Choosing efficient meta-heuristics to solve the assembly line balancing problem: A landscape analysis approach

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Abstract

It is widely known that the assembly line balancing problem (ALBP) is an NP-hard optimization problem. Although different meta-heuristics have been proposed for solving this problem so far, there is no convincing support that what type of algorithms can perform more efficiently than the others. Thus, using some statistical measures, the landscape of the simple ALBP is studied for the first time in the literature. The results indicate a flat landscape for the problem where the local optima are uniformly scattered over the search space. Accordingly, the efficiency of population-based algorithms in addressing the considered problem is statistically validated.

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1. Introduction

Assembly lines (ALs) are widely used in the lean production context to improve the manufacturing systems’ efficiency and to decrease the production per unit costs. The assembly line balancing problems (ALBPs) attempts to partition the tasks among the stations so that the precedence relationships among tasks are satisfied while one/more objective function(s) is/are optimized. ALBPs are categorized into two main areas in the literature [1]–[3], namely Simple ALBP (SALBP) and Generalized ALBPs (GALBP). The former deals with the simple ALBPs producing a single model of a product on a straight AL, while the latter considers more general problems that do not fit into the SALBP such as mixed-model, U-shaped, and two-sided ALBPs.

Although there are many extensions of ALBPs to date, yet the SALBPs has gained the attention of many studies in the ALBP context [4], [5]. The SALBP is divided into three main categories in the literature [6]: (1) SALBP-1 which attempts to optimize the number of stations ($M$) given the cycle time ($CT$) and (2) SALBP-2 which attempts to optimize the $CT$ given the $M$, and (3) SALBP-E which aims to minimize both of the $M$ and $CT$ or maximize the balance efficiency ($E$). SALBP-1 is most widely studied problem among different types of SALBP [6]–[8]. On the other hand, since any type of SALBP belongs to NP-hard combinatorial optimization problems (COPs), there is a trend in the literature to propose different meta-heuristics to deal with them [9]. The most recent studies proposing meta-heuristics for solving SALBP are reviewed as follows. For a comprehensive review of ALBPs, readers can refer to [10]–[13].

An improved immune algorithm was proposed by Zhang [6] with the ability to escape from the local optima to minimize the $M$ and the smoothness index ($SI$). A new simplified way of calculating the similarity between the antibodies was also proposed. A modified ant colony optimization algorithm was suggested by Zhong and Ai [14] in which a new heuristic was proposed to help the ants in finding more favorable solutions. To further improve the local search capability of the algorithm, a few assignment schemes were also considered. The objectives considered were to minimize the $M$, $CT$, and variation of workload. By hybridizing the immune algorithm and genetic
algorithm (GA), Zhang [6] proposed a hybrid algorithm to avoid the stagnation of the search in local optima. The objectives optimized were the number of stations and SI.

Although different meta-heuristics have been proposed in the literature, however, no general conclusion can be made regarding the superiority of a specific method over the others. In fact, no specific algorithm can outperform all other methods in addressing any COPs. Thus, when an algorithm outperforms other algorithms in a problem, it can only be said that it is more efficient than the others only for addressing the considered problem and specific instances.

On the other hand, there is an efficient approach to find the most appropriate type of meta-heuristics to address any problem by analyzing the fitness landscape (shape of the solution space) of it. Using the landscape analysis, the topology of the local optima within the problem’s search space is determined so that one can design/choose an algorithm which behaves more efficient than the others. In addition, knowing about the problem search space can guide us towards selecting a meta-heuristic with more exploration (population-based) or more intensification (single-solution) or a mixture of both (hybrid algorithms) capabilities, to solve the considered problem.

Since SALBP-1 has been considered as one of the most important decision problems both by academics and practitioners in the literature [6]–[8], this paper attempts to analyze its fitness landscape for the first time in the literature. In doing so, aside from the number of stations, the workload smoothness is also considered to be minimized as the secondary objectives. Moreover, based on the results of landscape analysis, a discussion about what type of meta-heuristics can perform better while addressing the considered SALBP-1 will be given.

