutions in sensible running time, but not necessarily the optimal solution. These algorithms include the ACO [58][59], tabu search (TS) [60], simulated annealing (SA) [61], and genetic algorithm (GA)[62][63].

In terms of exact algorithms, Arunapuram et al., (2003)[64] proposed an exact algorithm for solving the full truckload vehicle routing problem (FTVRP). The authors introduced a column generation method that takes advantage of the special structure of the linear programming sub-problems at the nodes of the branch-and-bound tree. The algorithm also took into consideration the time-window constraints and waiting costs. However, the exact algorithm is unable to solve the instances when the number of lanes exceeds 200.

Apart from that, Liu, et al., (2010)[65]utilized an assignment choice and directing issue in which a truck-load bearer undertook from shippers and different partners has to make a choice between a private vehicle or an outside transporter to serve each errand. The authors build up a memetic algorithm (MA) to solve the issue, where the computational results show that the proposed algorithm is effective and yield better results in a shorter time.

In addition, Sun, (2012)[66]proposed an adaptive PSO algorithm and GA algorithm with near neighbor interactions to solve it with a variant of the full truckload vehicle routing problem(FTVRP) in which vehicles were not required to return to the depot after they finish their task. The computational results demonstrated that the proposed algorithm is effective and feasible.

Also, Li & Lu (2014)[67]proposed a hybrid genetic algorithm to solve FTVRP in which there are more than one delivery points corresponding to the same pickup point, where one order is allowed to be served several times by the same vehicle, or different vehicles. Computational outcomes demonstrated that the genetic algorithm dependent on the improved sweep algorithm is a superior technique to solve this issue.

Besides that, Karim and Adil (2017) [68] was the first to propose the ACO approach to solve the full-truck load selective multi depot vehicle routing problem at time windows constraints (FT-SMDVRPTW). The motivation was based on using ACO algorithm metaheuristic for constructing the sets of routes related to the trucks while expanding the increased profit, which was implemented for solving the basic vehicle routing problem FT-SMDVRPTW and modified the algorithm to incorporate a robust optimization methodology. Results show that the proposed approach may obtain a high quality solution within a short period of computational time.

III. Application of ACO algorithm in scheduling problem

This paper highlights the scheduling problem which consists of transportation scheduling, overhauling gas turbine engines, train routing and timetabling problem. Modern facilities for different products consist of assembly units and a number of parts that may reach thousands or tens of thousands which require a special approach to regulate the production process in a limited time and at the lowest cost.

Various optimization techniques and metaheuristic techniques have been used to optimize the production scheduling where ACO algorithm is one of the metaheuristic techniques that has been used to solve the problem of multi-objective in manufacturing company. The problem of scheduling production in mathematical terms is a problem with multiple and somewhat complex solutions. An approximate solution can be found by heuristics, Monte Carlo method or solved by exact method such as Gomory's cut and mathematical programming [69]. The main optimality criteria are readjustment time minimization [70], total throughput time minimization [71], the minimum cost of schedule execution criteria [72], and etc. The optimum production schedule searching can be performed using dynamic programming, linear programming, evolutionary or combinatorial algorithms [73].The results of the analysis of multi-objective optimization algorithms and the current methods were to obtain the best solutions to real production problems in a relatively short time with the modification of the ant algorithm to enhance the best tracks found.

Jiang, (2017) [74]developed the production scheduling of oil refinery by using the disadvantages and advantages of ant colony algorithm. Since the ant colony algorithm has many advantages in solving combinatorial optimization problems, it is commonly used in commercial, academic, and industrial fields. Paying attention to the production of the oil refinery introduces the advantages of ant colony algorithm which is then used to optimize the traditional scheduling method to make the oil refinery satisfy the market demand, and save production costs. It can also improve the technology and increase the economic efficiency and management level.

The Artificial Bee Colony algorithm (ABC) was applied to solve the Flexible Job-Shop Scheduling Problem (FJSP) on the basis of the criteria of reducing the maximum total completion time [79]. The proposed algorithm focused on balancing the global exploration with the local exploitation, one of the stages of the algorithm, by focusing on several stages in reaching the final solution. In the first stage, several strategies have been incorporated to generate the first quality and diversified solution based on the method of searching for food sources of bees. In the second stage, the machines are assigned, and the sequences of operations are determined by designing a research tool to generate new adjacent food sources for the artificial worker bees. In the third phase, a local (primary) research strategy based on the critical path, which was incorporated into the framework of the research, was proposed with a view to develop the focus of control bees. In the meantime, a mechanism was proposed to modernize the population through the generation of bee's explorer in order to enhance the research behavior and to avoid inappropriate convergence in algorithm solutions, through a multi-stage approach and strategies to solve FJSP problems. The results were then compared with simulated tests of other techniques such as particle swarm optimization (PSO) (Ho et al., 2007)[75], Tabu Search technology [76], simulated annealing (SA) [76], and genetic algorithm (GA) [77]. The proposed algorithm has proven to provide more efficient and robust solutions [78].

