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Multi-objective optimization of transfer line balancing problem considering cycle time and energy expenditure

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Abstract

The transfer lines are among highly complex automated production systems that manufacture a large volume of identical or similar products with high demand. Recently, the design of environmentally friendly production systems has become the focus of more and more enterprises as one of the sustainable manufacturing strategies. In light of the recent energy-efficient manufacturing trends, this paper investigates the transfer line balancing problem (TLBP), considering both efficiency and energy aspects. The problem arises in the automated transfer lines equipped with dedicated machining centers and automated material handling systems, producing a large volume of specific products. The operations are performed at machines by realizing particular processing requirements, including machining features, inclusions, and exclusions considerations. The objectives to be minimized are the cycle time and the total energy consumption. The latter objective consists of machines' operating and non-operating energy costs. The problem is first formulated as a mixed-integer linear programming model. Due to the problem's complexity, an efficient multi-objective optimization algorithm based on the non-dominated sorting genetic algorithm (NSGA-II) is also proposed. The performance of the proposed algorithm is compared with the e-constraint method in terms of the Pareto-front metrics while solving various test problems and a case study. The computational results show the effectiveness of the proposed algorithm in dealing with the TLBP.

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1. Introduction

Transfer lines (TL) are highly complex automated production systems that manufacture large volumes of identical or similar products in high demand [1]. Automated TLs (ATL) are among the most common TLs used, e.g., in the automotive industry for machining cylinder heads or blocks [2]. The amount of investment in configuring the ATLs is significantly high. This is mainly due to the high installation cost of several computer numerical control (CNC) machines arranged through an automated transfer system such as overhead cranes [2]. Accordingly, manufacturers have attempted to increase the efficiency of their ATLs. One of the most important methods resulting in cost and time savings in ATLs is solving the transfer line balancing problems (TLBP) [3]. Generally, TLBP aims to

minimize the total investment costs in terms of the number of machines (including modules within machines) or cycle time (CT) [4] by optimally assigning operations to machines while considering some constraints such as precedence, inclusion, and exclusion relations [5].

In line with the European Commission's energy strategy, which emphasizes optimizing energy consumption [6], green manufacturing trends and the current energy crisis, many manufacturers have recently been urged to improve their energy efficiency [7]. In such circumstances, there has been a growing trend in the energy efficiency consideration in the study of assembly line balancing problems [8] and disassembly line balancing problems [9,10]. However, to the best of the authors' knowledge, the TLBP literature lacks research on optimizing energy consumption. Thus, this study aims to fill the existing

gap by (1) simultaneously minimizing CT and energy consumption in TLBP while considering real-world constraints (task-machine accessibilities, inclusion, exclusion), (2) proposing a mixed-integer linear programming (MILP) and multi-objective optimization (MOO) algorithm based on the non-dominated sorting genetic algorithm (NSGA-II) with customized encoding and decoding mechanisms, and (3) validating the proposed approach by addressing various test problems and a case study from the automotive industry.

The structure of this paper is organized as follows. In section 2, the related literature is reviewed. In section 3, the problem description and the proposed model are explained. Section 4 focuses on the proposed solution approach, while the computational results are presented in Section 5. Finally, Section 6 summarizes the paper with future research directions.

2. Literature review

Compared to the balancing assembly and disassembly lines, the balancing of transfer lines receives less attention in the literature. The TLBP was first mentioned and defined by Dolgui et al. [11]. They defined the TLBP for dedicated transfer lines. Borisovsky et al. [12] extend this approach to the reconfigurable transfer line. Guschinskaya et al. [13] compared several exact and heuristic solution methods for TLBP, i.e., shortest path approach, FISC heuristic, decomposition methods, hybrid method, and aggregate method [13]. Since then, metaheuristics have been extensively used to deal with TLBP, e.g., NSGA-II [14], Particle Swarm Optimization [15], and Cuckoo search algorithm [16]. Typical optimization goals are related to costs [17], cycle time/production rate [18], and the number of workstations [14].

