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Robust machine layout design under dynamic environment: Dynamic customer demand and machine maintenance

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ABSTRACT

The layout of manufacturing facilities has a large impact on manufacturing performance. The layout design process produces a block plan that shows the relative positioning of resources that can be developed into a detailed layout drawing. The total material handling distance is commonly used for measuring material flow. Manufacturing systems are subject to external and internal uncertainties including demand and machine breakdowns. Uncertainty and the rerouting of material flows have an impact on the material handling distance. No previous research has integrated robust machine layout design through multiple periods of dynamic demand with machine maintenance planning. This paper presents a robust machine layout design tool that minimises the material flow distance using a Genetic Algorithm (GA), taking into account demand uncertainty and machine maintenance. Experiments were conducted using eleven benchmark datasets that considered three scenarios: preventive maintenance (PM), corrective maintenance (CM) and both PM and CM. The results were analysed statistically. The effect of several maintenance scenarios including the ratio of the number of machines with period-based PM (PPM) to the number with production quantity-based PM (QPM), the percentage of machines with CM (%CM), and a combination of PMM/QPM ratios and %CM on material flow distance were examined. The results show that designing robust layouts considering maintenance resulted in shorter material flow distances. The distance was decreased by 30.91%, 9.8%, and 20.7% for the PM, CM, and both PM/CM scenarios, respectively. The PPM/QPM ratios, %CM, and a combination of PPM/QPM and %CM had significantly resulted in the material flow distance on almost all datasets.

1. Introduction

The costs related to material handling are typically 20%–50% of total manufacturing operating expenses. Effective layouts can reduce material handling costs by at least 10–30% (Tompkins, White, Bozer & Tanchoco, 2010). The total distance travelled by materials is a commonly used proxy for measuring the efficiency of layouts (Drira, Pierreval & Hajri-Gabouj, 2007).

Changes to the manufacturing environment may be caused by internal or external factors which disrupt the efficient flow of materials (Kulturel-Konak, 2007). External uncertainties include: variations in customer demand and product mix; changes to product design; shorter product life cycles; the discontinuation of products; or the introduction of new products (Sahin & Turkbey, 2009). Internal disturbances, such as machine breakdowns, reduce the number of available machines which can cause queuing that leads to uneven workload, longer flow-time, lower productivity and higher production costs. When flow is disrupted, downstream resources may be starved of work-in-process which can reduce utilisation. Maintenance activities may be planned or corrective 'fix it when it breaks' (Waeyenbergh & Pintelon, 2009). Both types of maintenance reduce the number of machines available, which can disrupt flow. With preventative maintenance production plans can take into account downtime, whereas corrective maintenance occurs randomly and needs to be addressed through control actions.

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To maintain production performance, alternative routings may be adopted to avoid interruption, but the flow distances may increase.

There is a substantial literature on the facilities layout problem and there have been several comprehensive reviews. Kusiak and Heragu (1987) surveyed formulations of the FLP and algorithms for solving deterministic problems. Meller and Gau (1996) reviewed methodologies, objectives, algorithms, and extensions that considered a time element (dynamic layout), uncertainty (stochastic layout) or multiple evaluation criteria (multi-criteria, robust or flexible layout). Dynamic layout problems take into account changes in material handling flow over multiple periods. Robust layouts aim to accommodate changes without the need for expensive reorganisation, whereas the re-layout approach produces a series of layouts for the various periods (Kulturel-Konak, 2007). Balakrishnan and Cheng (1998) presented an early review of the dynamic facilities layout literature, which categorised research according to: equal/unequal size departments; deterministic/stochastic material flow; and the algorithms adopted. Drira et al. (2007) surveyed the literature on facilities layout problems using a framework that included: the type of manufacturing system; facility shapes; layout configuration; material handling system; layout formulation; constraints; and optimisation methods. Kulturel-Konak (2007) reviewed research relating to dynamic and stochastic facility layout problems. Hosseini-Nasab, Fereidouni, Fatemi Ghomi and Fakhrzad (2018) reviewed 250 FLP-related papers published during the period 1987–2016 and applied a hierarchical classification based upon: layout evolution (static/dynamic); workshop characteristics (shape and dimensions, flow movement, type of manufacturing system and materials handling approach); problem formulation (objective function, problem representation, modelling approach, type of data, constraints); and resolution approaches (multi-objective, multi-attribute, single objective). However, the literature has not considered the integration of the FLP with machine maintenance, which is the research gap that is addressed by this paper.

The objectives of this paper are to: (i) review the literature on facilities layout design, uncertainties in production and maintenance policies; (ii) outline the Genetic Algorithm-based Layout Design (GALD) tool that was developed to solve robust machine layout design problems for systems that are subject to demand uncertainties and maintenance; (iii) describe the experimental design that was used to test the robust design approach with corrective, preventative and combined maintenance regimes; and (iv) investigate how the number of unavailable machines in each maintenance scenario affects the material flow distance.

Section 2 critically reviews appropriate literature. Section 3 outlines the development of the Genetic Algorithm tool for solving facilities layout problems, which is integrated with maintenance planning. The experimental results are presented in Section 4. Section 5 provides a discussion and highlights the conclusions of the work and identifies opportunities for future research.

2. Literature review

Drira et al. (2007) and Kulturel-Konak (2007) published comprehensive reviews of the facilities layout problem literature. A systematic review was undertaken using the ISI Web of Science database covering the period 2007 to May 2018 to identify the current status of the literature and research gaps. The initial searches used the keywords “layout design” and “facility layout” and found 308 papers. The definition of the facilities layout problem and its categorisation are presented in Section 2.1. The 308 papers were carefully screened to identify those relevant to dynamic layout design. The problem characteristics and the solution approach of the selected papers are shown in Section 2.2.

2.1. Facilities layout problem

Azadivar and Wang (2000, p.4369) defined the facilities layout problem (FLP) as “the determination of the relative locations for, and the allocation of, the available space among a number of workstations”. Singh and Sharma (2006, p.425) stated that “the output of the FLP is a block layout that specifies the relative location of each department. The detailed layout of a department can also be obtained later by specifying aisle structure and input/output point locations which may include flow line and machine layout problems”.

The FLP may be considered to be a static plant layout problem (SPLP), which produces an optimal layout that suits the current state of business (Rosenblatt, 1986). However, when there are changes over time, it is important to design facilities that can quickly and effectively adapt (Yin & Khoo, 2011). The dynamic plant layout problem (DPLP) involves the design of facility layouts based on a multi-period planning horizon. During this horizon, the material handling flows between pairs of departments in the layout may change (Balakrishnan & Cheng, 2009). It is necessary to determine an appropriate layout for each period, during which it is assumed that the flow data remains constant (Drira et al., 2007). The DPLP may be either a deterministic or stochastic problem. The decision on whether to change the layout should take into account the costs associated with material flow and the rearrangement of the layout (Rosenblatt, 1986). There are two alternative approaches to solving the DPLP: the agile approach which assumes low rearrangement costs and relocates machines from time-to-time; and the robust approach that assumes high relocation costs and aims to minimise total material handling costs in all periods using a single layout (Pillai, Hunagunda & Krishnan, 2011). Kouvelis, Kurawarwala and Gutiérrez (1992, p.287) defined a robust layout as “one that is ‘good’ (or close to optimal) for a wide variety of demand scenarios even though it may not be optimal under any specific demand scenario”. A robust layout design procedure attempts to minimise the total expected material handling costs over a specific planning horizon (Yang & Brett, 1998), so there is no rearrangement cost. To maintain the shortest material flow distance, the layout can be periodically redesigned. However, this has an impact on production time and costs due to facility movement and interrupted production. It may also require specialised labour and equipment, especially for large-size or heavy facilities (McKendall, Shang & Kuppusamy, 2006).

The DPLPs have been formulated as mathematical models. Balakrishnan (1992) presented the formulation for department layouts during the planning horizon with budget constraints and assumed equal-sized facilities. This model was adapted by Balakrishnan and Cheng (1998), McKendall et al. (2006), Rezazadeh, Ghazanfari, Saidi-Mehrabad and Sadjadi (2009), Sahin and Turkbey (2009), and Ulutas and Islier (2009). The flexible machine layout with dynamic environments was formulated as a quadratic assignment problem, in which unequal-size machines and machine position constraints (vertical or horizontal) were considered (Yang & Brett, 1998). Dunker, Radons and Westkamper (2005) and McKendall and Hakobyan (2010) considered the dynamic facility layout problem with unequal-area departments using a mixed-integer linear programming formulation. Baykasoglu, Dereli and Sabuncu (2006) studied the budget-constrained dynamic layout problem. Kia et al. (2012) used a mixed-integer non-linear programming model to design a dynamic cellular manufacturing system layout.

Facility layout design (FLD) problems are complex and non-deterministic polynomial time hard (NP-hard) problems (Pourvaziri & Naderi, 2014), which means the amount of computational time required to find a solution increases exponentially with problem size. Efficient metaheuristics have therefore been widely used for solving FLPs, including: Genetic Algorithms; Simulated Annealing; Tabu Search; Ant Colony Optimisation; Particle Swarm Optimisation; and Biogeography-Based Optimisation (Sooncharoen, Vitayasak & Pongcharoen, 2015). Genetic Algorithms have been a popular approach to solving facility layout design problems. Kia, Khaksar-Haghani, Javadian and Tavakkoli-Moghaddam (2014) found that GA can find near-optimal solutions in much less computational time than CPLEX software for almost all problems. Lenin, Siva Kumar, Islam and Ravindran (2013) demonstrated the effectiveness of GA for solving a single-row layout design problem. The results obtained from GA were more favourable than other approaches. Dapa, Loreungthup, Vitayasak and Pongcharoen (2013) reported that GA outperformed the Bat Algorithm and Shuffled Frog Leaping Algorithm in a multiple-row layout design. Vitayasak and Pongcharoen (2016) investigated the affects of breakdown maintenance and provided a cost-based decision framework for re-layout investment.

