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## A NEW APPLICATION OF THE GENERALIZED TRAVELING SALESMAN PROBLEM IN INDUSTRY 4.0 AND 5.0

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### Abstract

A novel application of the generalized traveling salesman is proposed. The practical problem considered is optimization of different optimization criteria in various models of a mixed assembly workstation. Several models that give rise to interesting optimization problems are discussed.

**Keywords:** generalized traveling salesman problem, flexible assembly workstation.

### 1 Introduction

The generalized traveling salesman problem (GTSP), also known as the ‘travelling politician problem’, deals with ‘states’ that have (one or more) ‘cities’ and the salesman has to visit exactly one ‘city’ from each ‘state’. In analogy with the traveling salesman problem, it is natural to consider the problem on directed graphs.

The definition of the generalized traveling salesman problem (TSP) below, based on Nobert and Laporte (1983) and Noon and Bean (1991), is as follows. Let  $G = (V, E)$  be an  $n$ -node graph whose edges are associated with non-negative costs. We will assume w.l.o.g. that  $G$  is a complete graph (if

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there is no edge between two nodes, we can add an edge with an infinite or large enough cost).

We denote the cost of an edge  $e = (i, j) \in E$  by  $c(i, j)$ . It is usual to allow different costs depending on the direction of the edge. The GTSP is called symmetric if and only if the equality  $c(i, j) = c(j, i)$  holds for every two nodes  $i, j \in V$ .

Let  $V_1, \dots, V_p$  be a partition of  $V$  into  $p$  subsets called clusters (i.e.  $V = V_1 \cup V_2 \cup \dots \cup V_p$  and  $V_\ell \cap V_k = \emptyset$  for all  $\ell, k \in \{1, \dots, p\}$ ,  $k \neq \ell$ ). The GTSP asks for finding a minimum-cost tour  $H$  spanning a subset of nodes such that  $H$  meets each cluster  $V_i$ ,  $i \in \{1, \dots, p\}$ . The problem involves two related decisions: choosing a node subset  $S \subseteq V$ , such that  $|S \cap V_k| \geq 1$ , for all  $k = 1, \dots, p$  and finding a minimum cost Hamiltonian cycle in the subgraph of  $G$  induced by  $S$ . Formally,

GENERALIZED TRAVELING SALESMAN PROBLEM, GTSP

**Input:** A graph  $G = (V, E)$  with weighting function  $c : E \mapsto \mathbb{R}_0$ , and a partition  $P_V = \{V_1, V_2, \dots, V_m\}$ , where  $V_i \cap V_j = \emptyset$  for all  $i \neq j$ , and  $\cup_{i=1}^m V_i = V$ .

**Question:** Find a cycle in  $G$  that contains a vertex from each set  $V_i$  such that its weight is minimal.

Here,  $\mathbb{R}_0$  denotes the set of non-negative real numbers.

Clearly, TSP is a special case of GTSP, where each of the clusters has exactly one element,  $|V_i| = 1$ . There are also several variations, for example asking for a cycle that must contain either exactly one or at least one vertex of each cluster, or allowing instances in which the sets  $V_i$  are not disjoint.

In this short note, we propose a new application of the generalized traveling salesman. The practical problem considered is to optimize various optimization criteria in various models of a mixed assembly workstation. It has motivated definition of several optimization problems that generalize the GTSP. The main contribution of this paper are definitions of the models that are, to the best of our knowledge, new in the area of application. The problem formulations may provide firm ground for future studies that will include development of heuristics and case studies on industrial applications. While, on one hand, the new applications may be of interest because they motivate further theoretical studies of related optimization problems, we believe that, on the other hand, the transfer of theoretical results directly to engineering studies and industrial applications is even more important.

The rest of the paper is organized as follows. In the next section we recall some related work. The number of sources cited is large because we wish to serve readers with both theoretical and practical expertise and interests. However, the material touches several popular research areas and therefore the section does not aim to be a comprehensive survey. Section 3

provides some details of the application that is currently a hot topic in the development of smart factories within industry 4.0 (and 5.0). The main contribution, elaboration of several models and related optimization problems is given in Section 4. In the last section we include conclusions and discuss some ideas for future work.

