International Journal of Production Research
Publication details, including instructions for authors and subscription information:
http://www.tandfonline.com/loi/tprs20

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Published online: 14 Nov 2010.

INT. J. PROD. RES., 2003, VOL. 41, NO. 5, 1045–1056

Incorporating heterogeneous distance metrics within block layout design

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This paper focuses on optimal design of block layouts when using more than one distance metric within a single facility. Previous work in block layout has assumed a single distance metric, usually the shortest rectilinear distance between department centroids, during the design step. However, most facilities have more than one method of material handling and alternative material handling systems can imply alternative distance metrics and cost structures. Specifically, up to three distance metrics within a single facility are considered—the shortest rectilinear distance between centroids (appropriate for automated guided vehicles and fork-lift trucks), the Tchebychev (maximum) distance (appropriate for overhead cranes) and the shortest Euclidean distance between centroids (appropriate for conveyor lines). Optimal block layouts using each of these distance metrics individually and then collectively are compared and contrasted. This approach can also be used to compare layouts when the choice of material handling system is not clear. It is argued that incorporating the distance metric that best reflects the planned material handling device is more realistic than previous formulations, avoids block layouts that are sub-optimal for the material handling systems installed, and is quite workable within a heuristic optimization framework.

1. Introduction

Optimal design of production facilities has appeared in the literature since the 1950s. The problem most commonly studied has been block layout where departments (work centres or cells) are sized and shaped, and then placed within a bounding facility. The design is usually based on minimizing material handling costs through either adherence to an adjacency matrix or, more commonly, explicitly minimizing the material flow volume weighted by handling cost and distance. For the latter objective function, it is usually assumed that there is a material flow $F(i, j)$ associated with each pair of departments (i, j), which generally includes a traffic volume in addition to a unit cost to transport that volume. There may also be fixed costs between departments i and j. The mathematical objective is to partition the facility into n subregions representing each of the n departments, of appropriate area, in order to:

$$\min \sum_{i=1}^{n} \sum_{\substack{j=1 \\ i \neq j}}^{n} F(i, j) d(i, j, \Pi), \qquad (1)$$

Revision received August 2002.

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International Journal of Production Research ISSN 0020–7543 print/ISSN 1366–588X online © 2003 Taylor & Francis Ltd
http://www.tandf.co.uk/journals
DOI: 10.1080/0020754021000049835

where $d(i, j, \Pi)$ is the distance (using a pre-specified metric, most the commonly shortest rectilinear distance between centroids) between department i and department j in the layout Π. Two surveys on block layout are by Kusiak and Heragu (1987) and Meller and Gau (1996), and a survey on discrete material movement through facilities is by Sinriech (1995).

Limited work has been done to improve upon the centroid to centroid distance measure of equation (1). Expected distance by integrating over the departmental areas (Bozer and Meller 1997) has been investigated. A larger body of work has considered movement of material along aisles, or flowpaths, from input and output points of departments (e.g. Banerjee *et al.* 1997, Benson and Foote 1997, Chhajed *et al.* 1992, Kane and Nagi 1997, Kim and Klein 1996). However, this work has focused on improving on the centroid aspect of equation (1) by considering intradepartmental flow patterns and material entry and exit points for the departments rather than explicitly integrating material handling system (MHS) considerations into the block layout objective function. Welgama and Gibson (1996) developed a knowledge-based system to select both MHS and block layout. They used a constructive algorithm to place departments, of pre-defined shape and area, starting at a central point. Rectilinear distance is used for all material flows and both capital and operating costs of the MHS are considered. Two objectives are considered—minimizing total facility area and minimizing total cost—and the Pareto optimal set of designs is identified for a 12-department problem. Chittratanawat and Noble (1999) considered layout, input and output points and material handling system design in a recent paper. They used a quadratic assignment problem (QAP) formulation of departments (all departments are physically interchangeable) and simultaneously optimized department placement, a single input/output (I/O) location per department and choice of material handling equipment type using the shortest rectilinear distance metric between I/O points and a tabu search metaheuristic. However, as in Welgama and Gibson (1996), they used the identical distance metric (shortest rectilinear) regardless of the MHS selected.

While the shortest rectilinear distance metric adequately represents many MHSs, it is not appropriate for some common ones. Furthermore, most industrial facilities employ multiple MHSs within a single facility, therefore invalidating the assumption of a single distance measure. These two motivations have prompted the approach reported herein.