2.2. Facilities layout design with uncertainties

Table 1 presents 74 of 308 FLP articles which considered uncertainties due to external and/or internal variabilities. There were 55 papers that only considered variability in customer demand. Demand profiles may be represented by material flow matrices, probability distributions, or empirical data. Internal factors include the number of machines, set up time, facility size, routing flexibility, machine maintenance, processing time, waiting time, human factors, and machine reliability.

There were only 10 papers that considered only internal variabilities: Azadeh, Moghaddam, Nazari and Sheikhalishahi (2016) that used a fuzzy multivariate approach to optimise the FLP with ambiguous data; Azimi and Soofi (2017) which applied Artificial Neural Networks and a hybrid non-dominated Genetic Algorithm to optimise layout and material handling; Chae and Regan (2016) that considered heterogeneous area constraints; Chang, Wu and Wu (2013) who considered cell formation, layout and intercellular sequences with flexible routings; Dong, Wu and Hou (2009) which considered the adding/removal of machines during each period; Khaksar-Haghani, Kia, Mahdavi and Kazemi (2013) that applied Genetic Algorithms for optimising multi-floor layouts with alternative process routings and flexible configurations; Li, Tan and Li (2018) who used an Artificial Bee Colony algorithm for optimising layout taking into account human factors; Neghabi, Eshghi and Salmani (2014) which adopted an adaptive algorithm for generating robust facility layouts without predetermining the length and width of departments; Salmani, Eshghi and Neghabi (2015) that used Mixed Integer Linear Programming and considered dynamic and uncertain values for the dimensions of departments; and Wang, Shin and Moon (2016) which considered layout design with unreliable machines. Only 9 papers studied both external and internal variabilities in FLP. There has been no previous research that has considered layout problems with dynamic demand and machine maintenance. This is the research gap considered by this research.

2.3. Machine breakdown

Machine breakdown has been one of the most studied disruptions in flexible job shop scheduling (Nouiri et al., 2017). The machine failure rate has been represented by the Poisson distribution (Schemeleva, Delorme, Dolgui & Grimaud, 2012) or generated randomly (Nodem, Kenne & Gharbi, 2011). Machine lifetime is commonly modelled using the Weibull distribution (Fitouhi & Nourelfath, 2012). The mean-time-to-failure has been represented by the normal distribution or the exponential distribution (Schemeleva et al., 2012). Corrective maintenance has also been considered in the context of robust scheduling for a flexible job-shop scheduling problem (Xiong, Xing & Chen, 2013). In terms of production scheduling, machine breakdown is stochastic, whereas preventative maintenance is planned (Sbihi & Varnier, 2008).

2.4. Preventive maintenance policies

Machines are subject to deterioration with usage and age. There is a substantial literature on maintenance that was reviewed by Garg and Deshmuth (2006). Preventive maintenance (PM) comprises “a series of tasks performed at a frequency dictated by the passage of time, the amount of production or machine condition” (Garg & Deshmukh, 2006, p.214). PM refers to “all actions performed in an attempt to retain a resource in a specified condition by providing systematic inspection, detection, and prevention of incipient failures” (Wang, 2002, p.470). Under a periodic policy, a unit is preventatively maintained at fixed time intervals and repaired if there are intervening failures, this is called fixed period maintenance or time-based maintenance (Safari & Sadjadi, 2011). Fig. 1 illustrates customer demand (D) changes over time period (P). PM policies can be periodic or based upon production quantities. In Fig. 1a, periodic-based PM (PPM) is scheduled every two periods. In Fig. 1b, the maintenance operations are performed according to a predefined production quantity (Q), known as production quantity-based PM (QPM), which is scheduled in periods 3 and 5. This policy is growing in popularity in industrial environments because these policies can decrease the cost of maintenance activities, which may be the largest part of an operational budget (Safari & Sadjadi, 2011).

2.5. Routing flexibility

Flexibility was defined as “the ability to effectively respond to change” (Buzacott & Mandelbaum, 1985, p.405). Flexibility helps address internal disturbances arising from machine breakdowns, variable task times, queuing delays, rejects and rework (Sethi & Sethi, 1990). There are eleven different types of flexibility: machine, material handling, operation, process, product, routing, volume, expansion, program and market. The flexibility to use alternative machines or routings helps mitigate problems with material flow that can arise when a particular machine becomes unavailable. Byrne and Chutima (1997) considered alternative machines to be those that could perform the same operations; whilst alternative routings could perform the same sequence of operations. A system with alternative production routes (flexible routes) can maintain high productivity when some machines have broken down or are under maintenance (Chang, 2007). Routing flexibility has been recognised as a fundamental characteristic of a manufacturing system's overall flexibility, as it enhances a system's ability to produce a given set of part types or part families without interruption. When routings are altered, material flow time and distances are likely to change.

3. Genetic algorithm for solving layout design problem

The Genetic Algorithm (GA) is a population-based, nature-inspired algorithm (Goldberg, 1989; Holland, 1962). A set of candidate solutions is generated as an initial set of solutions, which then undergoes an evolutionary search process. GAs use probabilistic transition rules to guide a highly exploitative search and also performs a multiple directional search by maintaining a population of potential solutions. In each iteration (generation) of the search process the crossover operator helps the GA move towards a local optimum (Hicks, 2006), whereas the mutation operator tends to move the search to a new neighbourhood which leads to increased diversity (Hicks, 2006; Islier, 1998).

Table 1
Problem characteristics based on demand profiles, dynamic conditions, layout configurations, and optimisation methods.

Authors	External factors				Internal factors												Approaches
	Flow matrix	Distribution function	Empirical data	Not explained	Number of machines	Set up time	Facility size	Routing flexibility	Machine maintenance	Processing time	Waiting time	Human factors	Machine reliability	Ambiguous data	Robust layout design	Re-layout design	
Abedzadeh, Mazinani, Moradinasab and Roghanian (2013)	/															/	GAMS software, PVNS algorithm
Altuntas and Selim (2012)		/													/		Rule-based data mining
Asl, Wong and Tiwari (2016)				/											/		Covariance matrix adaptation evolution
Asl and Wong (2017)	/															/	Modified Particle Swarm Optimisation
Ayodeji, Adeyeri and Ogunsua (2017)		/														/	Dynamic Programming
Azadeh, Motevali Haghighi and Asadzadeh (2014)		/					/								/		Data Envelopment Analysis Algorithm
Azadeh et al. (2016)														/	/		Fuzzy multivariate approach
Azevedo, Crispim and Pinho de Sousa (2017)	/															/	Quadratic programming
Azimi, Saberi and Studies (2013)		/														/	Hybrid Particle Swarm Optimisation
Azimi and Soofi (2017)									/	/	/				/		Artificial Neural Network hybrid GA
Balakrishnan and Cheng (2009)		/														/	Heuristic and Dynamic Programming
Bozorgi, Abedzadeh and Zeinali (2015)		/														/	Tabu Search
Chang et al. (2013)								/							/		Tabu Search
Chae and Regan (2016)							/								/		Linear Programming
Chan and Malmborg (2010)		/													/		Monte Carlo simulation
Chen (2013)		/														/	Hybrid Ant Colony Optimisation
Chen and Lo (2014)	/														/		Ant Colony Optimisation
Cheng Ying, Ab-Samat and Kamaruddin (2016)				/											/		Simulation, Analytic Hierarchy Process
Dong et al. (2009)					/											/	Modified Simulated Annealing
Drira, Pierreval and Hajri-Gabouj (2013)		/													/	/	Fuzzy Evolutionary Algorithm
Emami, S. and Nookabadi (2013)	/															/	GA, Differential Evolution, and SA
Fazlelahi, Pournader, Gharakhani and Sadjadi (2016)				/											/		Permutation-based GA
Ghosh, Doloi and Dan (2016)		/													/		GA and SA
Guan, Dai, Qiu and Li (2012)	/															/	Revised electromagnetism-like mechanism
Hanafy and ElMaraghy (2015)				/												/	Phylogenetic networks

(*continued on next page*)

Table 1 (*continued*)