## 2 Related work

Regarding the complexity of GTSP, it is well known that the (asymmetric) generalized traveling salesman problem can be transformed into a standard asymmetric traveling salesman problem with the same number of cities, and a modified distance matrix (Noon and Bean, 1993). Therefore, the asymmetric generalized traveling salesman problem is NP-hard. More precisely, it has been proved (Sahni and Gonzalez, 1976) that assuming  $P \neq NP$ , no polynomial-time TSP heuristic can guarantee  $A(I)/OPT(I) \leq 2^{p(N)}$  for any fixed polynomial  $p$  and all instances  $I$ . Better approximation results hold for the TSP with triangle inequality. Classical result of Christofides provides a  $3/2$ -approximation algorithm for symmetric TSP (Christofides, 1976). It is not known whether the factor  $3/2$  is the best possible, however, assuming  $P \neq NP$ , there exists an  $\varepsilon > 0$  such that no polynomial-time TSP heuristic can guarantee  $A(I)/OPT(I) \leq 1 + \varepsilon$  for all instances  $I$  satisfying the triangle inequality (Arora et al., 1992). As ATSP is a generalization of TSP, it is at least as hard as TSP. Very recently, a constant factor approximation for ATSP with triangle inequality has been developed by Svensson et al. (2020).

A number of practical applications of GTSP are given in Laporte et al. (1996) and (www 2). One application is encountered in ordering a solution to the cutting stock problem in order to minimize knife changes. Another is concerned with drilling in semiconductor manufacturing, see e.g., U.S. Patent 7,054,798 (www 2). Further examples listed in Laporte et al. (1996) include the covering tour problem, material flow system design, post-box collection, stochastic vehicle routing and arc routing. GTSP is also called the ‘Set TSP problem’ (www 1) or Equality Generalized Traveling Salesman Problem (E-GTSP) (Helsgaun, 2015). Furthermore, it should be noted that the same or very closely related problems are sometimes studied under different names. For example, the papers Gentilini et al. (2013) and Elbasioni et al. (2009) study the TSP with neighborhoods, and Gulczynski et al. (2006) close enough TSP, both being closely related to GTSP. Here we recall a selection of papers in which various algorithms, mainly heuristics were used to solve the GTSP, as our list is not meant to be a comprehensive survey. Several approaches were considered for solving the GTSP: a branch-and-cut algorithm for symmetric GTSP is described and analyzed

in Fischetti et al. (1997). In Noon and Bean (1991), a Lagrangian-based approach for asymmetric GTSP is given. Genetic algorithms were used in Snyder and Daskin (2006), and in Silberholz and Golden (2007). Gutin and Karapetyan (2009) proposed a reduction algorithm that can be used as a preprocessing that decreases the size and consequently the computation time of all solvers they consider. An efficient composite heuristic for the Symmetric GTSP is proposed in Renaud and Boctor (1998). An application of ant algorithms to GTSP is reported in Pintea et al. (2017). The asymmetric case of GTSP was also studied in Laporte et al. (1987).

As the asymmetric generalized traveling salesman problem can be transformed into a standard asymmetric traveling salesman problem with the same number of cities (Noon and Bean, 1993), any ATSP solver can be used for transformed GTSP. Furthermore, TSP is among the most studied optimization problems (www 2), and it seems that the majority if not all known heuristics were applied and tested, some of them also invented for TSP. The reservoir of ideas that may be used to solve the GTPS is thus enormous. However, while it is well known that competitive heuristics as a rule employ specific properties of the problem or even of the subset of the instances studied, we wish to recall that Occam's razor principle applies to design of heuristics as well (Žerovnik, 2015). This leads to conclusion that development of heuristics and/or approximation algorithms suited for specific variants of GTSP and/or specific domains may still be worth investigating.