The objective function of minimizing material handling costs is altered to reflect changes in unit handling costs and distance metrics according to the MHS used for a particular material flow. The formulation allows for heterogeneous MHS (and their corresponding costs and distance metrics) within a single facility. It is believed that this is the first use of mixed distance metrics within block layout design reported in the literature. While this approach is demonstrated on the unequal block layout problem using a flexible bay construct and a genetic algorithm (GA) metaheuristic, the use of heterogeneous distance metrics could readily be included in other formulations and solved by other optimization methods.

2. Problem formulation and optimization approach

The choice of distance metric should depend on the MHS (Heragu 1997, Tompkins *et al.* 1996). The movement of an overhead crane is best measured by the Tchebychev distance metric (the maximum of the movement in either the x or the y direction). However, fork trucks and automated guided vehicles (AGVs) have to

Distance metric	Example MHS
Euclidean	conveyor belts, monorails
Contour or Rectilinear	AGVs, forklift trucks, pallet jacks
Tchebychev	overhead cranes

Table 1. Common MHSs and their appropriate distance metrics.

follow the aisle structure travelling around departments and should be modelled using the contour distance metric (Norman *et al.* 2001) or the common rectilinear (Manhattan) metric. For other MHS, such as conveyors, a Euclidean distance metric is often appropriate (Heragu 1997). Table 1 lists common MHS and an appropriate distance metric for each. Note that distance might be measured from centroid to centroid, or from I/O point to I/O point, depending on the MHS and the formulation.

In this paper the total material handling cost for a block layout is expressed as follows:

$$\text{Total Cost(TC)}(\Pi) = \sum_{k=1}^{m} \sum_{i}^{n} \sum_{j \neq i}^{n} [(D_{kij})(F_{ij})(U_{kij}) + I_{kij}], \tag{2}$$

where

- D_{kij} distance between departments i, j using the pre-specified metric for MHS type k,
- F_{ij} flow volume of material flow between departments i, j,
- U_{kij} unit handling cost when MHS type k is used for flow between departments i, j,
- I_{kij} initial cost when MHS type k is installed for flow between departments i, j,
- n number of departments,
- m number of types of MHS.

Therefore, costs depend on the material volume, the distance travelled and the cost per unit distance for the particular material handling device. Optionally, first costs may be included. Purchase price and installation costs are among the first costs that may be considered for a given MHS. The formulation used is the flexible bay construct of Tate and Smith (1995) which places rectangular departments within a rectangular facility using cuts or slices first in one direction, then in the other, as shown in figure 1. Departmental areas and maximum allowable aspect ratios are predefined, the latter enforcing the squareness of departments. The exact departmental shapes are defined during the optimization routine to minimize the material handling costs as defined in equation (2). However, as mentioned earlier, other layout constructs, such as a slicing tree (Tam 1992b), could be used.

2.1. *Genetic algorithm*

The optimization approach also uses the Tate and Smith (1995) genetic algorithm (GA) that maintains the departmental sequence in boustrophedon order and the breaks between bays following the department permutation (figure 1). The genetic algorithm was selected for use because of its previous success in optimizing block

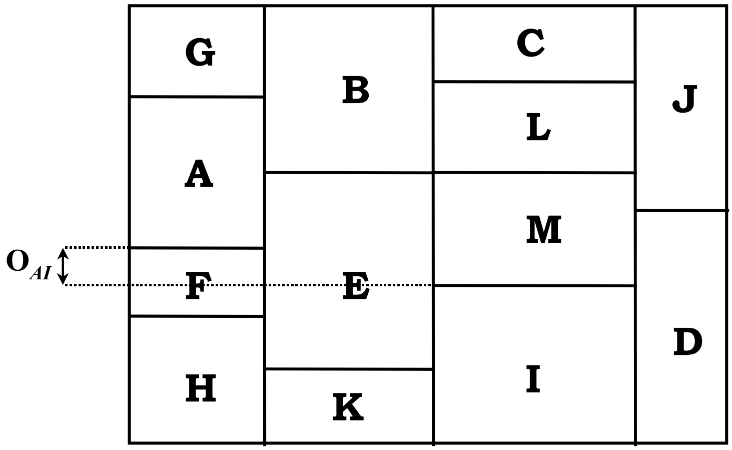

Figure 1. Typical flexible bay block layout. Encoding is G A F H K E B C L M I D J | 4 7 11.

layouts (Banerjee *et al.* 1997, Rajasekharam *et al.* 1998, Tam 1992a, Tate and Smith 1995, Wu and Appleton 2002). However, the heterogeneous MHS formulation is not dependent on the GA, and other optimization methods such as tabu search or simulated annealing could be used to equal effect.