The remainder of this paper is organized as follows. In Section 2, a description of the considered problem is provided. Section 3, the landscape analysis of the problem is presented. Finally, the concluding remarks are outlined in Section 4.

2. Problem description and formulation

The simple assembly line balancing problem considered in this study arises when a new assembly line has to be designed. Given a cycle time (CT), SALBP-1 aims to partition the tasks represented by \( i = \{1, 2, \ldots, N\} \) between a set of stations \( k = \{1, 2, \ldots, K\} \) arranged on a straight line so that the number of established stations is minimized. Each task is associated with a handling time denoted by \( t_i \). The total tasks’ times allocated to each station have to be less than the CT. Since this study aims to deal with MO-SALBP1, another objective i.e. the smoothness index (SI) is identified to be minimized as the secondary objective. This objective seeks to determine how the workloads are equally distributed between the stations where a lower SI shows a better workload equalization.

Due to production prerequisites, the tasks have to be processed according to a set of relationships among them, known as precedence relationship, which is usually shown by a precedence graph. An illustration of a sample precedence graph with 7 tasks is shown in Figure 1. In this Figure, the nodes indicate the tasks and the numbers above them show their associated processing times.

![Fig. 1. A sample of precedence graph with 7 tasks.](image)

2.1. Problem formulation

The symbols applied in the problem formulation are outlined in Table 1.

<table>
<thead>
<tr>
<th>Notation</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>( I, J )</td>
<td>Indices for tasks ( i, j = 1, 2, \ldots, n )</td>
</tr>
<tr>
<td>( k )</td>
<td>Indices for stations ( k = 1, 2, \ldots, m )</td>
</tr>
<tr>
<td>( n )</td>
<td>Number of tasks</td>
</tr>
<tr>
<td>( t_i )</td>
<td>Time of processing for task ( i )</td>
</tr>
<tr>
<td>( S_k )</td>
<td>Set of tasks assigned to station ( k )</td>
</tr>
<tr>
<td>( p_{ij} )</td>
<td>Precedence matrix: ( 1 ); if task ( i ) is the predecessor of task ( j ), otherwise 0</td>
</tr>
<tr>
<td>( m_{\text{max}} )</td>
<td>Maximum number of stations; ( m_{\text{max}} = \frac{\sum_{k=1}^{m_{\text{max}}} t_i}{\max_{k=1}^{m_{\text{max}}} t_i} )</td>
</tr>
<tr>
<td>( v_{ik} )</td>
<td>1; if task ( i ) is assigned to station ( k ); 0; otherwise</td>
</tr>
<tr>
<td>( w_k )</td>
<td>1; if station ( k ) is established; 0; otherwise</td>
</tr>
<tr>
<td>( M )</td>
<td>Number of stations</td>
</tr>
<tr>
<td>( SI )</td>
<td>Smoothness index</td>
</tr>
</tbody>
</table>

The considered problem i.e., MO-SALBP-1 can be formulated by the following mathematical model:

\[
\begin{align*}
\text{Min} & \quad (1) \quad M = \sum_{k=1}^{m_{\text{max}}} w_k \\
& \quad (2) \quad SI = \sqrt{\frac{\sum_{k=1}^{m_{\text{max}}} ((\max(t(S_k)) - t(S_k)) \times v_{ik})^2}{M}} \\
& \quad \sum_{k=1}^{m_{\text{max}}} v_{ik} = 1 \quad \forall i = 1, \ldots, n \\
& \quad \sum_{i=1}^{n} t_i v_{ik} \leq CT \times w_k \quad \forall k = 1, \ldots, m_{\text{max}} \\
& \quad \sum_{k=1}^{m_{\text{max}}} k v_{ik} \leq \sum_{k=1}^{m_{\text{max}}} k v_{jk} \quad \forall (i, j) \in Pr \\
& \quad t(S_k) = \sum_{i=1}^{n} t_i v_{ik} \quad \forall k = 1, \ldots, m_{\text{max}} \\
& \quad v_{ik}, w_k \in \{0, 1\} \quad i = 1, \ldots, n \quad k = 1, \ldots, m_{\text{max}}
\end{align*}
\]
Using Equation (1) the $M$ and the $SI$, are considered to be optimized as the objective functions. By Equation (2) it is assured that each task is assigned to only one station. Equation (3) ensures that the station times do not exceed the given $CT$. Moreover, Equation (3) guarantees that before the assignment of tasks to any station, it has been established before. Using Equation (4) the precedence relations between tasks are satisfied. The time of each station is calculated by Equation (5). Finally, Equation (6) determines the decision variables domain which is binary.

