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Systematic Literature Review Of Particle Swarm Optimization Implementation For Time-Dependent Vehicle Routing Problem

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ABSTRACT

Time-dependent VRP (TDVRP) is one of the three VRP variants that have not been widely explored in research in the field of operational research, while Particle Swarm Optimization (PSO) is an optimization algorithm in the field of operational research that uses many variables in its application. There is much research conducted about TDVRP, but few of them discuss PSO's implementation. This article presented as a literature review which aimed to find a research gap about implementation of PSO to resolve TDVRP cases. The research was conducted in five stages. The first stage, a review protocol defined in the form of research questions and methods to perform the review. The second stage is references searching. The third stage is screening the search result. The fourth stage is extracting data from references based on research questions. The fifth stage is reporting the study literature results. The results obtained from the screening process were 37 eligible reference articles, from 172 search results articles. The results of extraction and analysis of 37 reference articles show that research on TDVRP discusses the duration of travel time between 2 locations. The route optimization parameter is determined from the cost of the trip, including the total distance traveled, the total travel time, the number of routes, and the number used vehicles. The datasets that are used in research consist of 2 types, real-world datasets and simulation datasets. Solomon Benchmark is a simulation dataset that is widely used in the case of TDVRP. Research on PSO in the TDVRP case is dominated by the discussion of modifications to determine random values of PSO variables.

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1. INTRODUCTION

Transportation routes such as delivery routes for logistics services, urban public transport bus routes, or sales visit points are instances in the real world of vehicle routing problems (VRP). The VRP topic is a topic of optimization problems in the transportation sector. This topic was first introduced by Dantzig and Ramzer, and the scope of the discussion was expanded to become VRP by Clarke & Wright [1]. The purpose of optimization on the VRP topic is to determine the number of routes that the vehicle must take to visit all points with the minimum possible cost. The cost parameter in VRP is in the form of various resources that must be spent by the company such as mileage, fuel costs, or travel time. The VRP topic develops into several variants based on the constraints encountered in each optimization problem. Capacitated VRP is a VRP topic that is limited by vehicle capacity [2]. VRP with Time Window is a VRP that has a limited time that the driver has to visit the visiting point [3]. Multiple Depot VRP, VRP with Pick-Up, and Delivering are examples of other variants resulting from the development of VRP with several constraints [1]. Time Dependent VRP (TDVRP) is a VRP variant that has 2 limitations for routing. The first limitation is the vehicle capacity and the second limitation is the maximum time duration. The characteristics of the solution route for TDVRP must be able to be taken within a predetermined time limit called the time-dependent.

Based on the results of Breaker's research, the topic of TDVRP is one of the three VRP variants that has become the focus of many studies from 2009-2015, which is predicted to become the main topic of research on VRP in the following years. Research on TDVRP can be traced from research by Chryssi Malandraki and Mark S. Dassin (Malandraki & Daskin, 1992). This study discusses the mathematical formulation, characteristics, and implementation of the nearest-neighbor algorithm for TDVRP solution. Other studies on TDVRP conducted from 2004 to 2019 discuss the use of several heuristic algorithms for route arrangement. Genetic Algorithm (GA) and Particle Swarm Optimization are heuristic-evolutionary algorithms used in research on TDVRP or VRP in general. The application of GA for TDVRP was found in study [4]. This study combines GA with a crossover technique to develop a solution to the TDVRP problem. Another algorithm used for TDVRP is Tabu Search [5]. This study implements the Tabu Search algorithm to compile routes based on the shortest paths available between 2 visiting points. The effectiveness of the resulting route is compared with the route resulting from the implementation of the exact (deterministic) method which concludes that the Tabu Search algorithm has better performance than the exact method.

The PSO algorithm is a population-based evolutionary algorithm or swarm [6]. PSO is developed based on the characteristics of animals when they gather to carry out certain activities, such as flocks of birds during flight or migration and fish. The PSO algorithm works using 3 main parameters, particles, population, and iteration [7]. Particles indicate the location point to be visited. Population or swarm shows the collections of particles while iteration shows the number of repetitions of PSO activity. The repeated activity aims to find the best position of the particles in the population. The particle displacement process involves other parameters, namely particle velocity, inertial weight, cognitive and social information. The iteration stops when the optimization conditions are met [8]. The four parameters, the number of particles, the size of the swarm, the number of iterations, and the velocity of the particles are the initial parameters that must be initiated when implementing the PSO algorithm.

The TDVRP case developed from the VRP case which is an example of a case in the optimization field. The settlement of TDVRP or VRP cases is indicated by the existence of a transportation route. As an example of the optimization field case, a route generated must have optimization, minimization or maximization properties. The route resulting from the settlement of the TDVRP case must be optimal, meaning that the route has the minimum possible distance and or minimum travel time and or can be traveled by as few vehicles as possible [9].