The optimization objective of energy efficiency aims to decrease the energy consumption of production lines through line balancing. This objective is driven by climate change and the increased energy demands associated with Industry 4.0 [7,19]. The concept of optimizing energy efficiency has been present in the literature since 2014 [20] and has been extensively applied in the balancing of assembly lines (e.g., [7,21]) and disassembly lines (e.g., [22,23]). Typically, the energy consumption of a production line is calculated by considering the sum of operating energy and standby energy across individual workstations [21]. In some instances, additional energy consumers, such as lighting or conveyor belts, are also included in the optimization process [24]. An alternative approach to optimizing energy consumption involves reducing power peaks during production [25]. Due to conflicting objectives between energy efficiency and other key production metrics, such as cycle time or smoothness, optimization is often conducted using multi-objective metaheuristics [21,26]. Examples of such metaheuristics are Multi-Objective Ant Lion Optimizer [27] and NSGA-II [28].

However, the cycle time and energy efficiency have not been simultaneously considered optimization objectives, particularly in TLBP. Thus, this study aims to fill this gap by formulating the TLBP as MILP and developing a customized NSGA-II to address it.

3. Problem formulation

An ATL with single spindle heads is assumed, where a set of tasks i ($i = 1, \dots, NT$) are performed on a sequence of automated CNC machines j ($j = 1, \dots, NM$) connected with a gantry, with available tools, fixtures, and sides. Due to the availability of tools, fixtures, and part sides on each machine, tasks can be performed on a few machines given by a task-machine accessibility matrix ($MaTa_{ij}^{Fit}$). Regarding energy, the tasks can be carried out in different energy modes e ($e = 1, \dots, NE$) affecting the related task time ($time_{i,e}$) and energy consumption ($p_{i,e}$). The machine energy consumption is based on deterministic operation and standby times (sp_j). Aside from $MaTa_{ij}^{Fit}$, the assignment of tasks to machines is subject to their precedence relationships ($pre_{i,h}$), inclusion ($IN_{i,h}$) and exclusion ($EX_{i,h}$) constraints. However, the machines' failures and other limitations, such as their availabilities, are not considered. Hence, the main decisions in the considered TLBP are both assignments of tasks to machines and energy modes to tasks to optimize CT and total energy consumption (TEC). The notations and definitions used in the mathematical formulation are shown in Table 1, and the proposed MILP model is presented by Equations (1) to (12).

Table 1. Notations and definitions used in problem formulation.

Notation	Definition
<i>Parameters:</i>	
i, h	Task indices
j, m	Machine indices
e	Energy index
NT	Number of tasks
NM	Number of machines
NE	Number of energy modes
$time_{i,e}$	Time of task i performed in energy mode e
$p_{i,e}$	Processing energy consumption of task i in energy mode e per time unit
sp_j	Standby energy consumption of machine j per time unit
$pre_{i,h}$	1 if task i is the predecessor of task h ; otherwise, 0
$MaTa_{j,i}^{Fit}$	1 if machine j can perform task i considering fixture and tool accessibility; otherwise, 0
$IN_{i,h}$	1 if tasks i and h are included in a set of inclusion tasks; otherwise, 0
$EX_{i,h}$	1 if tasks i and h are included in a set of exclusion tasks; otherwise, 0
<i>Variables:</i>	
$x_{i,j} \in [0,1]$	1 if task i is assigned to machine j ; otherwise, 0
$y_{i,e} \in [0,1]$	1 if task i is assigned to energy mode e ; otherwise, 0
$z_{i,j,e} \in [0,1]$	Auxiliary variable for linearization
$CT \in \mathbb{R}^+$	Cycle Time
$TEC \in \mathbb{R}^+$	Total Energy Consumption

$$Min \text{ CT} \tag{1}$$

$$Min \text{ TEC} = \sum_{j=1}^{NM} \sum_{i=1}^{NT} \sum_{e=1}^{NE} time_{i,e} \cdot p_{i,e} \cdot z_{i,e,j} + \sum_{j=1}^{NM} (sp_j \cdot (CT - \sum_{i=1}^{NT} \sum_{e=1}^{NE} time_{i,e} \cdot z_{i,e,j})) \tag{2}$$