3. Landscape analysis

To be able to find a suitable meta-heuristic to address the considered problem, the search space of the problem instance should be investigated by the landscape analysis method. The landscape of a problem is characterized by solution representation, neighborhood, and objective function [15]. From a geographical point of view, by assuming the search space of the problem as a basic floor, the landscape of problem is comprised of plains, plateaus, valleys, cliffs, and etc. as shown in Table 2.

Table 2. Different types of landscape and their geographical shape [15].

<table>
<thead>
<tr>
<th>Landscape type</th>
<th>Geographical shape of landscape</th>
</tr>
</thead>
<tbody>
<tr>
<td>Flat, plain</td>
<td></td>
</tr>
<tr>
<td>Basin, valley</td>
<td></td>
</tr>
<tr>
<td>Rugged, plain</td>
<td></td>
</tr>
<tr>
<td>Rugged, valley</td>
<td></td>
</tr>
</tbody>
</table>

Based on the properties of the problem landscape, some specific types of search methods can be more effective than the others in finding the (near) optimal solutions. Through calculating and analyzing the ruggedness and the distribution measures which are representative of the distribution of the local optimum over the problem landscape, the type of meta-heuristics which can perform well in that context, can be confidently decided [16].

To be able to perform the analysis of landscape on the considered problem, first, the main features of SALBP-1 which generate its landscape are described as follows.

- **Solution representation**: There are two types of representation schemes in the ALBP literature i.e., task-oriented and station-oriented representations abbreviated as TOR and SOR, respectively. Considering that the TOR has outperformed the SOR in the literature in terms of convergence rate and quality of solutions [17], in this study the TOR scheme is chosen for the representation of the SALBP-1 solutions.

- **Neighborhood operator**: There are different neighborhood search operators in the ALBP literature which are basically dependent upon the chosen representation scheme. Considering the selected TOR for the solution representation, the following neighborhood generation operators are widely applied in the literature. Swap (swapping the content of two randomly chosen points on the solution representation), $k$-opt (swapping the content of $k$ randomly chosen points), insertion (inserting of a new randomly chosen point), inversion (putting the contents between two randomly chosen points in the reverse order), and etc. In this study, for the analysis of landscape of the considered ALBP, the Swap operator is chosen as the neighborhood search scheme.

- **Objective function**: Considering the SALBP-1 studied in this study with two considered objectives, the fitness ($F$) of each individual solution is measured by Equation (7).

$$
F = \alpha \frac{M - \min(M)}{\max(M) - \min(M)} + \beta \frac{SI - \min(SI)}{\max(SI) - \min(SI)}
$$

(7)

where $\min(M)$ and $\min(SI)$ are the minimums of $M$ and $SI$ found heretofore, respectively. Also, the $\max(M)$ and $\max(SI)$ are the maximums of $M$ and $SI$ obtained so far, respectively. Since minimizing $M$ is often considered to be much more important than minimizing $SI$, it is assumed that $\alpha \gg \beta$.