Authors	External factors: Flow matrix	Distribution function	Empirical data	Not explained	Internal factors: Number of machines	Set up time	Facility size	Routing flexibility	Machine maintenance	Processing time	Waiting time	Human factors	Machine reliability	Ambiguous data	Robust layout design	Re-layout design	Approaches
Hosseini and Seifbarghy (2016)				/												/	Multi-objective water flow like algorithm
Hosseini, Khaled and Vadlamani (2014)	/															/	Neighborhood Search and SA
Hosseini-Nasab and Emami (2013)				/												/	Hybrid Particle Swarm Optimisation
Jithavech and Krishnan (2010)		/													/		Simulation, Genetic Algorithm
Kaveh, Dalfard and Amiri (2014)				/												/	GA and fuzzy Simulation Algorithm
Khaksar-Haghani et al. (2013)								/							/		Improved GA
Kheirkhah and Bidgoli (2016)		/														/	Competition algorithm and SA
Kheirkhah, Navidi and Messi Bidgoli (2015)		/														/	PSO and Co-evolutionary Algorithms
Kia et al. (2012)			/		/			/								/	Simulated Annealing
Kia, Javadian, Paydar and Saidi-Mehrabad (2013)				/	/			/								/	Simulated Annealing
Kia et al. (2014)			/			/										/	Genetic Algorithm
Kia, Shirazi, Javadian and Tavakkoli-Moghaddam (2015)				/		/										/	Simulated Annealing
Kovács and Kot (2017)	/															/	Kanban principle
Krishnan, Jithavech and Liao (2009)		/														/	Genetic Algorithm
Kulturel-Konak and Konak (2015)				/			/								/		Hybrid SA
Kumar and Singh (2017)				/												/	Score-based two-phase heuristic approach
Li et al. (2018)										/						/	Artificial Bee Colony algorithm
Liu, Wang, He and Xue (2017)	/															/	Combination of algorithm and heuristics
Manoochehri and Mohammadjafari (2017)				/												/	Simulation technique
Mazinani, Abedzadeh and Mohebali (2013)				/												/	Genetic Algorithm
McKendall and Hakobyan (2010)	/															/	Tabu Search / Boundary Search Heuristic
Mohammadi and Forghani (2014)		/			/			/							/		Genetic Algorithm
Moslemipour and Lee (2012)		/														/	Simulated Annealing
Moslemipour, Lee and Loong (2017)		/			/		/								/		Dynamic Programming / Simulated Annealing

(*continued on next page*)

Table 1 (*continued*)

Authors	External factors				Internal factors												Approaches
	Flow matrix	Distribution function	Empirical data	Not explained	Number of machines	Set up time	Facility size	Routing flexibility	Machine mainte-nance	Processing time	Waiting time	Human factors	Machine reliability	Ambiguous data	Robust layout design	Re-layout design	
Nageshwaraniyer, Khilwani, Tiwari, Shankar and Ben-Arieh (2013)	/															/	Symbiotic Algorithm and Clonal Algorithm
Neghabi et al. (2014)							/								/		Adaptive algorithm
Nematian (2014)		/													/		A modified Branch and Bound method
Pillai et al. (2011)		/													/	/	Simulated Annealing
Pourvaziri and Nederi (2014)		/														/	GA and SA
Pourvaziri and Pierreval (2017)		/														/	Cloud-based multi-objective SA
Rabbani, Farrokhi-Asl, Rafiei and Khaleghi (2017)				/												/	SA, PSO, and Hybrid PSO
Rezazadeh et al. (2009)	/															/	Improved Particle Swarm Optimisation
Sahin and Turkbey (2009)		/														/	Simulated Annealing (SA) and Tabu Search
Salmani et al. (2015)							/								/		Mixed integer linear programming
Samarghandi, Taabayan and Behroozi (2013)		/														/	Fuzzy Tabu Algorithm
Shafigh, Defersha and Moussa (2017)			/		/			/								/	Simulated Annealing (SA)
Tavakkoli-Moghaddam, Javadian, Javadi and Safaei (2007)		/													/		Branch-and-Bound approach
Tayal and Singh (2017)		/														/	Integrated Firefly and SA-based approach
Tayal, Gunasekaran, Singh, Dubey and Papadopoulos (2017)		/														/	SA, Chaotic SA, Hybrid SA and MADM method
Turanoğlu and Akkaya (2018)		/														/	Hybrid Bacterial Foraging Optimisation
Ulutas and Islier (2015)			/													/	Clonal Selection based algorithm
Ulutas and Islier (2009)		/														/	Clonal Selection Algorithm
Vitayasak and Pongcharoen (2018)		/	/												/		Teaching-Learning-Based Optimisation
Vitayasak, Pongcharoen and Hicks (2017)		/													/		Backtracking Search Algorithm and GA
Wang, Yang and Chang (2017)			/												/		Mixed Integer Programming
Wang et al. (2016)													/		/		Queueing Theory
Xiao, Xie, Kulturel-Konak and Konak (2017)	/															/	Problem Evolution Algorithm
Zhao and Wallace (2014)				/											/		Simulated Annealing
Zhao and Wallace (2016)				/											/		Myopic approach
This work		/	/					/	/						/		Genetic Algorithm

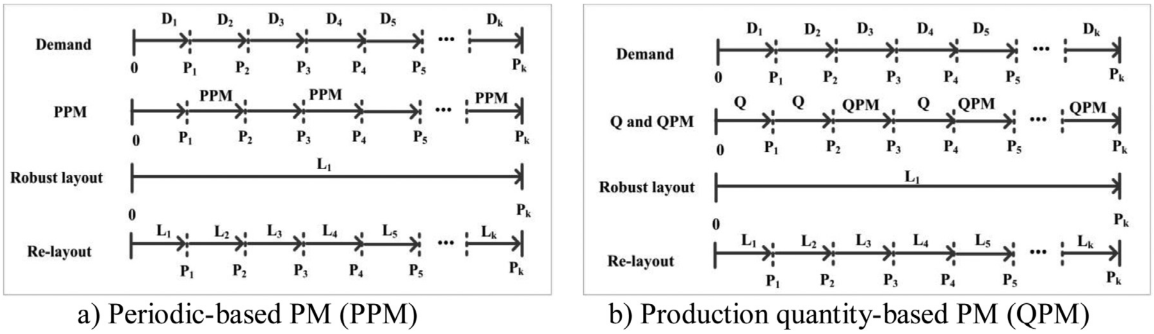

Fig. 1. Relationship between layout design approaches and type of preventive maintenance.

```
Input problem dataset (M, MW, ML, MS, N, PM plan)
Create demand level (Dgk) for each product associated with demand distribution
Randomly generate a list of machines requiring corrective maintenance according to %CM
Set attributes of the problem considered (FL, FW, G, P, %CM)
   Set GA parameters (Pop, Gen, Pc, Pm)
   Randomly generate initial population (Pop)
   Set a  = 1 (first generation)
   While a  ≤ Gen do
          For b = 1 to cross (cross = round ((PC x Pop)/2))) , perform crossover operations
       For c = 1 to mute (mute = round(Pm x Pop)) , perform mutation operations
       For each chromosome, arrange machines row by row based on FL , FW and G
       Replace the machines in maintenance with alternative machines
       For d = 1 to P, calculate material flow distance based on robust layout
       Perform elitist selection
       Chromosome selection using roulette wheel method
       a = a + 1
   End loop while
Output the best solution
```

Fig. 2. Pseudo code of GA for robust FLD.

5	2	10	6	7	12	4	9	8	1	3	11	13	14

Fig. 3. Chromosome representation (gene represents a machine number).

In this work, a GA was adopted for solving the facilities layout design (FLD) problem. The GA-based layout design tool includes both robust and re-layout design approaches for dealing with uncertainties that arise from dynamic customer demand and machine maintenance (based on three scenarios: only preventive maintenance, only corrective maintenance, and both preventive and corrective maintenance).

The GA pseudo-code for the proposed robust Facility Layout Design (FLD) problem shown in Fig. 2 has the following steps:

(i) problem encoding - chromosomes are produced that comprise a list of genes (each representing a machine number); the number of genes in each chromosome is equal to the number of machines to be arranged (see Fig. 3);

(ii) load the input data - the number of machines (M), the dimensions of machines (width: M_W x length: M_L), the number of products (N), the machine sequences (M_S) and the preventative maintenance (PM) plan for each machine;

(iii) specify the Genetic Algorithm parameters: the population size (Pop), the number of generations (Gen), the probability of crossover (P_c), the probability of mutation (P_m), floor length (F_L), floor width (F_W), the gap between machines (G), the number of periods (P) and the percentage of machines that require corrective maintenance (%CM) per period. All parameters can be identified via the user interface window of the program as shown in Fig. 4;

(iv) create the demand levels for each product in each period (D_{gk});

(v) randomly generate a list of machines that require CM according to the %CM;

(vi) randomly generate initial chromosomes according to population size (*Pop*);

(vii) apply crossover and mutation operators to generate new offspring considering P_c and P_m. The two-point centre crossover operator (illustrated in Fig. 5a) and two-operations random swap mutation operator (see Fig. 5b) were applied in this work.

(viii) arrange the machines sequentially row-by-row, from left to right, starting at the first row and taking into account F_L with a gap (G) between adjacent machines. The machine width is parallel to the x-axis. The machine length is parallel to the y-axis. Fig. 6 illustrates the placement of the machines relating to the genes in the child chromosome shown in Fig. 5b).

When there is not enough space for placing the next machine at the end of the row, it is placed in the next row. If floor width (F_W) is insufficient, the program will report the extra space required for placing all of the machines. Vehicles moving between rows move from the left or the right side of the row and then up or down to the destination row. The flow distance was evaluated for the shortest route. For example, there are two routes from machine 4 to machine 11; route A would be selected as it is shorter.