$$\sum_{j=1}^{NM} x_{i,j} = 1; \forall i \tag{3}$$

$$\sum_{e=1}^{NE} y_{i,e} = 1; \forall i \tag{4}$$

$$\sum_{i=1}^{NT} \sum_{e=1}^{NE} time_{i,e} \cdot z_{i,e,j} \leq CT; \forall j \tag{5}$$

$$\sum_{j=1}^{NM} x_{i,j} \leq \sum_{g=1}^{NM} g \cdot x_{h,g}; \forall i, h \in \{pre_{i,h} = 1\} \tag{6}$$

$$x_{i,j} = x_{h,j}; \forall i, h \in \{IN_{i,h} = 1\}, \forall j \tag{7}$$

$$x_{i,j} + x_{h,j} \leq 1; \forall i, h \in \{EX_{i,h} = 1\}, \forall j \quad (8)$$

$$x_{i,j} \leq MaTa_{i,j}^{Fit0}; \forall i, j \quad (9)$$

$$z_{i,j,e} \leq y_{i,e}; \forall i, j, e \quad (10)$$

$$z_{i,j,e} \leq x_{i,j}; \forall i, j, e \quad (11)$$

$$Z_{i,j,e} \geq y_{i,e} + x_{i,j} - 1; \forall i, j, e \quad (12)$$

The first objective in Equation (1) is to minimize the *CT*. The second objective in Equation (2) is to minimize *TEC* calculated based on the sum of operational and standby energy. Equation (3) ensures that each task can be assigned to only one machine, and Equation (4) ensures that each task is assigned to only one energy mode. Equation (5) calculates the *CT* as the maximum workload of all machines. Equation (6) satisfies the precedence relationships among tasks. Equation (7) ensures that inclusion constraints are satisfied, while Equation (8) ensures that exclusion constraints are satisfied. Equation (9) guarantees that each task can only be assigned to machines capable of performing the task. Equations (10) to (12) enable the linearization of the model by defining the dependencies between the binary decision variables $x_{i,j}$, $y_{i,e}$, and the auxiliary variable $z_{i,j,e}$.

4. Multi-objective optimization approach

Owing to the successful application of the NSGA-II [29] in different MOO applications, e.g., [30,31], this algorithm is adopted in this section to address the discussed TLBP. The main procedure of NSGA-II is discussed as follows. A population of solutions (*pr*) with size *popsize* is created, where each row represents a random permutation of numbers 1 to *NT*. Each solution in *pr* is decoded by two decoding steps named TaEmAs and TaStAs. Tasks are assigned to energy modes using the TaEmAs procedure, as shown in procedure 1. This step randomly allocates the energy modes to the tasks based on the permutation vector of each solution in *pr*.

Procedure 1: TaEmAs decoding

1. **Input:** *NT, NE, pr*
2. Initialize *SE*-vector
3. **for** $e = 1$ to *NE*
4. Choose a random number $W(e)$ between 0 and *NT*.
5. Normalize $W(e)$ as $W_N(e)$ so that $\sum W_N(e) = NT$
6. Assign ranges for $W_N(e)$: $Ra(e) = [\sum W_N(e-1)+1, \sum W_N(e-1)+\sum W_N(e)]$
7. Update $SE \leftarrow \{Ra(1) \leftarrow 1, Ra(2) \leftarrow 2, \dots, Ra(NE) \leftarrow NE\}$
8. **for** $lo = 1$ to *NT*
9. Update TaEmAs←Compare *lo*-th locus of *SE* with *pr* and assign related energy mode to related task in TaEmAs.
10. Record $W_N(lo)$ to $W_N(NE-1)$ in *pr*
11. **Return** TaEmAs

The TaStAs decoding assigns tasks to stations using a greedy algorithm for each solution, as shown in procedure 2. This step selects tasks based on the priority vector (the lower the numbers, the higher the task priority) and assigns them to the current machine considering the precedence relationship (*pre*) and the task-machine accessibility ($MaTa^{Fit0}$) constraints while considering a theoretical lower bound for *CT* calculated by

$LCT = \sum_i time_{i,TaEmAs(i)}/NM$. Using TaEmAs decoding, some solutions might be infeasible due to IN and EX constraints and the number of used machines. Thus, such solutions are identified and excluded from the current population using a feasibility check. Next, the fitness functions of each feasible solution are calculated in terms of both *CT* and *TEC* using Equations (1) and (2), respectively.