Based on the description above, much research about TDVRP has been conducted, but few of them discussed PSO's implementation. This article presented as a literature review which aimed to find research gap about implementation of PSO to resolve TDVRP cases. The results of this study are expected to be able to contribute within the scope of operations research to determine the characteristics of TDVRP and PSO in the process of developing optimal transportation routes.

2. METHOD

The research was conducted in 5 stages, preparation, searching, screening, data extraction, and reporting as shown in Figure 1.

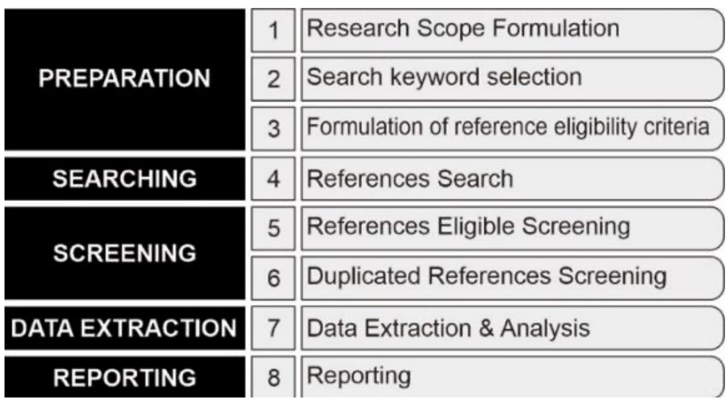

Figure 1. Research Flowchart

The first stage, preparation, consists of 3 activities, defining the research scope, the selection of search keywords, and defining the article's eligibility criteria. The research scope obtained will assist in the formulation of the research problem in the form of a research question (RQ). Research questions for this study are grouped into two categories, regarding TDVRP and the application of PSO to TDVRP cases. Table 1 shows the formulation of the two categories of RQ.

Table 1. Research Questions

Categories	Research Question
TDVRP	RQ1: What is the definition of TDVRP?
	RQ2: What is the goal of completing the TDVRP?
	RQ3: What datasets were used in the research on TDVRP?
PSO	RQ4: What are the PSO parameters used for the TDVRP case?

RQ1, RQ2, and RQ3 are used to define the characteristics of TDVRP, including the definitions that have been used in the other studies, the purpose of completing the TDVRP, and the form of the dataset. RQ4 is used to formulate research areas on PSO.

The formulation of the research scope as part of the SLR protocol is also used to define the problem boundaries. The limitation of the problem becomes a reference for the selection of article search keywords. Table 2 shows the keywords used for the article search.

Table 2. The Reference's Keyword Searching

Code	Keyword
Key1	"Time Dependent Vehicle Routing Problem" OR "TDVRP"
Key2	"Vehicle Routing Problem" AND "Particle Swarm Optimization"
Key3	"Time Dependent Vehicle Routing Problem" AND "Particle Swarm Optimization"
Key4	"Particle Swarm Optimization" AND "Vehicle Routing Problem"

The compiled keywords used for the searching process in 2 main databases, ScienceDirect and Springer. The eligibility criteria for articles are as follows (1) Articles published in the range 2010 to 2020, (2) Articles published by accredited national journals and reputable international journals, or international seminars, (3) Articles in the category of engineering articles or algorithm implementations for solving TDVRP, (4) Articles in the category of survey articles and systematic literature reviews on TDVRP, and (5) Article on PSO algorithm implementation techniques within the scope of VRP.

The second stage is article search. At this stage, articles are searched on a predetermined database based on keywords that have been compiled in the preparation stage. The search results are processed at the filtering stage. At this stage, a selection is made to eliminate duplication of articles followed by a selection of the suitability of the articles found with the article criteria in the preparation stage of step 3. The fourth stage is data extraction, containing data and information retrieval activities needed to answer RQ1, RQ2, RQ3, and RQ4. The fifth stage is the preparation of the SLR report.

3. RESULTS AND DISCUSSION

Reference search was conducted based on three keywords that have been formulated as shown in Table 3. The searching process was conducted in reference databases, ScienceDirect and Springer Link. The search returned a total of 132 references. The search results are then filtered based on the formulation of the article's eligibility criteria. Table 3 shows searching and screening results.