The GA works with a set of solutions (population) of constant size p. Each solution is coded as a variable length string of the layout where there is a one to one correspondence between each encoding and each layout (see figure 1). The encoding is a permutation of departments, and it specifies the departments' order within the layout, with a concatenated string indicating where the bay breaks within the permutation occur. New block layouts are created through blending (crossover) and perturbation (mutation) of the current set of solutions. Solutions are evaluated using the objective function and the best n solutions are retained for the next generation.

Parents are selected based on the following: a uniform random number between 1 and $\sqrt{p}$ is chosen, then squared. The result is truncated and taken to be the rank of the parent to be selected (where string zero is the best string in the population). This selection gives reproductive preference to better ranked solutions, while allowing all solutions some probability of reproduction. Crossover is accomplished through a variant of uniform crossover (Goldberg 1989), where two parents create one offspring. Each location in the offspring's sequence is occupied by the department in the corresponding location from one or the other parent with equal probability, so that all common locations in the parents are carried over to the child. Conflicts are then resolved to ensure that each department occurs exactly once in the offspring's encoding. The number and location of bay breaks in the solution is taken without change from one parent or the other, with equal probability. Mutation consists of altering the permutation (50%), or adding (25%) or deleting (25%) a bay. The permutation mutation is inversion between two randomly selected departments. For the bay mutation there is one that splits an existing bay into two adjacent bays and one that merges two adjacent bays into one (by concatenation). Crossover and mutation are performed independently of each other, with all solutions (parents and offspring) that are currently available equally likely to be mutated.

2.2. *Objective function*

To augment the objective function in equation (2), two penalties are added. The first penalty is specific to the new ideas in this paper and that is to penalize departmental placements involving Tchebychev distances that are not located on a direct horizontal or vertical axis. That is, departments that cannot be connected with a single vertical or horizontal line. (Note that a penalty is not needed for either Euclidean or rectilinear distances, as these two metrics imply a valid path between any two departments, regardless of where the departments are placed within the facility.) Consider departments A and I of figure 1. If there were a Tchebychev flow between them, an overhead crane, or equivalent, could not be placed with a single horizontal or vertical run. A situation such as this is penalized according to the minimum distance required to align the departments, in this case the offset distance between A and I in the vertical direction, labelled O_{AI}. Specifically, the Tchebychev penalty function is:

$$\text{Tchebychev Penalized TC}(\Pi) = \left(\sum_{k=1}^{m}\sum_{i}^{n}\sum_{j\neq i}^{n}[(D_{kij})(F_{ij})(U_{kij}) + I_{kij}]\right) \times \left(\frac{\sum_{k=1}^{m}\sum_{i}^{n}\sum_{j\neq i}^{n} D_{kij} + \sum_{i}^{n}\sum_{\substack{j\neq i\\ k=\text{Tchebychev}}}^{n} O_{ij}}{\sum_{k=1}^{m}\sum_{i}^{n}\sum_{j\neq i}^{n} D_{kij}}\right), \qquad (3)$$

where O_{ij} is the offset distance between departments i and j that violate the Tchebychev constraint. This is a straightforward penalty that serves to inflate the pre-Tchebychev objective function from equation (2) by the ratio of the total flow distance in the facility plus the offset distances to the total flow distance in the facility. Certainly, other penalty equations could be devised; however, this one has the advantage of using both the pre-penalized total cost and the amount of constraint violation (the $\sum_{i}^{n}\sum_{j\neq i/k=\text{Tchebychev}}^{n} O_{ij}$ term in equation (3)). Equation (3) substitutes for equation (2) for layouts that contain Tchebychev violations.

The second penalty function comes directly from Coit *et al.* (1996), which penalizes departments that fail to meet the maximum aspect ratio constraint, α, i.e. which are not square enough. Specifically, the aspect ratio is:

$$\alpha = \max\{L_i, W_i\}/\min\{L_i, W_i\},$$

where L_i is the length and W_i is the width of department i, and equation (2) or (3) is modified as follows:

$$\text{Penalized TC}(\Pi) = \text{TC}(\Pi) + N^3[\text{TC}(\Pi_{BF}) - \text{TC}(\Pi_B)], \qquad (4)$$