(ix) replace the machines in maintenance with alternative machines;

Once a machine becomes. unavailable, for example being under maintenance, an alternative machine with same type

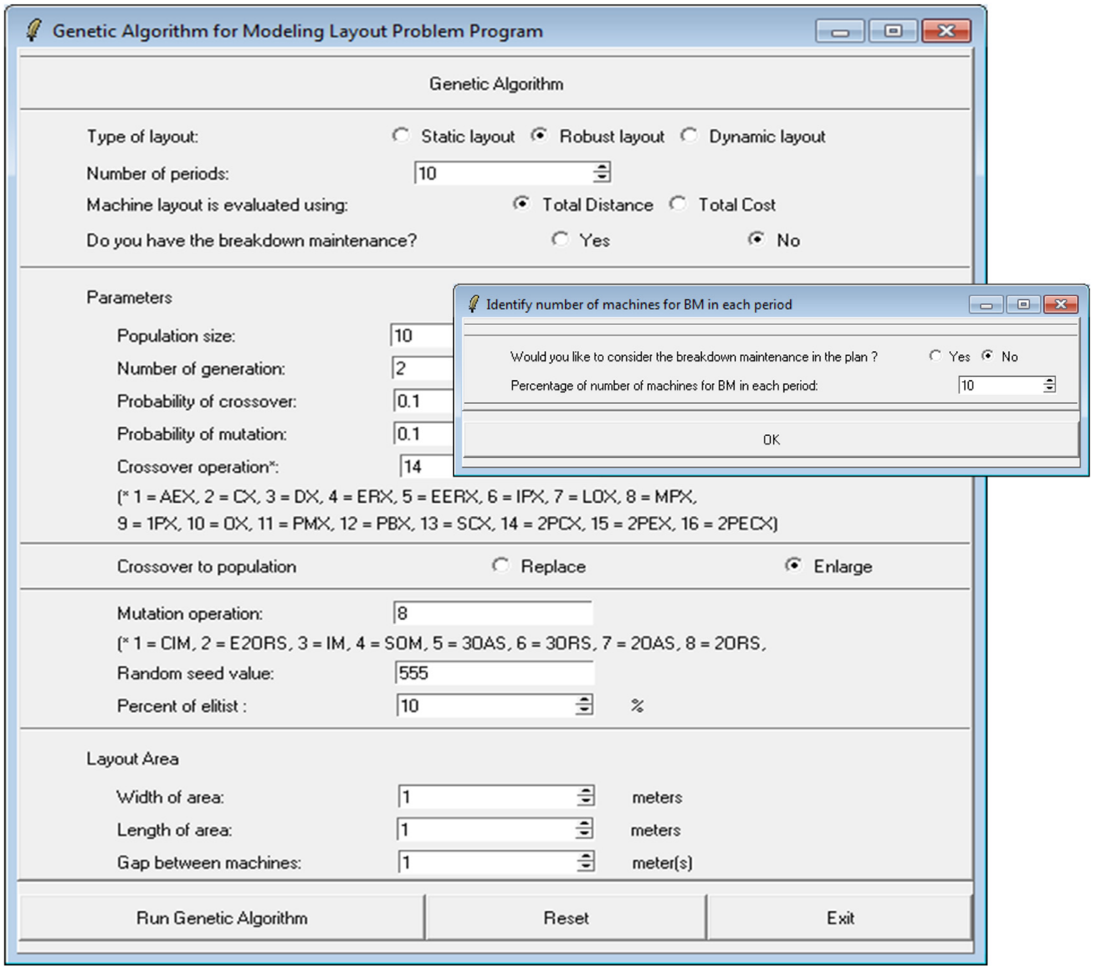

Fig. 4. User interface window of the program.

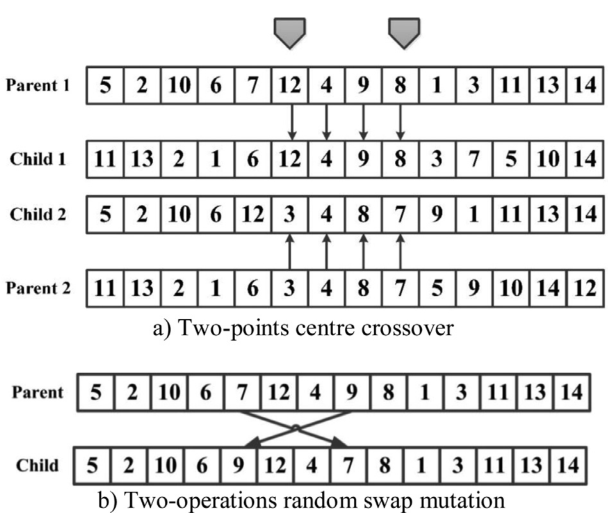

Fig. 5. Mechanism of genetic operators (Murata & Ishibuchi, 1994).

will be prioritised first. Otherwise, a set of pre-defined alternative machines types (e.g. lower-classed machines) will be selected to cover all of the operations for the unavailable machine. The processing route is changed to reflect the alternative machine(s). For example, Fig. 7 assumes the machine sequence 1-2-3. The total material handling distance is MFD1. If machine 3 is unavailable, machine 11 can be used an alternative, leading to the sequence 1-2-11. The distance for this route is MFD2. When machine 3 is available again the sequence returns to 1-2-3. If the lower-classed machine can only perform some of the operations required, a second alternative machine may be required to cover the remaining operations performed on the unavailable machine. Fig. 7 provides an example. If machine 8 and machine 9 (8-9) are alternative machines for the unavailable machine 3, the new machine sequence is 1-2-8-9.

(x) calculate the fitness value (material flow distance) for chromosome (a) in each period (d) by applying the fitness function. The fitness function (Z) for the efficiency of robust layout design minimises total material flow distance (MFD) as defined by Eq. (1). In case of machine maintenance, Eq. (1) is still valid for determining the total material flow distance (MFD*) but the added star symbol "*" differentiates the maintenance case with alternative machines from the case without maintenance or alternative machines (MFD).

$$Minimise\, Z = \sum_{i=1}^{M}\sum_{j=1}^{M}\sum_{g=1}^{N}\sum_{k=1}^{P} d_{ijgk} f_{ijgk} D_{gk}, \tag{1}$$

M is the number of machines, i and j are machine indexes (i and $j = 1, 2, 3, \ldots, M$) ($i \neq j$). N is the number of product types, g is a product index ($g = 1, 2, 3, \ldots, N$) and P is the number of time periods, k is a time period index ($k = 1, 2, 3,$

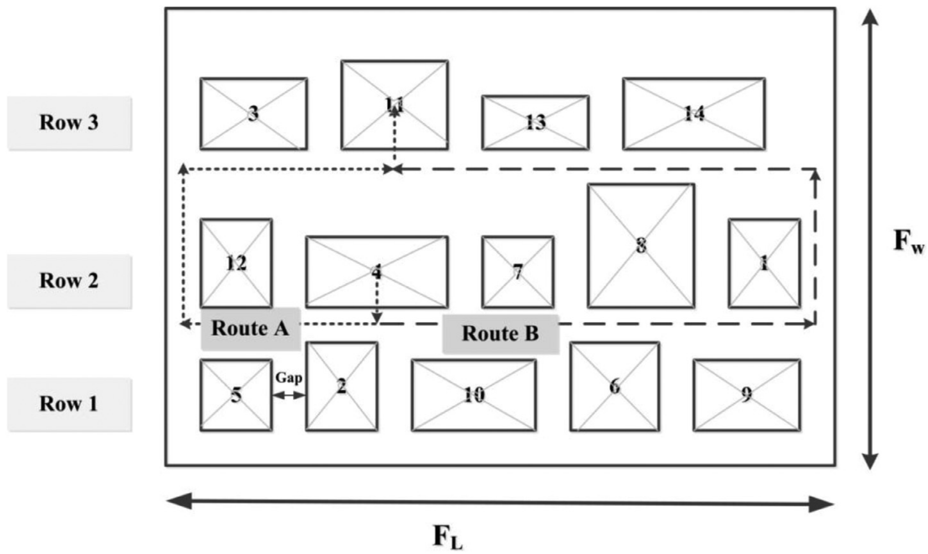

Fig. 6. Example of multiple-row machine layout design (Vitayasak & Pongcharoen, 2015).

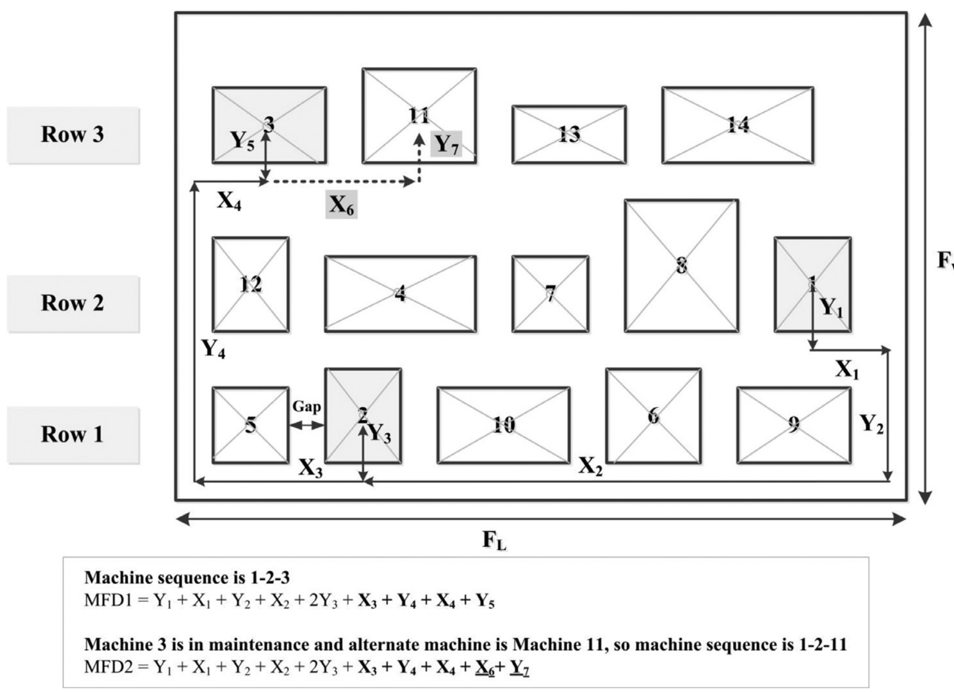

Fig. 7. Example of changes in the processing route and material flow distance.