Table 3. Searching and Screening Result

Source		Science Direct	Springer Link
Searching		36 articles	96 articles
	By publication year	29 articles	96 articles
	By reference type	29 articles	11 articles
Screening	By Discussion area	29 articles	8 articles
	By Discussion Topic	29 articles	8 articles
	By Duplicate references	0 articles	0 articles
Eligible Reference		29	8

The first reference screening is carried out based on the criteria for the suitability of the reference, which consists of the year of publication, the type of reference, the field of discussion, and the topic of discussion. References selected based on the year of publication are references published in the 2010 to 2020 range. The type of reference used is a reference in the form of an article (paper), not a book or part of a book. The reference discussion area used is related to operational research or optimization. The topic of discussion chosen is TDVRP and PSO. Topics about VRP and variants other than TDVRP are not used. The topic about the PSO used is the PSO used in the TDVRP or VRPTW topic. The results of the analysis of the data that has been extracted from the collected references are arranged according to the RQ which has been formulated as follows:

3.1. TDVRP Definition

Questions in RQ1 are aimed at knowing the definition of TDVRP and what distinguishes TDVRP from other variants of VRP. TDVRP is defined as a transportation route problem that uses travel time constraints to obtain an optimal route [9][16][17][18]. The topic of TDVRP was first introduced by Malandraki and Daskin [19][20]. The constraints used in TDVRP consist of (1) each customer must be served (visited) a maximum of one time. (2) all vehicles must depart from the depot and return to the depot at the end of the trip and (3) vehicles must not carry transportation exceeding its capacity [21]. The main difference between TDVRP and VRP is the use of variable travel time between 2 consumers. VRP has the same or constant travel time for all distances, while TDVRP has varying travel times depending on traffic congestion [22]. The difference between TDVRP and other variants of VRP, VRPTW even though it uses a time variable, lies in the definition of the time window. The time variable in VRPTW refers to the time allowed for the driver to serve consumers [9][23].

TDVRP definition can be derived from the definition of VRP. VRP topics can be categorized into 2 groups based on the nature of the constraints used, Static VRP and Dynamic VRP [24]. Static VRP has problem constraints that are constant in value, such as the maximum duration of travel time, number of requests, and travel costs. static VRP weaknesses are found when used for cases built from real-world conditions. Dynamic VRP (DVRP) is a VRP that has different problem limits on the available edges. In Static VRP, the travel time variable has the same value for all existing edges, while in DVRP the travel time variable can have different values[24]. The definition of DVRP is another definition of TDVRP. Each TDVRP variant is confirmed to have the same constraint, that is vehicle carrying capacity. If an article mentions TDVRP without special constraints, the TDVRP variant is certainly a Capacitated TDVRP variant[18].

3.2. TDVRP Purpose

Questions in RQ2 were asked to find out the main purpose of research on TDVRP. The TDVRP case resolution aims to compile the optimal route found in all articles. The differences were found to relate to the definition of the optimal route in each study. The optimization of transportation routes in terms of costs or travel costs. This definition of travel costs is a variation of the purpose of completing the TDVRP in several studies. Travel costs can be in the form of the number of routes generated, the total travel time of all routes generated, and the total duration of travel time [9][25][24][26]. The number of vehicles used is also a variation of the optimal criteria for a route [23]. The fewer vehicles used, the more optimal the route. Different criteria were found in the TDVRP case with the scope of discussion on green-vehicle and logistics services. Green-vehicle is a TDVRP topic that discusses the arrangement of optimal routes to minimize air pollution by minimizing fuel use [22][27]. In the case of green-vehicles, the route optimization is viewed from the amount of fuel used to complete all the resulting routes [22]. Case studies of logistic routes provide another criterion for optimizing vehicle routes. Characteristics of goods, such as product durability or product life from producer to consumer, which is transported can be a constraint as well as a route optimization criterion. [28]. Characteristics of the way goods are distributed, such as the use of hubs/terminals, create another definition of the optimal route formed [29]. The number of requests for goods is another characteristic of the TDVRP case that affects route optimization. TDVRP cases generally have a variable demand for goods found at each point of the consumer. Different cases developed from the real world show that consumers sometimes do not mention the number of goods needed, as found in supermarkets or retailers [30].

3.3. TDVRP Dataset

Questions in RQ3 were asked to determine the form of the dataset used in the TDVRP study. The types of datasets found and used in research articles are categorized into two categories, real-world and instance datasets. Real-world datasets are datasets that are compiled based on the real conditions of the highway network. Real-world datasets are commonly used for logistics and green-vehicle TDVRP topics [17][24][31]. An instance dataset is a dataset created for simulating VRP cases. The found instance dataset uses the Solomon Benchmark dataset [25][21][26][31]. The use of the Solomon Benchmark dataset for the TDVRP case must go through adjustments. This is because the Solomon dataset is structured for simulating VRP cases and variants without any travel time variables. Solomon Benchmark dataset adjusted by adding a travel time scale variable which is divided into 5 time periods into 4 working time profiles for the dataset used [18][11]. The five-time periods represent working hours in the morning, afternoon, rest, afternoon, and evening. Beside Solomon Benchmark, other datasets had been used on several research projects. Christofides, Mingozzi, and Toth datasets used in [32] for simulation of combination of PSO with multiple phase neighborhood search–greedy randomized adaptive search procedure (MPNS–GRASP) algorithm. Dethloff dataset with Salhi and Nagy dataset in [33] used to simulate the combination of PSO with Variabel Network Descent.