In this paper for the first time in ALBP literature, an analysis of the landscape of SALBP-1 is performed on a medium-sized standard test problem which can be accessed in [18]. To this purpose, a typical local search algorithm namely Threshold Accepting is chosen as the neighborhood search algorithm to find the local optimum in the ALBP search space. In this algorithm, a deterministic acceptance function is defined by Equation (8) as follows.

$$
P_i(\Delta s, s') = \begin{cases} 
1 & \text{if } Q_i \geq \Delta(s, s') \\
0 & \text{otherwise}
\end{cases}
$$

(8)

where $Q_i$ is the threshold in $i$th iteration and $\Delta(s, s')$ computes the change in the objective value of current solution $s$ and the neighborhood solution $s'$. The detail of the threshold accepting algorithm is given in Figure 2. The number of generated neighborhoods in each iteration of this algorithm is given. The value of threshold $Q$ is updated iteratively according to the annealing schedule until it reaches to zero.

![Fig. 2. The threshold accepting algorithm.](image-url)
A population of 500 uniformly found solutions of SALBP-1, which are a permutation of integer numbers between 1 to N as the task priorities, is generated as the uniform initial solution named as U. Then, the threshold accepting algorithm is applied to each individual of population U, to find a local optimum for each of them. Accordingly, a population of local optimum is found named as O.

The landscape analysis applies two types’ of statistical measures called distribution and correlation criteria. The distribution criteria indicate the spatial position (topology) of local optima over the problem search space and are divided to (1) distribution and (2) entropy. On the other hand, correlation criteria measure the ruggedness of the search space by analyzing the correlation between the solutions relative distances and their fitness functions which can be measured by (3) fitness distance correlation [16]. These measures are described as follows.

3.1. Distribution

Assuming a population of solutions as P, the average distance $d_{mm}(P)$ and the normalized average distance $D_{mm}(P)$ are computed by Equations (9) and (10), respectively.

$$d_{mm}(P) = \frac{\sum_{s\in P} \sum_{t\in P\setminus s}\text{dist}(s,t)}{|P|(|P|-1)}$$  \hspace{1cm} (9)$$

$$D_{mm}(P) = \frac{d_{mm}(P)}{\text{diam}(S)}$$  \hspace{1cm} (10)$$

where $|P|$ computes the size of population $P$ and the diameter $\text{diam}(S)$ equals to the maximal distance among the individuals in population $P$ in the search space which is calculated by Equation (11).

$$\text{diam}(P) = \max_{s,t\in P}\text{dist}(s,t)$$  \hspace{1cm} (11)$$

in which the distance $\text{dist}(s,t)$ is calculated as the number of different values between solutions $s$ and $t$. Considering the solution representation in this study, $\text{diam}(P) = N - 1$.

The $D_{mm}(P)$ measures the distribution of solutions in population $P$. A small distribution measure shows a concentration of the solutions relative distances and their fitness functions which can be measured by (3) fitness distance correlation [16]. Thus, to be able to decide about both the distribution and topology of local optima in a small region of the landscape for population $O$.

3.2. Entropy

The entropy concept is about the diversity of a population in the problem landscape. A weak entropy specifies that the solutions are regularly distributed in the search space, while a high entropy, on the contrary, implies that the solutions are irregularly scattered [16]. Considering the ALBP solution representation, the following entropy indicator calculated by Equation (13) is applied in this study.

$$\text{ent}(P) = \frac{1}{n} \log \sum_{i=1}^{N} \sum_{j=1}^{N} \left( \frac{n_{ij} \log n_{ij}}{|P|} \right)$$ \hspace{1cm} (13)$$

where $n_{ij}$ is the number of times the task priority $i$ is assigned to position $j$ in population $P$. After applying the threshold accepting algorithm, the entropy variation $\Delta_{\text{ent}}$ between populations $U$ and $O$, is calculated by Equation (14) as follows.

$$\Delta_{\text{ent}} = \frac{(\text{ent}(U) - \text{ent}(O))}{\text{ent}(U)}$$  \hspace{1cm} (14)$$

Table 3, shows the results of distribution measures for the considered medium-sized SALBP-1.