Procedure 2: TaStAs decoding

1. **Input:** *NT, NM, time, pr, pre, MaTa^{Fit0}, IN, Ex, TaEmAs, LCT*
2. Define a set of unallocated operations: $P \leftarrow 1$ to *NT*;
3. Open first station: $macc = 1$; initialize station time $sstime = 0$
4. **While** $P \neq \emptyset$
5. Pick task set from *P* that meets *pre* and $MaTa^{Fit0}$ for *macc*.
6. **If** $|valid\ tasks| = 1$: Pick task *i*; continue with line 8
7. **If** $|valid\ tasks| > 1$: Pick one task *i* with the lowest priority (*pr*) index
8. **If** $sstime + time(i, taemas(i)) \leq LCT$
9. Assign *i* to *macc*; update *sstime, pre, P*
10. **Elseif** $sstime + time(i, taemas(i)) > LCT$
11. **If** $macc < NM$
12. **If** $MaTa^{Fit0}$ allows
13. Set $macc = macc + 1$;
14. Assign *i* to *macc*, update *sstime, pre, P*.
15. **If** $MaTa^{Fit0}$ does not allow
16. Assign *i* to *macc*, update *sstime, pre, P*.
17. **If** $macc = NM$
18. Assign *i* to *macc*, update *sstime, pre, P*.
19. **If** $|valid\ tasks| = 0$;
20. Pick one task *i* that only meets *pre*.
21. Assign *i* to either the next upper or next lower accessible machine. The choice depends on the previous TaStAs and *pre*; update *sstime, pre, P*.
22. In case of an assignment to the next upper machine: set $macc =$ next upper machine and $sstime = 0$;
23. **Return** TaEmAs

After the decoding steps, all the resulting solutions in the current population are sorted according to the non-dominated ranks (NR) and crowding distance (CD), as explained by Deb et al. [29]. Next, the best solutions are chosen based on the tournament selection, considering their NR and CD. The algorithm then generates new solutions using the two-point crossover with crossover rate (P_c) and the swap mutation operators with mutation rate (P_m) as explained by Fathi et al. [32]. Once again, the above decoding steps, followed by fitness function evaluation, are applied. Finally, the original and new populations of individual solutions are combined, considering their NR and CD. The above steps are iterated until a maximum number of generations (*G*) is reached, resulting in the non-dominated solutions (NDS) over the Pareto-front.

5. Computation results

This section compares the proposed NSGA-II with an exact MOO method based on the e-constraint method (e.g., [33,34]). This comparison is conducted based on different performance indicators, namely, the quantity of obtained NDSs ($|NDS|$), the elapsed time (second), hypervolume (HV), spacing metric (SM), and diversity metric (DM) as explained by Nourmohammadi et al. [35]. A set of test problems from [36] were taken and adopted to perform the computational

experiments. Additionally, a case study from the automotive industry was considered. The characteristics of all instances are presented in Table 2. In this table, columns 1 to 8 present the instance number, problem size, instance name, NT, NM, ACC (accessibility ratio), IN (inclusion ratio), and EX (exclusion ratio), respectively.

Table 2. The characteristics of the test instances.

No.	Size	Problem	NT	NM	ACC	IN	EX
1	Small	Mertens	7	2	0.86	0.14	0.14
2		Bowman	8	3	0.92	0.25	0.125
3		Jaeschke	9	4	0.89	0.22	0.22
4		Jackson	11	3	0.91	0.18	0.18
5		Mansoor	11	3	0.91	0.18	0.18
6		Mitchell	21	6	0.94	0.1	0.28
7		Roszieg	25	4	0.9	0.12	0.12
8	Medium	Heskiaoff	28	8	0.96	0.11	0.11
9		Buxey	29	7	0.92	0.1	0.11
10		Sawyer	30	8	0.98	0.07	0.13
11		Lutzl	32	8	0.96	0.13	0.09
12		Gunther	35	6	0.96	0.11	0.11
13		Kilbridge	45	9	0.96	0.04	0.11
14		Hahn	53	8	0.99	0.02	0.04
15	Large	Warnecke	58	7	0.96	0.07	0.07
16		Tonge	70	8	0.98	0.04	0.01
17		Wee-Mag	75	8	0.99	0.07	0.07
18		Mukherje	94	9	0.98	0.05	0.03
19		Barthold	148	9	0.98	0.03	0.02
20		Scholl	297	18	0.99	0.02	0.01
21		Case study	150	10	0.14	0.02	0.02