where N is the number of departments that violate the aspect ratio constraint, TC(Π) is the objective function from either equation (2) or (3) for layout Π, $\text{TC}(\Pi)_{BF}$ is the objective function value (total cost) of the best feasible solution found and $\text{TC}(\Pi)_B$ is the objective function value (total cost) of the best solution found prior to applying the aspect ratio penalty. Again, a number of different penalty functions could be devised. This one (equation (4)) has the advantage of simple calculation (counting the number of infeasible departments) and using the search history. Penalty functions of this format have proven successful in previous work with genetic algorithm optimization of combinatorial problems (Coit and Smith 1996, Coit *et al.* 1996, Joines and Houck 1994, Smith and Tate 1993, Smith and Coit 1995). If either penalty is not used, the search is likely to identify facility designs that will not work in practice. Either the departmental shapes will be impractical (long and narrow with a large aspect ratio) or departments that require an overhead crane will not lie on a direct horizontal or vertical line with each other.

2.3. *Optimization parameters*

The GA uses a population size of 200 and each run is terminated when the best feasible solution found does not change for 20 000 generations. The mutation probability is 50% and a maximum of 80% of the current population can be replaced by mutated solutions. This is a relatively high mutation (perturbation) probability, but to balance this randomness the method of choosing the subsequent generation is elitist. Children and parents are pooled and the best p are retained. Generated solutions, i.e. mutants and children, are not guaranteed to be unique. Solutions in the initial population are randomly generated with $\sqrt{n}$ bays on average.

3. Computational experience

Test problems that modify well-known problems from the literature were studied. Specifically, the 10 department van Camp *et al.* (1991) problem and the 20 department Armour and Buffa (1963) problem were adapted by assigning a MHS to each flow. Six variants of each problem were developed. The first three consisted of homogeneous distance metrics—that is, wholly Euclidean, rectilinear or Tchebychev—while the last three contained mixtures of each metric assigned randomly according to the pre-set probabilities shown in table 2. Exact problem data are contained in the Appendix. The unit costs, U_{kij}, are set to 1.00 and the fixed costs, I_{kij}, are set to 0. A maximum aspect ratio constraint of 3 is imposed on all departments, resulting in a fairly constrained problem.

To improve computational efficiency and search reliability, the problems with all Tchebychev and mixed MHS metrics are seeded with solutions found during the wholly rectilinear and Euclidean designs. Seeding simply places the top two solutions found during the Euclidean and rectilinear design optimizations (that is, a total of four solutions) in the initial population of the Tchebychev and mixed problems. Therefore, for seeding runs, 196 members of the population were randomly generated and four were the top solutions from the rectilinear and Euclidean runs (two from each). Runs without seeding took an average of 23% longer for the van Camp problem and 28% longer for the Armour and Buffa problem. Moreover, without seeding, the GA exhibited more sensitivity to a random number seed; that is, more

Distance metric	Problem designation											
	VC1	VC2	VC3	VC4	VC5	VC6	AB1	AB2	AB3	AB4	AB5	AB6
Euclidean	100	0	0	50	25	25	100	0	0	14.52	14.52	17.74
Rectilinear	0	100	0	25	50	25	0	100	0	72.58	67.74	70.97
Tchebychev	0	0	100	25	25	50	0	0	100	12.90	17.74	11.29

Table 2. Probabilities assigned to flows for each test problem.

Problem	Total cost	CPU seconds
VC1	20 320.52	510.59
VC2	23 470.60	438.32
VC3	18 975.52	480.70
VC4	19 901.17	276.91
VC5	21 995.89	274.55
VC6	20 279.22	278.32
AB1	498.81	1792.33
AB2	593.36	1454.27
AB3	None found*	–
AB4	569.23	1069.11
AB5	590.06	1477.86
AB6	571.66	1239.75

* See footnote † on this page.

Table 3. Total cost and computational time of best feasible solution found over 10 GA runs.

search variability in the total cost of the final design. For the van Camp problems, seeding reduced variability over ten runs with different random number streams from a coefficient of variation of 5.4% to zero. For the Armour and Buffa problems, seeding reduced variability over ten runs from 7.5% to 1.5%. While seeding is not imperative to this method, it is an easy way to improve the speed and reliability of the search.