…, *P*). d_{ijgk} is the material flow distance for product *g* from machine *i* to *j* in period *k*, f_{ijgk} is the frequency of material flow for product *g* from machine *i* to *j* in period *k*, and D_{gk} is the customer demand for product *g* in period *k*.

The following assumptions were made to simplify and formulate the problem: 1) material handling between machines is operated via pick-up and drop-off points (P/D points) located at the machines' centroids; 2) the material flow distance between P/D points was measured from the front of machines; 3) the machines were arranged in multiple rows; 4) each machine had either one alternative machine or a group of alternative machines; 5) in case of a random breakdown, an available alternative machine is used during the time period; 6) automated guided vehicles move on rectilinear lines along the perimeter of the shop floor; 7) the gap between machines is constant; 8) preventive maintenance plans are periodic (PPM) or based upon production quantities (QPM); and 9)for the QPM, the maintenance operations are performed when the summation of customer demand equals the predefined production quantity.

(xi) select elite chromosomes according to percentage of sorted chromosomes (%Elite) in Eq. (2) using the elitist selection mechanism. The chromosomes are sorted according to the material flow distance (MFD). The best chromosome has the shortest MFD;

$$\text{Elite chromosome} = \%\text{Elite x Population size (Pop)} \qquad (2)$$

The elitist selection mechanism (Fig. 8) reproduces the best%Elite chromosomes in the next generation, which is used in step xii). A value of 10% was used.

(xii) choose chromosomes by using roulette wheel selection - the probability of selecting an individual is proportional to its

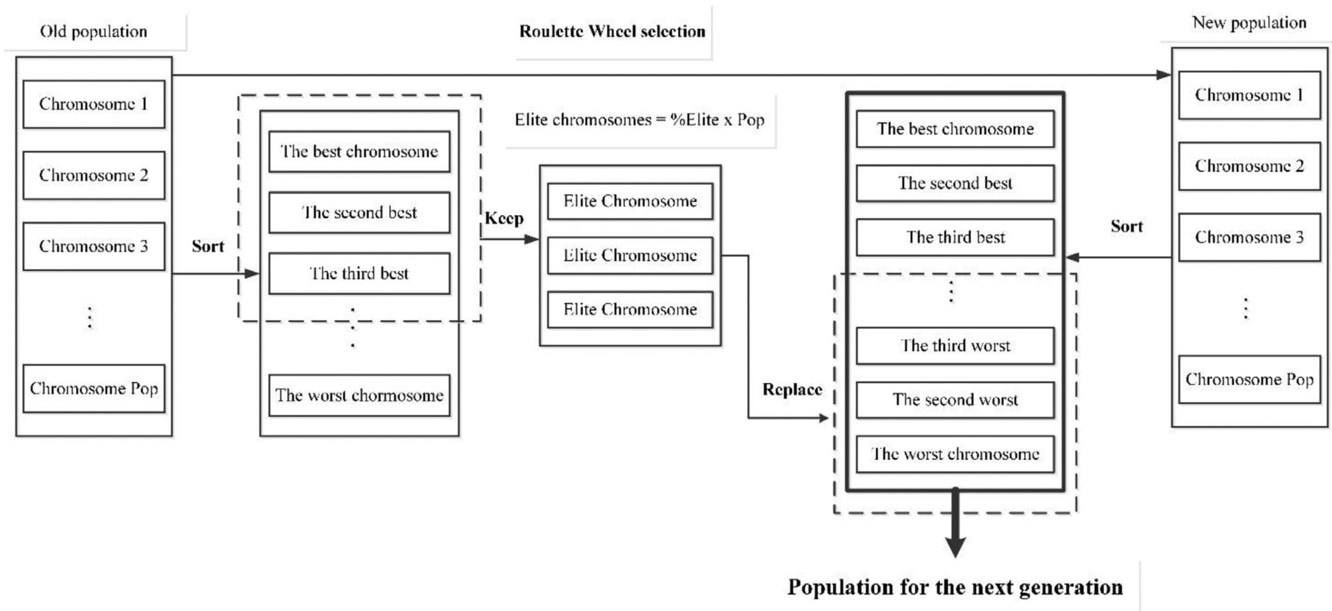

Fig. 8. Mechanism for Elitist selection and Roulette wheel selection.

relative fitness. The roulette wheel is 'spun' repeatedly to produce a new population of the same size as the initial population. Then, the chromosomes in the new population are sorted in accordance with their fitness. The least fit chromosomes are replaced with elite chromosomes;

(xiii) the GA process is terminated after the specified number of generations and the best-so-far solution is reported and shown as a graphic.

The selection of GA parameters (population size, number of generations and the probabilities of crossover and mutation) has a large impact on their performance (Pongcharoen, Chainate & Samranpun, 2007). The appropriate settings of the GA parameters for the machine layout problems were considered by Vitayasak (2011), in which an analysis of variance (ANOVA) suggested that the probability of crossover (P_c) and mutation (P_m) should be set at 0.9 and 0.5, respectively, with 50 chromosomes and 50 generations. The genetic operators adopted in this work were Two-point Centre Crossover (2PCX) and Two Operation Random Swap (2ORS) (Vitayasak & Pongcharoen, 2011). The GA based layout design tool was developed and coded in a modular style using the Tool Command Language and Tool Kit (Tcl/Tk) programming language (Ousterhout, 2010).

Table 2
Datasets.

Datasets	Number of machines (M)	Number of products (N)
10M5N	10	5
10M10N	10	10
20M10N	20	10
20M20N	20	20
20M40N	20	40
30M15N	30	15
30M30N	30	30
40M20N	40	20
40M40N	40	40
50M25N	50	25
50M40N	50	40

Table 3
Summary of product demand distributions and machine sequences for 10M5N.

Product	Product demand distribution	Machine sequence
1	Uniform (100, 200)	2-1-6-5-8-9-3-4
2	Uniform (50, 100)	10-8-7-5-9-6-1
3	Normal (180, 50)	9-2-7-4
4	Normal (300, 120)	8-10-5-9-6
5	Exponential (1/200)	2-4-8-10-7

4. Experimental design and analysis

The computational experiments were conducted using eleven datasets (Vitayasak & Pongcharoen, 2018), which had different numbers of non-identical machines, with various product types as shown in Table 2. Each type of product had different demand profiles and machine sequences, as shown in Table 3. Demand profiles can be uploaded into the program using either empirical data or by selecting a probability distribution (exponential, normal distribution, or uniform). The user can select the number of time periods. In the computational experiments ten time-periods were considered. The layout design approach was based on 'robust design', without machine relocation. The experiments were conducted on a personal computer with an Intel Core i5 2.8 GHz CPU and 4 GB DDR3 RAM.

To investigate the effect of number of unavailable machines on material flow distance, the following three maintenance scenarios were considered: Scenario I: only preventive maintenance (PM); Scenario II: only corrective maintenance (CM); and Scenario III: both PM and CM.

For scenario I, the ratio of the number of machines with period-based PM to the number with production quantity-based PM (PPM/QPM) in each period was studied at three levels, 20/80, 50/50, and 80/20. For scenario II, the percentage of machines with corrective maintenance (%CM) was also considered at three levels, 10%, 20% and 30%. For scenario III, two levels of PMM/QPM ratio (20/80 and 80/20) and two levels of %CM (10% and 30%) were studied. During periods of maintenance alternative machines were used, which required changes to the routings.

Each experiment was replicated thirty times using different random seeds with a full factorial design. There were eleven

Table 4
Comparison of MFD and MFD* for scenario I: PM.