The selected parameter values influence the effectiveness of metaheuristic algorithms [37–39]. In this study, the parameters of the NSGA-II were tuned using the Taguchi method [40,41]. Accordingly, the parameter settings for the small size problems were $Popsiz$ e=100, P_c =0.8, P_m =0.2, G =300, while for the medium size and large size problems, the parameters were set to $Popsiz$ e=200, P_c =0.9, P_m =0.1, G =300. The NSGA-II was coded in MATLAB, while the e-constraint method was coded in GAMS and solved by CPLEX solver on a PC with Core i7 CPU 1.30 GHz and 16 GB RAM. The stopping condition of NSGA-II was set to when the maximum number of generations (G) was reached, while the e-constraint method was stopped when the CPLEX solver reached a zero gap or an elapsed time of 10 hours.

The computational experiment of the NSGA-II and e-constraint methods are graphically presented in Fig. 1 to Fig. 5. In Fig. 1, the resulting number of NDS ($|NDS|$) by both methods over the test instances is shown. It can be observed that the $|NDS|$ found by NSGA-II is always more than e-constraint, with limited offset points, particularly when the problem size increases. Fig. 2. shows the elapsed time in seconds for both methods on a logarithmic scale. The time spent by the NSGA-II has risen smoothly relative to the problem size growth, while the e-constraint method shows an exponential increase in time with some fluctuations due to the nature of the problems. Considering HV, NSGA-II demonstrates a better performance over the e-constraint method, as shown in Fig. 3. However, the SM diagrams in Fig. 4 show that the NDS of the e-constraint compared to NSGA-II show a more uniform dispersion over the Pareto front and considering this metric e-constraint method is the better approach. Finally, considering the DM diagrams in Fig. 5, both methods show analogous performance, indicating

that the diversity of the NDSs over the Pareto front is similarly distributed. The above results show that the decision-makers can implement the proposed MOO approach to find promising NDS for the TLBP within a reasonable computational time.

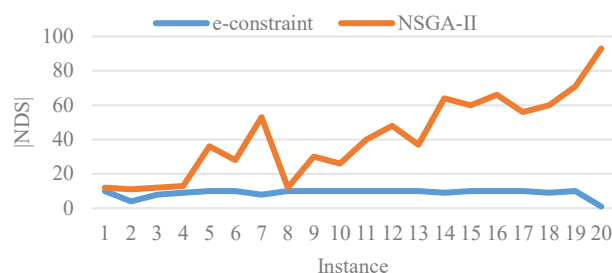


Fig. 1. Comparison of |NDS| by NSGA-II and e-constraint.

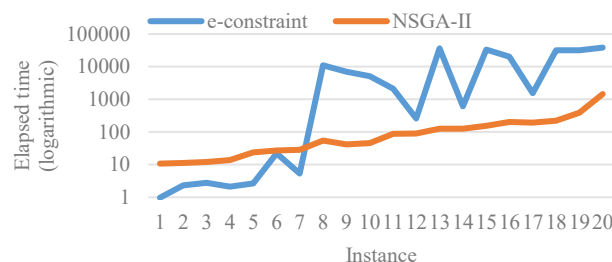


Fig. 2. Comparison of Elapsed time (s) by NSGA-II and e-constraint.

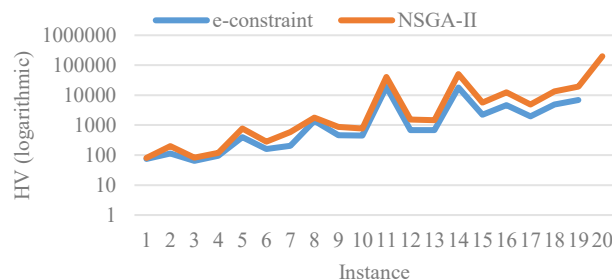


Fig. 3. Comparison of HV by NSGA-II and e-constraint.