### **3 Motivation: Flexible assembly with mobile robot**

Numerous research activities in new technologies of Industry 4.0 go hand-in-hand with the research of Industry 5.0 technologies which again puts the human worker in the focus. Many tasks at smart industrial assembly workplaces require manual ergonomic workstations which must be smart, flexible and agile. Also a worker must be digitalized, his activities must be simulated in advance and optimally combined with the activities of a collaborative robot. With this regard a huge variety of workers activities should be taken into account (Nogueira et al., 2018; Borgss et al., 2019). When designing ergonomic work conditions and jobs regarding the product all possible information on products, job processes, tools, machines, tasks, limitations, etc. should be considered (Leber et al., 2018). It is of utmost importance to predict the single times required to complete individual work tasks by the worker and also by the collaborative robot. This may be very helpful when planning of necessary staff, material requirements and in prediction of productivity (Rasmussen et al., 2018; Dianat et al., 2018; de Mattos et al., 2018; Lanzottia et al., 2019).

Due to increasing competition in the global market and to meet the need for rapid changes in product variability, it is important to introduce self-configurable and smart solutions, especially in manual assembly stations and also within the entire process chain, to ensure more efficient, flexible, agile and ergonomic performance of the manual assembly process. For example, in Turk et al. (2020a), a smart assembly workstation is discussed that is self-configurable according to the anthropometry of the individual worker, the complexity of the assembly process, the product characteristics, and the product structure. See also Dianat et al. (2018) and Tornstrom et al. (2008).

In general, both ergonomic design of an assembly workstation and reliable estimation of execution time of basic manual assembly tasks (Turk et al., 2020b) may not be straightforward. Below we assume that before considering practical instances of the optimization problems, the corresponding study has been done and hence we are given the necessary data. Besides optimization of the production speed, it is worth to consider some other aspects of the production process. Therefore, the assumed available data include, in addition to production times, also some quantities corresponding to the manual assembly station itself and especially to the working conditions and consequently the satisfaction and well-being of the worker. With this regard, the working process should be structured according to ergonomic rules combined with the digitalization of the information flow and Poka-yoke approach, including the low-cost intelligent automation. In our formal models, we work with configurations of the assembly workstation. The configuration is associated with (or, defined by) its features, including:

- height adaptation and positioning of the table,
- adaptation of the buffers position to achieve primary gripping position,
- pick-by-light approach,
- digitalized product structure, which should automatically change with the new product or product variant,
- digitalized instructions on monitor or through augmented reality,
- setup of the chair,
- setup of the assembly nest, including its rotation and positioning ability,
- the person working at the workstation,
- lighting with automatically adapted luminosity according to the workers needs,

- the content (material) of the boxes should be put optimally in accordance with the product structure, assembly sequence and mass of the product parts etc.

Note that if two workers may work using the same settings, there may be a difference in their speed, so we consider these as two different configurations. Of course, for different workers often also the type of setup will be different, depending on product structure, its variety and the number of product parts. Clearly, in such cases we need to model the change when only the workers are shifted without altering other settings.

#### 4 The general model

Given a product  $P$  to be assembled, there may be a number of settings of the workplace that are feasible for this particular task. Note that by our definition, the configuration  $C$  determines both the product  $P(C)$  and the worker  $W(C)$  who is foreseen to work at this configuration. In other words, given a product  $P$  there may be several workers that can do the job, and for each of the workers there may be several feasible configurations. Furthermore, with each configuration  $C$  we may associate several features, for example, we can define:

- $T(C)$ , the time needed for worker  $W(C)$  to complete the task related to product  $P(C)$ ;
- $R(C)$ , the reliability of the operation performed at configuration  $C$ , which can in turn be defined as the proportion of products of poor quality, or by some other measure;
- $S(C)$ , a parameter (here called suitability) when person  $W(C)$  assembles product  $P$  and the workplace is at configuration  $C$ , which can be given either as a number, a vector, or even as an element of a set, e.g. {excellent, good, poor, forbidden}; for example, 'poor' may mean that it is likely that working in this configuration for a longer period is a health hazard for the worker.