Dataset	Value	MFD based on PPM/QPM (metre)			MFD* based on PPM/QPM (metre)		
		20/80	50/50	80/20	20/80	50/50	80/20
10M5N	Mean	732,542.5	682,908.9	671,328.9	**691,865.7**	**668,652.3**	**665,583.0**
	SD	24,647.6	20,695.9	20,238.0	4119.6	11,341.9	13,758.9
	Min	713,598.0	664,472.9	654,634.8	689,136.2	661,275.3	654,634.8
	Max	832,939.7	736,192.5	722,275.7	705,477.0	702,680.3	700,175.2
10M10N	Mean	1,976,667.4	1,892,978.1	1,859,314.2	**1,365,585.7**	**1,555,505.8**	**1,713,101.3**
	SD	49,187.6	16,297.4	20,541.5	30,343.5	18,713.4	14,422.8
	Min	1,861,464.9	1,873,784.0	1,810,030.5	1,332,408.9	1,539,135.7	1,700,812.0
	Max	2,016,763.9	1,932,690.0	1,881,312.6	1,455,138.8	1,635,094.6	1,742,679.4
20M10N	Mean	4,001,771.7	3,940,840.1	3,729,899.9	**3,592,326.6**	**3,634,375.6**	**3,614,821.5**
	SD	78,242.4	79,494.8	68,393.4	73,249.1	43,154.5	44,409.6
	Min	3,829,033.9	3,821,550.9	3,599,206.3	3,465,857.2	3,539,722.1	3,539,102.4
	Max	4,101,750.6	4,085,982.0	3,842,643.8	3,766,232.0	3,722,638.0	3,727,000.0
20M20N	Mean	11,513,726.3	10,783,205.5	10,843,729.9	**9,977,229.7**	**10,189,105.8**	**10,627,060.1**
	SD	299,771.8	298,390.9	240,696.3	244,037.1	121,587.8	115,279.7
	Min	11,071,694.1	10,333,942.9	10,463,019.1	9,597,502.4	9,989,522.6	10,432,751.3
	Max	12,130,858.2	11,517,033.3	11,454,630.8	10,524,709.4	10,486,443.6	10,862,024.5
20M40N	Mean	21,401,460.7	19,986,017.0	20,544,511.3	**18,412,155.3**	**18,938,010.2**	**19,970,511.5**
	SD	512,797.8	578,927.0	323,605.9	391,668.2	230,848.5	232,269.3
	Min	20,603,137.2	18,731,438.0	19,999,276.1	17,817,505.4	18,475,407.8	19,590,558.5
	Max	22,339,703.9	21,082,385.4	21,104,899.6	19,093,318.0	19,437,762.3	20,595,303.8
30M15N	Mean	8,789,956.5	8,551,413.8	8,643,304.4	**7,956,149.15**	**8,440,682.20**	**8,483,438.64**
	SD	163,832.5	191,461.6	173,280.2	194,371.04	131,806.11	87,145.06
	Min	8,515,022.2	8,255,329.1	8,206,987.7	7,466,729.75	8,179,130.67	8,328,513.24
	Max	9,175,074.3	8,926,977.0	8,949,400.7	8,438,340.21	8,715,695.05	8,701,946.22
30M30N	Mean	19,301,863.60	18,487,734.83	18,690,797.41	**17,204,962.04**	**17,396,236.45**	**18,214,404.94**
	SD	435,923.13	516,278.59	380,761.66	402,715.31	353,777.78	263,081.10
	Min	18,372,318.53	17,551,378.72	17,995,914.35	16,445,449.33	16,716,437.07	17,375,926.59
	Max	20,179,254.75	19,818,815.62	19,456,224.74	18,125,773.31	18,031,117.12	18,725,122.02
40M20N	Mean	18,858,370.7	17,337,722.43	17,809,046.9	**17,318,043.57**	**17,225,214.19**	**17,255,004.23**
	SD	511,956.3	447,197.64	488,921.8	296,621.80	365,120.69	378,466.45
	Min	17,894,054.6	16,480,907.34	16,853,058.9	16,508,074.48	16,539,613.57	16,600,313.04
	Max	20,246,679.0	18,345,406.56	18,957,250.8	17,975,588.85	17,916,696.26	18,277,513.32
40M40N	Mean	32,803,402.4	**30,982,086.8**	31,641,802.8	**31,298,488.0**	31,035,390.7	**31,345,619.6**
	SD	801,659.0	722,317.8	650,073.4	726,381.7	711,805.7	620,078.0
	Min	30,977,346.9	29,219,342.9	30,194,195.0	30,232,613.4	29,534,475.2	30,301,396.8
	Max	34,205,187.1	32,381,014.5	32,864,760.4	32,875,952.8	32,327,958.4	32,969,441.4
50M25N	Mean	30,416,821.5	28,333,573.0	29,107,471.2	**29,229,012.2**	**28,160,455.8**	**28,469,378.4**
	SD	760,184.5	633,765.3	650,899.3	594,235.6	493,595.3	595,960.7
	Min	28,813,572.1	26,841,331.4	27,568,289.9	28,053,520.0	27,109,933.9	27,433,665.5
	Max	31,820,838.4	29,787,280.8	30,314,566.6	30,417,033.0	29,194,486.7	29,549,430.7
50M40N	Mean	43,031,913.11	40,691,396.66	41,268,975.91	**40,460,200.71**	**39,490,367.57**	**40,344,555.51**
	SD	952,627.77	918,014.12	879,344.63	972,265.88	592,128.02	751,780.72
	Min	40,965,451.37	38,282,898.46	39,139,888.29	39,055,623.37	38,466,880.56	38,826,428.61
	Max	45,404,975.41	42,428,452.96	43,581,746.30	44,343,340.20	40,718,144.44	42,392,739.34

datasets, thirty replications, three levels of the PPM/QPM ratio, and three levels of %CM, which gave a total of $11 \times 30 \times 3 = 990$ runs for scenario I and II. In scenario III, two levels of PMM/QPM ratio and two levels of %CM were studied with eleven datasets, and thirty replications, so the total number of computational runs was $2 \times 2 \times 11 \times 30 = 1320$ runs.

The experiments considered robust layout design under dynamic demand and machine maintenance. The objective was to minimise the material flow distance (*MFD**). The distance travelled obtained from the layout design without consideration of maintenance was termed *MFD*. The *MFD* for scenario II was adopted from the previous work (Vitayasak & Pongcharoen, 2015). Both *MFD** and *MFD* were calculated using Eq. (1). The computational results obtained from the robust layout design without and with consideration of machine maintenance are described in the following subsections.

4.1. Layout design without and with consideration of machine maintenance

The material flow distances obtained from two layout design approaches without and with consideration of maintenance (*MFD* and *MFD**) are shown in Tables 4, 5, and 6. When maintenance considerations are not included, the *MFD* is determined based on the machine-processing route; whilst when machine maintenance is considered, the *MFD** is evaluated from the alternative machine-processing route.

The layout design with consideration of maintenance operations (PM, CM or both PM and CM) resulted in shorter travel distance for almost all the datasets. *MFD** was reduced by up to 30.91% (10M10N dataset, with the 20/80 ratio), 9.8% (40M20N dataset, with 30%CM), and 20.7% (10M10N dataset, with a 20/80 for PM and 30%CM) compared to MFD for scenarios I, II, III, respectively. The shorter distances were achieved by the design approach that considered alternative machines in the machine-processing routes. However, the *MFD** based on 50/50 PPM/QPM and 40M40N datasets in scenario I were longer due to the use of alternative machines and their location. The experimental results and differences in *MFD* and *MFD** for each scenario were analysed statistically (discussed in Section 4.2).

The PPM/QPM ratios in scenario I, %CM in scenario II, and both PMM/QPM ratio and %CM in scenario III effected both *MFD* and *MFD**. Changes in the flow distances had no obvious patterns for example, the proportion of PPM in PPM/QPM ratios resulted in

Table 5
Comparison of MFD and MFD* for scenario II: CM.

Dataset	Value	MFD based on %CM (metre)			MFD* based on %CM (metre)		
		10	20	30	10	20	30
10M5N	Mean	595,992.6	648,008.0	718,537.9	**590,735.3**	**635,137.6**	**654,871.8**
	SD	18,962.6	22,179.8	19,694.1	16,296.5	12,580.0	4934.4
	Min	578,595.5	629,746.0	703,029.4	578,595.5	626,338.8	650,562.2
	Max	649,594.9	701,533.4	774,072.3	625,753.0	673,371.0	668,980.6
10M10N	Mean	1,743,496.2	1,820,137.3	1,900,532.4	**1,714,028.2**	**1,768,381.9**	**1,743,789.8**
	SD	23,439.5	13,037.3	25,364.2	14,977.4	6627.3	5350.4
	Min	1,724,716.2	1,798,904.2	1,831,347.7	1,705,903.0	1,762,266.7	1,732,380.9
	Max	1,806,196.4	1,865,916.6	1,918,760.8	1,768,640.5	1,782,853.8	1,759,054.9
20M10N	Mean	3,542,104.0	3,628,745.5	3,941,721.4	**3,502,114.8**	**3,486,977.2**	**3,660,302.0**
	SD	70,083.5	90,727.4	93,797.2	65,178.1	57,637.9	53,742.4
	Min	3,405,568.5	3,491,732.5	3,751,832.7	3,374,479.0	3,385,945.7	3,572,248.2
	Max	3,697,350.4	3,825,789.1	4,136,080.9	3,612,987.2	3,590,665.7	3,776,400.2
20M20N	Mean	10,886,407.5	11,491,341.5	10,040,630.5	**9,975,829.5**	**10,271,479.3**	**10,775,891.3**
	SD	377,961.7	379,507.2	64,521.2	150,438.9	136,099.6	122,597.3
	Min	10,135,672.5	10,873,095.3	9,911,473.3	9,634,447.2	9,986,824.9	10,549,215.6
	Max	11,917,048.8	12,629,320.2	10,145,030.9	10,164,784.6	10,494,467.5	11,066,485.3
20M40N	Mean	20,347,121.1	21,261,068.2	20,815,688.1	**20,055,976.8**	**20,538,439.4**	**19,792,882.4**
	SD	318,814.4	355,670.7	361,285.2	256,549.6	255,692.7	244,704.3
	Min	19,887,820.5	20,614,947.8	20,049,924.7	19,521,965.0	19,990,144.4	19,385,382.5
	Max	21,181,869.2	22,179,471.9	21,493,810.5	20,638,112.7	21,214,033.3	20,368,678.3
30M15N	Mean	8,276,170.0	8,489,326.7	9,056,617.6	**8,112,260.89**	**8,109,334.22**	**8,517,554.15**
	SD	213,714.2	209,076.6	197,351.2	160,677.68	136,576.21	122,294.57
	Min	7,915,148.6	8,041,397.4	8,663,135.8	7,716,345.63	7,912,373.96	8,342,702.04
	Max	8,642,410.7	8,884,425.3	9,448,623.8	8,369,170.86	8,407,071.29	8,866,532.80
30M30N	Mean	18,488,449.3	19,213,555.9	19,924,934.3	**18,056,501.0**	**18,570,871.1**	**18,870,939.7**
	SD	345,013.1	376,796.3	390,559.1	290,811.3	257,302.4	425,340.4
	Min	17,813,400.0	18,531,809.7	19,075,102.0	17,529,610.1	18,153,692.7	18,285,164.3
	Max	19,047,688.1	19,999,742.7	20,852,219.5	18,538,341.9	19,296,918.2	19,878,511.9
40M20N	Mean	17,166,328.0	17,680,469.6	19,807,215.4	**16,963,181.88**	**16,918,410.83**	**17,865,200.18**
	SD	596,320.1	711,828.6	628,823.9	450,898.81	386,285.35	427,203.26
	Min	16,275,826.0	16,382,959.9	18,444,970.6	16,003,309.77	16,191,351.68	16,949,237.51
	Max	18,793,575.0	19,249,222.1	20,954,182.8	17,939,692.95	17,785,665.63	18,571,965.60
40M40N	Mean	30,354,735.4	32,107,292.1	34,014,129.5	**30,014,644.7**	**31,471,994.4**	**31,977,370.8**
	SD	710,209.0	732,868.0	913,114.6	688,480.4	724,316.4	496,761.8
	Min	28,861,378.3	30,625,120.7	32,160,002.9	28,700,335.2	30,208,296.0	30,629,629.6
	Max	31,531,345.4	33,591,573.4	36,340,903.2	31,406,586.2	32,832,899.7	32,865,393.8
50M25N	Mean	27,178,003.2	30,270,244.4	30,870,860.1	**27,092,641.4**	**29,081,579.6**	**28,831,111.7**
	SD	668,805.8	1,470,163.5	1,062,502.1	568,595.4	572,029.1	635,753.7
	Min	25,890,014.3	28,608,583.1	29,248,548.6	25,769,239.5	27,571,531.5	27,526,568.9
	Max	28,643,707.9	34,650,791.3	33,655,833.1	28,551,539.0	29,899,271.5	30,363,093.6
50M40N	Mean	38,665,200.8	40,623,452.1	42,813,257.3	**38,410,673.5**	**39,068,770.5**	**39,716,291.9**
	SD	926,397.9	875,337.7	1,029,425.4	996,253.1	579,898.0	1,572,021.9
	Min	36,759,326.4	38,525,081.4	40,711,956.5	36,490,243.4	37,972,072.9	35,925,018.8
	Max	40,206,702.1	42,427,400.6	45,364,718.2	41,594,068.6	39,965,774.8	41,252,991.8