It is important for cloud users to provide effective task scheduling technology as cloud computing relies on the expected pricing model [79]as well as to end the cloud user's tasks as quickly as possible in cloud computing environments (Motavaselalhagh et al., 2015)[80]. SACO algorithm with slave ants is a novel ACO algorithm that produce timetable assignments of cloud clients to virtual machines (VMs) in cloud computing environments in an efficient manner by avoiding long pathways, and solves the NP hard problems in an effective way [18].

A new approach to the ACO algorithm was proposed to solve the resource-constrained project scheduling problems, such as single machine tardiness, flow-shop, and job-shop, using two methods of pheromone evaluation to find the best solutions. The results showed the efficiency of the proposed algorithm with some changes in the performance's evaluation[81].

A. Supply Chain Management in Transportation Scheduling problem

Supply chain management (SCM) has become a potentially valuable way of securing competitive advantages and improving organizational performance in a highly competitive market[82]. In a supply chain management, supply, schedule plan, logistics, and demand are the four interrelated and inseparable elements. The management effect of SCM mainly depends on the important element which is the scheduling of vehicle transport times. The transportation vehicle scheduling problem in SCM has been widely discussed by numerous researchers and practitioners.

Researchers have attempted to study different transportation problem with various algorithms. For example, Schyns (2015)[83], Mavrovouniotis & Yang (2015)[84]and Kuo et al. (2016)[85] studied the dynamic vehicle routing problem (DVRP) with different constraints and proposed an improved algorithm based on Tabu Search and ACO, respectively. Also, Ardjmand, et al. (2015)[86], Escobar, et al. (2014)[87] and Ardjmand, et al. (2016)[14] used genetic algorithm and TS algorithm to research on the location-routing problem (LRP). Apart from that, Kalayci & Kaya, (2016)[88] as well as Zhou, et al. (2016)[89]used a hybrid algorithm by combining local search and genetic algorithm to solve VRP with simultaneous delivery and pickup. Also, Schweiger & Sahamie (2013) [91] and Lin, et al. (2015)[16] addressed the reverse logistics network design problem. Other types of transportation vehicle scheduling problems had also been widely discussed by a number of researchers (see for example [92][93][94][95][96][97][98][99].

B. *Overhauling Gas Turbine Engines*

In the late 1970s,a diagnosis was given for the performances of gas turbines by isolating and evaluating the changes in the performance of the engine unit, engine faults, the problems of the devices, and the knowledge of the parameters measured along the path of the gas in the engine [100].

Note that, changes in the engine speed are required to determine the fundamental change in the engine's operation. This is done by using the Kalman filter to estimate multiple engine errors at the same time. In the past decade, artificial neural networks (ANN) have been used as a device to identify the same errors with the Kalman filter and the two methods have shown an acceptable success[101].

Furthermore, some researchers have addressed the problem of median filter weight optimization where algorithms for calculating the integer weights of weighted median filters were proposed[102]. Both recursive and non-recursive filters were considered but the study focused on center weights. A numerical approach for the optimization of recursive median filters was presented in the study of [103]. They found that higher integer weights led to duplication in the filter and low integer space was sufficient for the given problem. Filter design spaces can often be multimodal which means that there can be more than one minimum point. Therefore, the gradient-based numerical optimization can settle into a local minimum point. To address this issue, the use of global optimization methods in filter design has grown substantially. Also, particle swarm optimization was used to solve the parameter estimation problem of nonlinear dynamic rational filters [104]. Besides that, genetic algorithms have also been used for optimizing stack filters using a root mean square error (RMSE) approach.

On the other hand, ACO was used for the design of infinite impulse response (IIR) filters [105]. Since the error surface of IIR filters are generally multimodal, global optimization methods such as ACO are well suited for their design. ACO is a relatively new approach in solving combinatorial optimization problems. Note that a heuristic method is an approach to solve problems that employ a practical method which is not guaranteed to be optimal or perfect, but sufficient for the immediate goals. Heuristics are often treated as rules of thumb or educated guesses. Since ACO is a heuristic method, it provides satisfactory solutions, unfortunately these solutions may not prove to be optimal and the convergence of such methods cannot be guaranteed. Raikar & Ganguli (2017)[105]in their paper addressed the problem of finding the integer weights of weighted recursive median (WRM) filters using ACO. The algorithm is demonstrated for signals simulating jet engine single (abrupt) and gradual faults. The WRM filter is demonstrated for abrupt and gradual faults in gas turbines and is found to yield noise reduction of 52–64 % for simulated noisy signals considered in the paper.

C. *Train routing problem and timetabling*

Railways play a major role in transporting passengers and cargoes in many countries in the world, especially in the last fifty years. Many methods have been developed to solve the problems of train tracks such as the linear programming, simulation and meta-algorithms. At present, evolutionary algorithms have been applied on different types of scheduling, routing and timing with good results obtained[106][107][108].