Table 3 contains results for each problem in terms of the total cost and computational time.† All runs were performed on a Sun Microsystems SPARC station with a CPU type of sparcv9+vis. Computational time, using the seeding strategy, is quite modest for a design problem with an average of 330 seconds for the 10-department problem and 1407 seconds for the 20-department problem. To examine further the benefit of using MHS during block layout design, the best solutions of the Euclidean and rectilinear metrics (the most common distances used in block layout optimization) with the best for each of the heterogeneous problems are compared in table 4. Note that using either Euclidean or rectilinear metrics as a surrogate for all MHS results in block designs that incur higher material handling costs. In the cases in table 4, the additional cost ranges up to 10%, with the rectilinear distance metric being a worse surrogate than the Euclidean one. Of course, how much higher are the material handling costs is dependent on the problem data, number of departments and their shapes and sizes, flow volumes and costs, and the MHS to be used. Furthermore, it is likely that a block layout identified using only a rectilinear (or Euclidean) distance metric will contain violations for those departments that will use the Tchebychev distance as in the AB5 and AB6 problems.

Figures 2 and 3 show two of the van Camp problems—VC4 and VC5—as solved by (a) the method of this paper with heterogeneous distance metrics, (b) the Euclidean surrogate and (c) the rectilinear surrogate. The MHS flowpaths are imposed, using a scheme of a solid line for Tchebychev, a short dashed line for

† No feasible solution for the entirely Tchebychev Armour and Buffa (AB3) problem could be found. In all layouts identified, at least some departments violated the Tchebychev constraint. It is hypothesized that no feasible solution exists to this particular problem instance.

Metric used in optimization	Problem designation					
	VC4	VC5	VC6	AB4	AB5	AB6
Heterogeneous	19 901.17	21 995.89	20 279.22	569.23	590.06	571.66
Euclidean Surrogate	19 986.68	22 520.55	20 279.22	576.41	Not feasible	576.19
Rectilinear Surrogate	21 907.35	22 768.74	22 108.34	576.22	Not feasible	Not feasible

Table 4. Total cost comparisons.

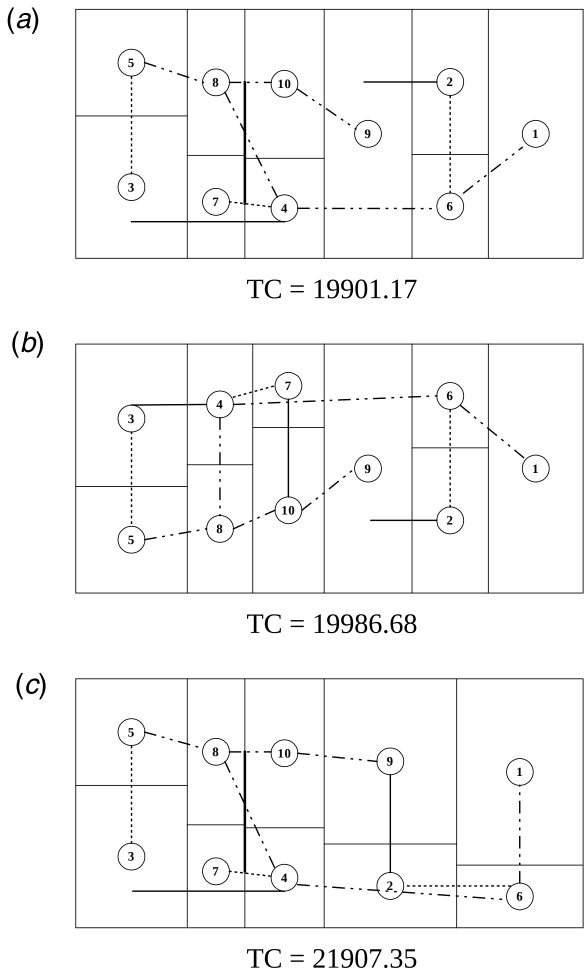

Figure 2. VC4 optimized using: (*a*) heterogeneous distance metrics; (*b*) Euclidean distance; and (*c*) rectilinear distance with flow paths and total cost.

rectilinear and a long dashed line for Euclidean distances, so that a visual comparison can be made. The objective function (total cost) of each layout is also shown. While the block layouts have similarities, optimizing while considering the MHS to be used for each flow results in designs that are more cost effective. As a surrogate, the Euclidean method is slightly better than the rectilinear one for these problems, even in the case of VC5, where most of the flows are rectilinear.