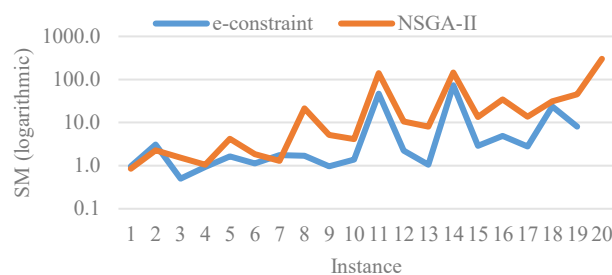


Fig. 4. Comparison of SM by NSGA-II and e-constraint.

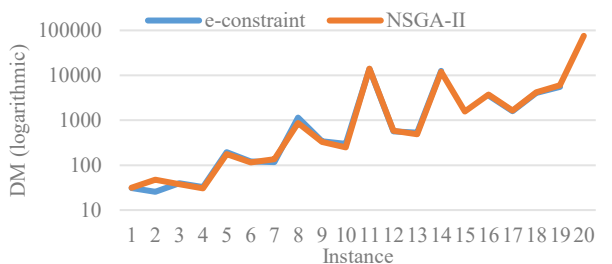


Fig. 5. Comparison of DM by NSGA-II and e-constraint.

Moreover, the solution approach could find Pareto solutions in the case study, as shown in Fig. 6. indicating how changes in

CT and TEC can simultaneously impact productivity and energy effectiveness. The resulting NDS supports the decision-makers in finding efficient solutions with trade-offs between productivity and energy efficiency in ATLS. In other words, the Pareto fronts in the case study can support the decision-making regarding how they can improve their energy sustainability without losing their economic competitiveness. A further study agreed by the company to decrease their production plan by up to 5% during low demand seasons showed that in the highlighted production plan in Fig. 6, the company could increase its energy efficiency by 26% and reasonably reduce productivity by 4.8% while maintaining its competitiveness.

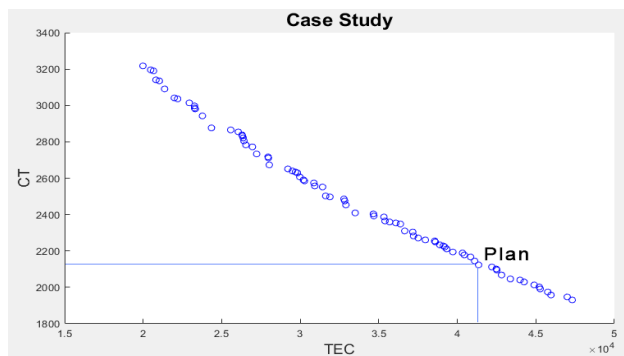


Fig. 6. Case Study NDS.

6. Conclusions

This study deals with the transfer line balancing problems (TLBP) to minimize cycle time and energy consumption, which are two conflicting objectives. The latter objective consists of machines' operating and non-operating energy costs. The problem is formulated as a mixed-integer linear programming. Furthermore, a multi-objective optimization algorithm based on NSGA-II is proposed with customized solution generation mechanisms. The performance of the proposed algorithm is compared with an exact e-constraint method over many test instances and a case study from the automotive industry. The computational results show the effectiveness of NSGA-II in finding reasonable solutions within a reasonable computational time in terms of the number of non-dominated solutions, the elapsed time, and hypervolume. The case study results could support decision-making to find a trade-off between productivity and energy efficiency.

As a future research direction, including other sustainability criteria, such as gas emissions, into TLBP can be considered. Moreover, other production systems with different machining configurations and layouts, such as parallel and U-shaped, can be explored. Furthermore, the availabilities of the machines and failures through integrating the proposed approach with the simulation methods can be further studied. Moreover, developing solution methods with customized mechanisms for addressing new TLBP can be among the future research directions.

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