Railway traffic activities have been steadily increasing in the most recent decades. Railroad foundation chiefs need to confront this ever increasing request guaranteeing a good quality of administration. This, added to the restricted space and assets accessible to construct a new framework in bottleneck zones, has invigorated lately the advancement of productive routes for enhancing the dependability of the activity. This dependability comprises in the ability to run trains following a predefined plan. Ordinarily, a various leveled basic leadership approach is embraced when arranging railroad tasks, bringing about a progression of tractable issues for which man-made brainpower and activities look into methodologies that have been proposed. These issues can be gathered in three dimensions: vital, strategic and operational[109].

Railways may face unanticipated emergency problems such as an increase in the number of passengers or strong winds that hinder train traffic. An anticipation of these problems must be dealt with seriously and effectively, so that the real-time railway traffic management problem (rtRTM) achieves to schedule methods and routing tracks in order to reduce the delay that may occur. The rtRTM problem is affected by the number of alternative routes available for each train. The ACO algorithm is used to solve the train routing selection problem (TRSP) system at two levels. The Tactical Level depends on data and time of calculation, while the Operational level depends on the traffic with a specific calculation time. The results showed that the performance of ACO-TRSP is more effective compared to the other proposed techniques, so the implementation of ACO algorithm on TRSP allows improvement of the performance to (rtRTM)problem [110].

In the previous related literature, the real-time train routing selection problem is formulated as an integer linear programming formulation solved via an algorithm inspired by the ant colonies behavior [97]. This problem is solved starting from a subset of routing alternatives and computing the near-optimal solution of the simplified routing problem [97]. They studied on how to select the best subset of routing alternatives for each train among all possible alternatives to improve the state of the art in terms of the minimization of train consecutive delays.

Apart from that, railway rolling stock planning is a basic schedule in railway transport, which assigns physical train units to a given timetable services and determines a roster of the train units [8]. This planning also involves a scheduling of periodical inspection for the train units. They proposed ACO based approach to solve this planning problem. A study by Gholami & Sotskov, (2012)[111]solved the problem of the train schedule, in which genetic algorithm was developed to guide and schedule trains to achieve an effective timetable and trajectories which may reduce train delays in the transmission from source to destination. Many countries in the world have only one railway route, connecting two consecutive stations, where one train can move from station No. 1 to station No. 2 while the train remains at station No. 2 waiting for the arrival of the train from Station No. 1 and vice versa. This delay causes an increase in fuel consumption and material losses to the railway company.

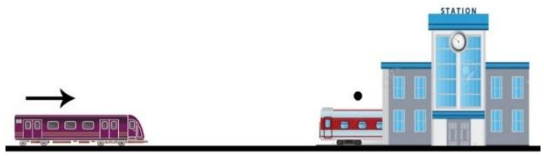

Fig. 5: Case of a train delay arising in a single-road railway. [111]

Tormos et al., (2008)[112]used GA for timetabling to optimize the new trains on a railway line, which is working or not working, on other trains with fixed timetables. The schedule for the new trains is obtained using GA that includes a guided process to build the initial population. Vincent and Minlong,(2009)[113] proposed a simulation strategy in light of the GA to solve the speed railroad timetabling issue. A two-row table is made, where the first row represents the type of the train while the second row represents the departure time of the train, and the number of columns in the table is the same as the number of trains to be scheduled.

Apart from that, Wegele & Schnieder, (2004)[114] suggested an algorithm to construct a timetable using a branch-and-bound algorithm developed to obtain an initial solution where a GA has been used to improve the current solution iteratively. The goal of this issue was to minimize the annoyance to passengers. An innovative GA to construct a feasible train timetable in terms of a train order was introduced by Liu & Kozan, (2011)[115]. In particular, the proposed algorithm comprises of several recursively used procedures like blocking-time-determination, best-starting-time determination, conflict checking procedure, tune-up procedure, conflict-eliminating procedure, as well as fine-tune procedure to ensure the plausibility of a timetable by fulfilling the blocking, no-wait, deadlock-free, and conflict-free constraints.

IV. Conclusion

This paper reviews the introduction of the ACO algorithm, some applications, and research progress related to the work of this algorithm which focuses on the applications on pipeline networks (oil, gas, and water), as well as their applications in scheduling problems (transportation scheduling problem, job-shop scheduling problem, overhauling gas turbine engines, as well as train routing problem and timetabling). The ACO algorithm approach is capable of finding the near optimal solution for improving the oil, gas and water line networks as well as improving scheduling problems but sometimes require a longer computing time when dealing with big data. Future work may be carried out focusing on the recommendation of hybrid ACO with other algorithms strategy that combines two or more algorithms to produce less computing time with high-performance efficiency.

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