3.4. PSO parameters used for the TDVRP case

Questions in RQ4 were asked to find out the form of using the PSO algorithm for solving TDVRP cases. PSO is an algorithm developed based on the swarm intelligence algorithm proposed by Kennedy and Eberhart [34][32]. PSO simulates the social behavior of social organisms (animals) using the movement of these organisms within the group (swarm). The migration process is carried out repeatedly to adapt to the conditions around the animal and the conditions of the group.

PSO is a metaheuristic algorithm that works intending to find local-optima values [32] [35]. The final result of the PSO algorithm is a solution to the optimization problem which is indicated by the position of several particles arranged in a multi-dimensional matrix [36][37]. PSO which was introduced by Kennedy and Eberhart was initially only used for continuous problems so that it could not be used to solve discrete cases such as VRP [38]. The PSO used in research on VRP is a development of the initial PSO, which is called Discrete PSO [38]. PSO development in several studies makes this algorithm can be used for combinatorial optimization cases such as traveling sales problems (TSP), VRP and scheduling problems [23][3][39]. The choice of PSO for the case of combinatorial optimization is because PSO has a simple concept, easy to implement, and has fast convergence properties [33]. Another reason for choosing PSO over other metaheuristic algorithms is because PSO only requires two variables to be calculated in each iteration, namely particle position, and velocity [40].

Particle position and velocity are the main elements of PSO to achieve convergence, which in turn forms the sought solution. The search for a solution is carried out based on the position of some particles and a collection of particles to find the best position related to the best solution of the problem at hand [27]. PSO works iteratively until certain conditions are met, which are formulated in the form of a fitness function. The fitness function is a function that determines the completion of the algorithm. The iteration in PSO will be stopped when the fitness function is satisfied. The fitness function in PSO is influenced by the characteristics of the case at hand. The fitness function can be the number of iterations [40].

The variables used in PSO consist of several kinds based on how values have been assigned. Variable values are categorized into two, random and nonrandom. Random values in PSO can be defined as random values or range values. The number of particles or population size (swarm) is a variable category with random values. Inertial weight is a random variable with a range value, which is used to control the speed of particle movement [41]. The velocity and position of the particles are included in the variables with nonrandom values because the values of the two variables are determined using mathematical equations. However, at the initial stage (initiation), the value of the particle velocity is zero, while the value of the variable position of the particle is set randomly [37]. The number of iterations is also included in the variable with a random value. Some studies use various iteration values, which are determined by the researchers themselves. The acceleration coefficient includes a variable with a range value. The acceleration coefficient is used to control the distance of particle displacement in 1 iteration. Low values allow the particle to travel far from the target area before being pulled back, while high values result in sudden movement toward, or through, the target area. Acceleration coefficient values range from one to two. This value was chosen by trial-error until PSO convergence was reached [42].

Random values on several PSO's variables became gaps for researchers to develop PSO. Several researchers develop PSO convergences by combining PSO with other algorithms either to increase PSO performance or to tackle multiple objectives of VRP constraints [43]. Beside exploiting the PSO variables random values, research that is based on PSO, focused on comparing original PSO with hybrid PSO to create the optimum route from different VRP cases. PSO can be combined with discrete algorithms such as branch and bound, mixed integer linear programming or with other metaheuristic algorithms such as Simulated Annealing [44] and neural-like PSO [45]. PSO development can be carried out at any stage as found in several studies on hybrid-PSO. PSO is combined with the Random-Topology algorithm to form groups of particles after several iterations are completed [46].

4. CONCLUSION

This study presented systematic literature review about implementation of PSO to resolve TDVRP cases to find research gaps for the future research. The main objective of the research is to define the characteristics of TDVRP, including definitions, criteria for optimal routes, datasets, and parameters used in the PSO. The results of extraction and analysis of 37 reference articles showed that the main feature of TDVRP lies in the duration of travel time between the 2 locations. The optimal route is determined from the cost of the trip, including the total distance traveled, the total travel time, the number of routes, and the number of vehicles used. The Solomon Benchmark dataset is the dataset that is widely used in the case of TDVRP. PSO parameters consist of 2 categories based on value initiation, random and nonrandom. Parameters with random values become research gaps that are used in several studies to improve PSO performance.

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