<table>
<thead>
<tr>
<th>$P$</th>
<th>$O$</th>
<th>$d_{mm}(U)$</th>
<th>$D_{mm}(U)$</th>
<th>$d_{mm}(O)$</th>
<th>$D_{mm}(O)$</th>
<th>$\Delta_{D_{mm}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>500</td>
<td>500</td>
<td>336.92</td>
<td>0.3329</td>
<td>337.9731</td>
<td>0.334</td>
<td>-0.0033043</td>
</tr>
</tbody>
</table>

According to the results in Table 3, the relatively small values of $D_{mm}(U)$ and $D_{mm}(O)$ specify that there is a concentration of the local optima in a small region of the landscape for population $O$.

Table 4, shows the results of entropy measures for the considered medium-sized SALBP-1.

<table>
<thead>
<tr>
<th>$P$</th>
<th>$O$</th>
<th>$\text{ent}(U)$</th>
<th>$\text{ent}(O)$</th>
<th>$\Delta_{\text{ent}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>500</td>
<td>500</td>
<td>0.4255</td>
<td>0.4377</td>
<td>-0.02867</td>
</tr>
</tbody>
</table>

The entropy only specifies the regular or irregular distribution of local optimal on the landscape and does not provide information about the extent of distribution, as both single and multiple concentrations can share the same high entropy. On the other hand, distribution criteria can provide additional information about the concentration of local optima [16]. Thus, to be able to decide about both the distribution and concentration of the local optima in the search space, the approximate topology of local optima considering both $\Delta_{D_{mm}}$ and $\Delta_{\text{ent}}$ is provided in the landscape analysis literature [16] as shown in Table 5. According to this Table, there are three main topologies of local optima: Uniform, Multimassif, and On-massif.

Table 5. The topology of local optima according to distribution and entropy variations [15].

<table>
<thead>
<tr>
<th>$\Delta_{\text{ent}}$</th>
<th>$\Delta_{D_{mm}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low variations</td>
<td>Low variations</td>
</tr>
<tr>
<td>High variations</td>
<td>High variations</td>
</tr>
<tr>
<td>High variations</td>
<td>High variations</td>
</tr>
</tbody>
</table>

The landscape analysis according to distribution and entropy variations [15].

![Uniform Landscape](Uniform.png)
![Multimassif Landscape](Multimassif.png)
![On-massif Landscape](On-massif.png)
For the considered SALBP-1, the low variations for both $\Delta_{pmn}$ and $\Delta_{ent}$ indicate that the distribution of local optima in the search space of the problem is uniform.

### 3.3. Fitness-distance correlation

This measure aims to provide information about the correlation between the solutions’ quality and their distance to the global optimum. This information can inform us about the search space complexity [16]. To calculate the correlation measure, the set of fitness function values $F = \{f_1, f_2, ..., f_{|P|}\}$ and the associated set of distances to the global optimum $D = \{d_1, d_2, ..., d_{|P|}\}$ have to be calculated first. Then, using Equation (15) the fitness-distance correlation $r$ is computed.

$$
r = \frac{\text{Cov}(F, D)}{\sigma_F \sigma_D} \quad (15)
$$

where $\sigma$ is the standard deviation of values and the covariance of $F$ and $D$ is calculated by Equation (16).

$$
\text{Cov}(F, D) = \frac{1}{|P|} \sum_{i=1}^{|P|} (f_i - \mu_F)(d_i - \mu_D) \quad (16)
$$

where $\mu$ is the average of values. The resulting $r$ can be equal to a large negative, a near zero, and a large positive value, which can be interpreted as follows. A large negative $r$ indicates a misleading landscape in which employing an inappropriate search operator results in more distance from the global optimum. A zero value of $r$ shows a difficult landscape where there is no relation between the solution fitness and the distance from the global optimum. Finally, a large positive $r$ implies a straightforward landscape in which when the fitness of solution improves, their associated distance from the global optimum decrease [15].