shorter distances (both *MFD* and *MFD**) in 10M5N dataset, whilst the *MFD** increased in the 10M10N, 20M10N, 20M20N, 20M40N, and 30M15N datasets. In scenario II, a number of machines in CM increased but the distance varied, in some cases shorter, in other cases longer. These results show that production conditions can make the layout more or less efficient.

The graphical layouts produced by the program with and without maintenance consideration are shown in Fig. 9a) and Fig. 9b), respectively, both figures are the machine arrangements produced by one replication of the 40M20N dataset in the 10%CM case from scenario II. In period 10, 2-3 (MC2-MC3) is part of the machine sequence for product no.12. In Fig. 9a) machine 3 is unavailable because of CM, and machine 31 (MC31) is the alternative machine. The sequence was changed to 2-31 (MC2-MC31). The flow distance between MC2 and MC31 in Fig. 9a) is shorter than in Fig. 9b) due to the layout design.

4.2. Statistical analysis on the experimental results

The experimental results in Table 4, 5, and 6 were analysed using the Student's *t*-test and analysis of variance (ANOVA).

4.2.1. The student's t-test

The Student's *t*-test was used to test differences in the means *MFD* and *MFD** for the three scenarios shown in Table 7. For scenario I, there were statistically significant differences (*P*-value < 0.05) with a 95% confidence interval, except for the 50/50 PPM/QPM ratio for problems 40M20N and 40M40N, and the 80/20 PPM/QPM ratio for the 40M40N problem. For scenario II, there were statistically significant differences in the means of *MFD* and *MFD** except for 10%CM for the 10M5N, 40M20N 40M40N and 50M40N problems. For scenario III, the *P*-values were less than 0.05 for all datasets, so there were statistically significant differences in the mean of *MFD* and *MFD**. These results emphasised that effective layout design cannot overlook machine maintenance.

4.2.2. Analysis of variance (ANOVA)

The effects of PPM/QPM ratios in scenario I, the percentages of CM in scenario II (%CM), and both PPM/QPM ratios and %CM in scenario III on material flow distance were analysed using an ANOVA to calculate *P* values as shown in Table 8. For scenario I, the results showed that The PPM/QPM ratios significantly affected the material flow distance with a 95% confidence interval, since the *P* values are less than 0.05 except for 40M20N and 40M40N.

Table 6
Comparison of MFD and MFD* for scenario III: PM and CM.

Dataset	Value	MFD based on PPM/QPM (metre)				MFD* based on PPM/QPM (metre)			
		20/80 with %CM:		80/20 with %CM:		20/80 with %CM:		80/20 with %CM:	
		10	30	10	30	10	30	10	30
10M5N	Mean	756,154.2	759,314.1	711,630.5	774,386.9	**696,449.1**	**682,969.7**	**689,155.4**	**690,297.0**
	SD	13,883.2	19,098.0	16,444.3	19,695.7	2988.0	7388.5	3499.3	6947.8
	Min	740,685.2	748,179.5	701,040.9	752,025.0	692,655.0	679,476.9	687,224.1	685,348.6
	Max	820,830.6	822,493.2	757,159.5	820,557.4	704,306.4	716,359.4	705,154.0	707,057.2
10M10N	Mean	1,696,411.2	1,625,937.8	1,919,182.4	2,003,574.7	**1,363,107.2**	**1,299,582.2**	**1,696,411.2**	**1,625,937.8**
	SD	12,532.6	22,534.9	28,228.1	29,694.8	24,383.2	17,638.0	12,532.6	22,534.9
	Min	1,676,742.0	1,613,265.3	1,863,424.6	1,930,963.5	1,340,688.4	1,281,094.1	1,676,742.0	1,613,265.3
	Max	1,718,454.6	1,669,606.3	1,964,517.5	2,051,139.6	1,420,904.3	1,342,070.7	1,718,454.6	1,669,606.3
20M10N	Mean	4,119,919.6	4,133,927.1	3,908,550.1	4,005,296.5	**3,595,637.1**	**3,567,280.8**	**3,750,587.2**	**3,667,979.3**
	SD	95,199.3	98,473.9	82,028.7	94,047.0	62,974.0	84,852.4	53,481.9	65,916.9
	Min	3,890,903.3	3,963,443.5	3,679,723.0	3,826,392.1	3,465,971.8	3,409,105.7	3,652,461.3	3,575,148.0
	Max	4,279,254.9	4,285,285.7	4,060,176.6	4,158,645.2	3,733,667.8	3,780,967.2	3,889,113.3	3,834,580.3
20M20N	Mean	11,684,238.3	11,587,409.5	11,436,897.2	11,632,622.8	**9,784,872.0**	**9,704,728.0**	**10,640,238.3**	**10,580,494.1**
	SD	567,227.3	393,346.9	266,980.2	286,861.7	229,961.4	249,658.8	115,081.6	126,464.7
	Min	10,178,930.6	10,836,389.6	10,991,330.4	11,228,632.5	9,320,756.7	9,240,327.7	10,450,294.7	10,416,982.1
	Max	12,506,884.6	12,325,671.3	12,091,105.6	12,338,001.2	10,340,840.9	10,161,215.5	10,874,935.8	10,968,645.8
20M40N	Mean	21,547,184.5	21,955,526.9	20,961,451.7	21,383,550.2	**18,351,926.2**	**17,952,853.6**	**19,647,857.8**	**19,339,586.6**
	SD	586,510.4	651,830.5	351,224.6	468,077.5	395,256.3	373,085.4	181,672.6	251,284.2
	Min	20,404,044.1	20,898,599.4	20,347,095.3	20,491,165.3	17,365,794.3	17,373,888.9	19,201,604.1	18,873,281.5
	Max	22,693,245.3	23,264,730.7	21,503,352.5	22,172,473.9	19,154,074.6	18,846,545.3	20,013,134.3	19,854,377.1
30M15N	Mean	9,103,269.9	9,233,038.8	8,896,745.1	8,987,536.6	**8,267,592.0**	**8,021,975.1**	**8,529,552.3**	**8,552,366.8**
	SD	169,537.0	171,008.2	173,206.4	184,264.6	140,270.5	148,486.1	140,431.2	135,258.0
	Min	8,819,073.4	8,963,978.0	8,549,216.6	8,468,788.2	8,060,902.7	7,728,910.4	8,317,774.1	8,266,294.8
	Max	9,527,748.8	9,604,435.3	9,173,632.1	9,222,950.2	8,588,666.9	8,360,262.2	8,775,369.8	8,856,695.1
30M30N	Mean	19,505,928.3	19,762,956.4	19,601,415.9	19,428,292.6	**16,932,208.1**	**17,363,912.1**	**18,923,550.0**	**18,520,402.3**
	SD	505,868.8	572,729.5	370,660.4	397,525.0	280,582.2	415,910.7	319,813.1	323,064.5
	Min	18,482,344.2	18,796,062.8	18,983,931.9	18,701,559.1	16,253,491.5	16,561,240.6	18,243,241.7	17,880,132.1
	Max	20,720,940.2	20,737,246.1	20,303,728.3	20,185,673.3	17,436,314.9	18,564,151.2	19,483,474.2	19,100,631.7
40M20N	Mean	20,088,567.2	20,622,426.6	19,320,811.0	19,820,034.4	**17,871,005.5**	**18,206,122.4**	**18,052,155.3**	**17,931,324.5**
	SD	668,154.1	641,100.3	506,074.1	611,456.3	341,064.0	373,018.9	424,514.7	380,688.6
	Min	18,925,914.0	19,444,805.3	18,085,390.0	18,444,970.6	17,206,286.8	17,639,624.0	17,442,744.0	17,317,107.6
	Max	21,436,825.7	21,962,994.3	20,085,304.0	20,954,182.8	18,476,883.6	19,025,693.3	19,313,919.9	18,744,777.1
40M40N	Mean	34,524,264.6	35,205,647.0	34,234,719.4	34,661,170.4	**32,227,970.6**	**32,019,455.4**	**32,683,300.5**	**32,504,726.6**
	SD	944,627.4	933,575.1	865,431.9	857,340.2	840,403.8	679,697.4	617,009.5	597,281.1
	Min	32,200,672.3	33,130,117.1	32,262,815.8	32,259,884.6	30,986,173.3	30,810,745.5	31,501,492.7	31,074,336.7
	Max	35,961,923.5	36,710,861.5	36,393,348.9	36,193,284.5	34,097,699.1	33,571,654.4	34,434,440.4	33,529,452.6
50M25N	Mean	32,774,478.7	32,651,407.2	30,839,771.0	31,046,583.7	**30,023,350.7**	**29,835,449.8**	**29,922,703.3**	**29,095,235.1**
	SD	834,599.6	877,062.3	621,845.2	784,307.3	531,123.2	462,479.7	1,606,028.9	536,007.8
	Min	31,354,594.9	31,028,567.0	29,245,455.1	29,411,674.2	28,816,579.1	28,708,173.9	28,455,958.5	27,843,837.0
	Max	34,948,695.9	34,827,671.8	31,739,507.5	32,347,650.6	31,014,303.3	30,671,972.6	34,676,639.3	30,338,961.7
50M40N	Mean	44,086,719.7	44,636,696.3	43,086,633.8	43,174,077.6	**41,169,524.8**	**41,188,981.3**	**41,030,026.2**	**40,977,432.1**
	SD	994,298.1	1,021,741.6	1,044,123.1	1,042,832.8	684,203.7	760,165.2	855,671.1	840,875.4
	Min	41,722,477.5	42,411,002.7	40,555,375.7	40,054,726.3	39,994,590.8	39,816,605.2	39,447,020.7	39,780,973.9
	Max	46,434,531.2	47,486,809.8	45,290,685.9	45,435,725.5	42,636,809.1	42,899,341.2	42,546,100.7	43,250,507.1