Clearly, we can define a complete graph where the vertices are the configurations and the weights are defined as follows. Given two configurations,  $C_i$  and  $C_j$ , denote the time needed to switch from  $C_i$  to  $C_j$  by  $c(C_i, C_j) = c(i, j)$ . Note that we may have  $c(i, j) \neq c(j, i)$  hence the asymmetric version of the problem. Note that instead of time, the weights  $c(i, j)$  on directed edge may have a more general meaning, the cost of operation.

Assume we need to complete the order that is a list of tuples (product, quantity), c.f.  $(P_1, n_1), (P_2, n_2), \dots, (P_k, n_k)$ . Given a set of available configurations, assuming that the set includes at least one feasible configuration

for each of the products, the task is to define the order of production that takes minimal time (or, optimizes some other criteria).

With each product, we can associate several configurations, i.e. all  $C$  with  $P(C) = P$ . The set of all configurations is thus naturally partitioned into the sets that correspond to the products.

Formally, the general problem is defined as follows:

GENERIC ASSEMBLY WORKPLACE PLAN, AWP

**Input:** A directed graph  $G = (V, A)$  with weighting functions  $c : E \mapsto \mathcal{E}$ ,  $f : V \mapsto \mathcal{V}$ . An order of products and quantities  $\{(P_1, n_1), (P_2, n_2), \dots, (P_m, n_m)\}$ , where each product  $P_i$  is associated with a set of configurations  $V_i \neq \emptyset$ . This gives the partition  $\{V_1, V_2, \dots, V_m\}$ , where  $V_i \cap V_j = \emptyset$  for all  $i \neq j$ , and  $\cup_{i=1}^m V_i$ .

**Question:** Find a tour in  $G$  that contains exactly one vertex from each set  $V_i$  such that the objective function is optimal.

Note that the weighting functions  $c$  and  $f$  are very general here. The edge weighting function  $c$  will in most cases map to  $\mathcal{E} = \mathbb{R}_0$ . The weights of vertices (configurations) may also be simply production times, i.e.  $f : V \mapsto \mathbb{R}_0$ . In many cases,  $f$  may model more features of the configuration, for example  $f(C) = (T(C), R(C), S(C))$ .

Below we discuss and define a number of more specific problems related to more specific models. To this aim, we will have to elaborate:

- necessarily, the objective function(s) and
- additional assumptions and/or limitations on the instances.

## Objective functions

Let us start with a model where we only minimize time, and consider first a rather general case. Denote by  $C_{w(i)}$  the configuration that follows the configuration  $C_i$  in the tour  $w$ . Hence, in general, the production time of a product  $P_i$  depends on the configuration  $C(P_i) \in V_i$  and the quantity  $n_i$ , and the objective function is thus:

$$T(w) = \sum_i (T(C(P_i), n_i) + f(C_i, C_{w(i)})). \quad (1)$$

First simplification may be to assume that the quantities of each product are low enough so that they can be made without interruption, and consequently the time needed depends linearly on the quantities:

$$T(w) = \sum_i (n_i T(C(P_i)) + f(C_i, C_{w(i)})). \quad (2)$$

If we add another assumption, namely that the production time does not depend on the configuration, then the first term does not depend on the tour, and we have the objective function:

$$T(w) = \sum_i f(C_i, C_{w(i)}). \quad (3)$$

Observe that (3) implies *AWP* under the last assumption is equivalent to *GTSP*. In other words:

**Theorem 4.1** *Problem AWP is a generalization of GTSP, and is NP-hard.*

### Multicriterial optimization

As already indicated before, in modelling the assembly workplace it is natural to consider other criteria besides time only. The criteria (1)-(3) may be supplemented by e.g. reliability:

$$R(w) = \sum_i (R(C(P_i), n_i)), \quad (4)$$

or/and suitability (ergonomicity):

$$S(w) = \sum_i (S(C(P_i), n_i)), \quad (5)$$

to obtain a multicriterial optimization problem with objective function:

$$(T(w), R(w), S(w)).$$

### Stochastic optimization

Until now, we have assumed that we are given a fixed order of products and quantities  $\{(P_1, n_1), (P_2, n_2), \dots, (P_m, n_m)\}$ . In modern times, industrial production is largely shifted from mass production to small, often custom designed series, and to production on demand for a known end customer. Thus it is important to consider the versions of optimization problems that are stochastic. Here we discuss the situation where we have, instead of a fixed order, a set of likely orders, or pre-orders, that are to be confirmed or altered ‘just before production’. We are interested in computing an a priori plan of production that will be optimal on average. In other words, given probabilities of orders in the provisional order, we wish to plan an a priori plan of production that will have minimal expected cost. For simplicity, assume that we only wish to minimize time.

First, recall the probabilistic traveling salesman problem (PTSP) (Jaillet, 1988) that generalizes the TSP aiming to find an a priori tour that



has minimal expected length. The cities that need not be visited are not skipped, while the other cities are visited in the order that is defined by the a priori solution. PTSP was among the first stochastic versions of problems in combinatorial optimization.

Similarly, AWP with general objective function (1) can be generalized to probabilistic AWP. The goal is to find an a priori tour that visits all clusters that are present in the realization of the order, and has minimal expected cost. We assume that probabilities of each pair  $(P_i, n_i)$  are known. This may be possible to estimate, for example, when we work for known customers.

Formally, the stochastic version of the problem can be defined as follows:

#### PROBABILISTIC ASSEMBLY WORKPLACE PLAN, PAWP

**Input:** A directed graph  $G = (V, A)$  with weighting functions  $c : E \mapsto \mathcal{E}$ ,  $f : V \mapsto \mathcal{V}$ . An order of products and quantities  $\{(P_1, n_1), (P_2, n_2), \dots, (P_m, n_m)\}$ , with probabilities  $p_i$  giving the probability that the  $i$ -th order will be confirmed, and where each product  $P_i$  is associated with a set of configurations  $V_i \neq \emptyset$ . This gives the partition  $\{V_1, V_2, \dots, V_m\}$ , where  $V_i \cap V_j = \emptyset$  for all  $i \neq j$ , and  $\bigcup_{i=1}^m V_i$ .

**Question:** Find a tour in  $G$  that contains exactly one vertex from each set  $V_i$  such that the expected weight of the tour is minimal.

## 5 Conclusions and future work

In this short note, we have provided a new application of the generalized traveling salesman. The practical problem, various models of mixed assembly workstation, has motivated definition of several optimization problems that generalize the GTSP. The contribution of this paper is the definition of the models that are novel to the best of our knowledge.

This is the first step in the research that will be continued along several avenues. On one hand, we are going to gather instances from design of particular workstations in real industrial environment thus building a database of realistic instances. On the other hand, we are going to study heuristics for the general optimization problem and its specific variants. The heuristics that we are going to start with is the remove and reinsert heuristics (Žerovnik, 1995; Brest and Žerovnik, 1999, 2005; Pesek et al., 2007; Zupan et al., 2016). Basically the same idea appears, under a different name, in Lahyani et al. (2017). This heuristics is very simple in its basic version, which means that it can be easily generalized and/or adapted to similar

problems. In short, remove and reinsert heuristics is a multistart local search, more precisely: iterative improvement, type heuristics. After constructing an initial tour, a series of small perturbations are made that are accepted if the objective function is improved. Both the tour construction and the perturbations are based on the basic procedure that inserts a node into the existing tour that traverses the active nodes. When constructing the tour, a small subset of nodes is activated at first and an optimal tour is found. Then, the inactive nodes are activated in random order and inserted. Perturbation starts with a selection of active nodes that are unactivated, and then again reinserted in random order. For details, we refer to the previous studies.

In particular, in the past, remove and reinsert heuristics was tested both on probabilistic TSP (Žerovnik, 1995) and on asymmetric TSP (Brest and Žerovnik, 1999, 2005), and has proved very competitive.

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