For this study, the calculated fitness-distance correlation measure was 0.12 and since it is a relatively near zero value, thus the SALBP-1 problem landscape belongs to difficult search space category.

### 3.4. Discussion of the results of landscape analysis

By employing the fitness landscape, we can form an idea about how the search space of a problem looks like. Now, we can decide on the most suitable meta-heuristic to be applied in addressing the considered test problem.

The results of analysis of landscape for the considered SALBP-1, indicate that the landscape of the problem contains a plain shape where the local optimum are uniformly scattered on the search space of the problem. However, the fitness-distance correlation measure showed that the problem is complex and difficult to solve since there is no relation between the solution fitness and the distance from the global optimum. As a result, in such landscape with uniformly scattered local optima, the exploration of the search has a higher priority than its exploitation to make sure that different local optima are found and compared with each other. Thus, the population-based meta-heuristics such as GA, particle swarm optimization, and imperialist competitive algorithm with more exploration capability can perform more efficiently than the local search algorithms such as simulated annealing (SA), variable neighborhood search (VNS).

Among the population-based meta-heuristics, GAs have been widely applied in addressing different ALBPs due to the demonstrated success in the results they have achieved [19]. Moreover, to further improve the performance of GAs, some studies have attempted to adopt it appropriately to the considered ALBP characteristics. For instance, the representation type of GAs has been developed so that the solution space of the problem can be efficiently searched. As mentioned previously, there are two main representation schemes named task-based [20] and station-based [21] applied in the literature. Moreover, to evaluate the fitness of each individual in the population, one/multiple objective function(s) has/have been considered in the literature. The main objectives considered in SALBP are the number of stations and/or CT [22] and $E$ [23], most of the times accompanied by $SI$ [24] to obtain better balanced solutions. Finally, developing/applying proper operators for GAs to generate new individuals has been attentively performed which can be reviewed in the literature, e.g., [19].

On the other hand, if the landscape of the problem was a basin valley, since the local optima of the search are in onemassif form, the single-solution meta-heuristics such as SA, VNS, and etc. can behave more efficiently than the population-based meta-heuristics.

Finally, if the problem landscape was comprised of multiple valleys and the distribution of optimal solutions on the search space was multimassif, an efficient meta-heuristic has to be equipped with both exploration (breadth search) and exploitation (depth search) properties [16]. In such condition, population-based meta-heuristics hybridized with single-solution based algorithms such as hybrid GA-VNS or ICA-SA algorithms can perform more efficiently than the others in addressing the considered problem.

### 4. Conclusion

The assembly line balancing problem (ALBP) is known to be NP-hard even in its simplest form called simple ALBP (SALBP). Thus, there has been a growing trend towards employing meta-heuristics to solve different types of ALBPs as well as SALBP. In this study for the first time in the literature a landscape (search space) analysis of the SALBP was performed while aside from the number of stations, the workload smoothness index was minimized as the secondary measure. According to the results of landscape analysis, it was found that the search space of the problem includes several local optima uniformly scattered on the search space. However, since there is no relation between the solutions fitness and their distance from the global optimum, the problem is difficult to solve. As a result, to efficiently solve the problem using meta-heuristics, the exploration of the search space has a higher priority than its exploitation to make sure that different local optima are found and compared with each other. Thus, in such circumstance, the population-based meta-heuristics such as genetic algorithm and imperialist competitive algorithm with
more exploration capability can perform more efficiently than
the local search algorithms such as simulated annealing.

As a future research direction, applying the landscape
analysis on other types of ALBPs such as U-shaped, two-sided
and mixed-model ALBPs to be able to choose more efficient
meta-heuristics in addressing them, can be further studied.

Acknowledgements

This study is supported by the European Union’s Horizon 2020
research and innovation program under grant agreement no.
723711 through the MANUWORK project.

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