Table 7
P values for *t*-test for scenario I, II, and III.

Dataset	scenario I PPM/QPM:			scenario II %CM			scenario III			
							20/80 with %CM		80/20 with %CM:	
	20/80	50/50	80/20	10	20	30	10	30	10	30
10M5N	0.000	0.000	0.000	0.254	0.008	0.000	0.000	0.000	0.000	0.000
10M10N	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
20M10N	0.000	0.000	0.000	0.026	0.000	0.000	0.000	0.000	0.000	0.000
20M20N	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
20M40N	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
30M15N	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000
30M30N	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
40M20N	0.000	0.290	0.000	0.143	0.000	0.000	0.000	0.000	0.000	0.000
40M40N	0.000	0.774	0.076	0.065	0.001	0.000	0.000	0.000	0.000	0.000
50M25N	0.020	0.000	0.000	0.020	0.000	0.000	0.000	0.000	0.000	0.000
50M40N	0.000	0.000	0.000	0.310	0.000	0.000	0.000	0.000	0.000	0.000

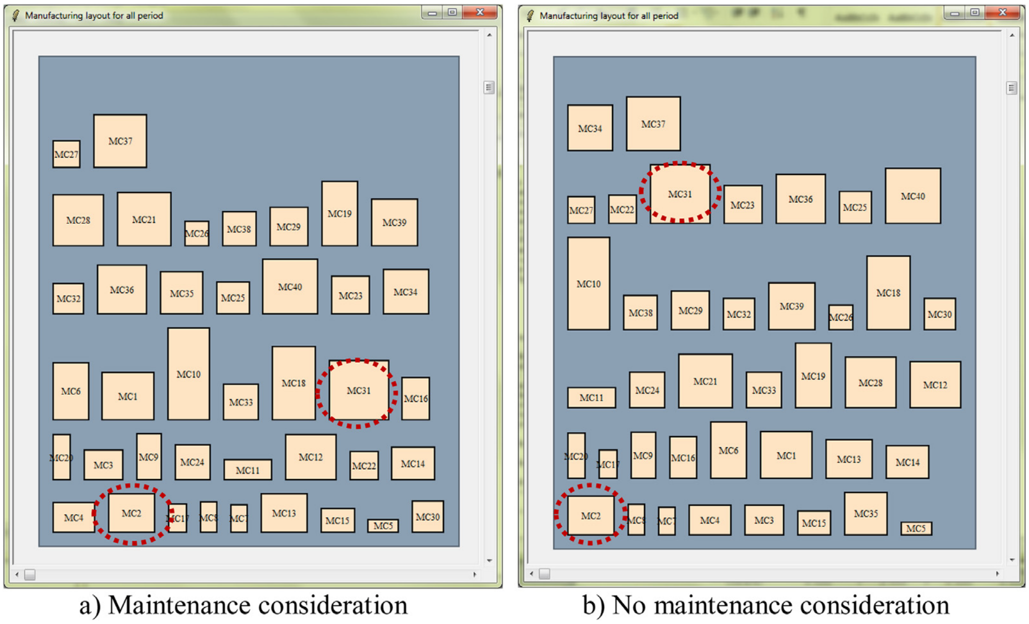

Fig. 9. Graphical layout for robust design for 40M20N dataset in 10%CM for scenario II.

Table 8
P values of ANOVA for scenario I, II, and III.

Dataset	scenario I	scenario II	scenario III		
	PPM/QPM	%CM	PPM/QPM	%CM	PPM/QPM * %CM
10M5N	0.000	0.000	0.000	0.000	0.000
10M10N	0.016	0.000	0.000	0.000	0.339
20M10N	0.000	0.000	0.000	0.000	0.000
20M20N	0.000	0.000	0.000	0.000	0.000
20M40N	0.000	0.000	0.000	0.000	0.000
30M15N	0.000	0.000	0.000	0.000	0.000
30M30N	0.000	0.000	0.000	0.818	0.000
40M20N	0.808	0.000	0.717	0.000	0.000
40M40N	0.176	0.000	0.000	0.001	0.000
50M25N	0.000	0.000	0.000	0.079	0.000
50M40M	0.000	0.000	0.225	0.909	0.803

The results suggest that the number of machines with each type of PM had an effect on the flow distance. For scenario II, %CM significantly affected the material flow distance. An increase in the number of CM machines caused more changes in machine sequences, so *MFD* increased. However, the machine sequences depended upon the alternative machines defined. For scenario III, the PPM/QPM ratios, %CM, and their interaction were significant factors with a 95% confidence interval for almost all datasets. The influence of the number of machines receiving maintenance machines on material flow distance confirms that maintenance scenario should be recognised in the layout design.

5. Discussions and conclusions

This paper has presented the development of an approach that integrates maintenance planning with the design of non-identical machine layouts subject to dynamic demand, which addresses a gap in the literature. The GA aims to minimise the total material flow distance. The computational experiments were carried out using eleven datasets with different demand distributions. The analysis considered three maintenance scenarios with PPM/QPM (ratios of 20/80, 50/50 and 80/20). Three levels of corrective maintenance were considered 10%, 20% and 30%. A combination of PMM/QPM with ratios of (20/80 and 80/20) and two values of %CM (10% and 30%) were studied. The material flow distances can decrease or increase when some machines were maintained during each period. This was caused by changes in the routings due to the use of alternative machines.

Designing robust machine layouts considering machine maintenance leads to reduced material flow distances up to 30.91%, 9.8%, and 20.7% for PM, CM, and PM and CM scenarios, respectively. The distances obtained from designing the layout without and with maintenance consideration had statistically significant differences in the means. The PPM/QPM ratios, %CM, and a combination of PPM/QPM and %CM had significantly resulted in the material flow distance in almost all datasets.

It can be beneficial for companies to consider both demand and machine uncertainty when designing layouts, providing that the future demand and availability of machines are properly forecasted and planned. Further research could consider the option of allowing machines to be rotated by the algorithm.

Declaration of competing interest

The authors declare that they have no conflict of interests on the work reported in this paper

CRediT authorship contribution statement

Srisatja Vitayasak: Methodology, Writing - original draft, Funding acquisition. **Pupong Pongcharoen:** Methodology, Conceptualization, Visualization, Investigation, Supervision, Project administration, Writing - review & editing, Funding acquisition. **Christian Hicks:** Writing - review & editing.

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