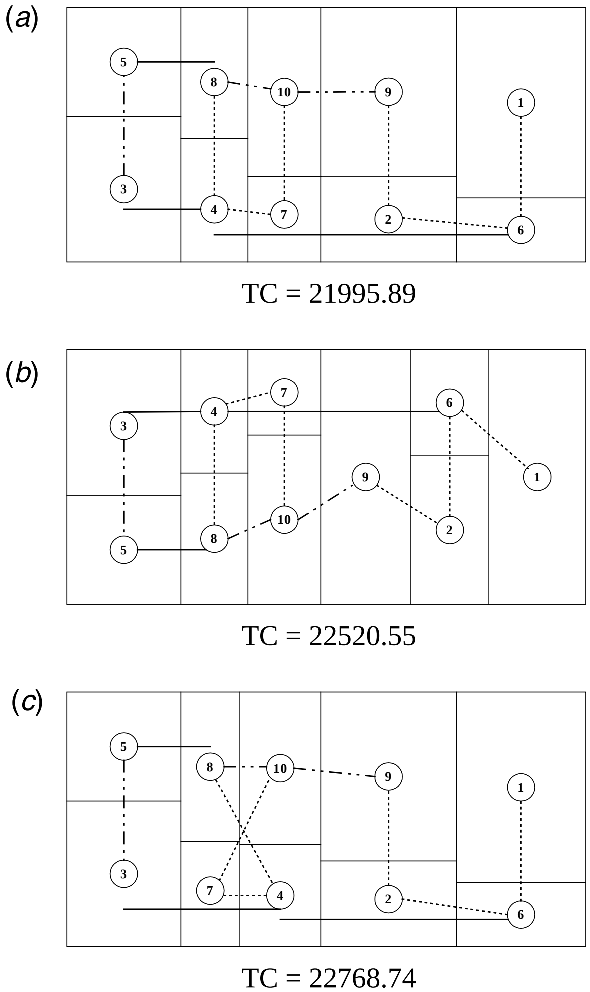

Figure 3. VC5 optimized using: (*a*) heterogeneous distance metrics; (*b*) Euclidean distance; and (*c*) rectilinear distance with flow paths and total cost.

4. Conclusions

This paper has demonstrated how the choice of material handling system can be explicitly included during the block layout design phase for a facility by altering the objective function. It is shown that performing the design optimization using the distance metric that best reflects the MHS to be used for each flow results in layouts with lower costs than using either a Euclidean or rectilinear distance surrogate for all flows. While this idea was demonstrated using the flexible bay formulation of the unequal area block layout problem, it can be used in other block layout settings, from the QAP to the slicing tree. In either a QAP formulation (equal sized and shaped blocks) or a slicing tree (alternating horizontal and vertical cuts), the material handling distance metrics would operate similarly as in this paper where the rectilinear and Euclidean distance metrics would run between departmental centroids in a city grid manner or a shortest path manner, respectively. The Tchebychev distance metric would run along a direct vertical or horizontal path between departments, and would necessitate the same constraint to align the departments, as in this paper. Similarly, while a genetic algorithm was used as the optimization vehicle, many other optimization methods could be used.

This method could also be used in 'what if' analysis. For example, if there is more than one candidate MHS for one or more of the flows in the facility, the block layout can be designed using different distance metrics to gauge the effect of change in MHS on the relative location of the departments and the cost of material handling. Future work will involve using something other than the centroid to centroid measure, such as the distance from I/O to I/O, and then incorporating the contour (perimeter) distance metric (Norman *et al*. 2001) along with the Euclidean, rectilinear and Tchebychev metrics. In summary, this paper proposes a straightforward extension to block layout design that is quite tractable and results in an optimization problem that better reflects the physical and cost realities of the facility.

Acknowledgement

Part of this research has been supported by the US National Science Foundation grant DMI 9908322.

Appendix

Depts.		Flow	VC1	VC2	VC3	VC4	VC5	VC6
1	6	218.0	E	R	T	E	R	E
2	6	148.0	E	R	T	R	R	T
2	9	296.0	E	R	T	T	R	E
3	4	28.0	E	R	T	T	T	R
3	5	70.0	E	R	T	R	E	T
4	6	28.0	E	R	T	E	T	T
4	7	70.0	E	R	T	R	R	E
4	8	140.0	E	R	T	E	R	T
5	8	210.0	E	R	T	E	T	R
7	10	28.0	E	R	T	T	R	R
8	10	888.0	E	R	T	E	E	T
9	10	59.2	E	R	T	E	E	T

Table A1. Flows for original van Camp *et al*. (1991) test problem and distance metrics for the test problems.

Depts.		Flow	AB1	AB2	AB3	AB4	AB5	AB6
1	2	1.8	E	R	T	R	E	R
1	3	1.2	E	R	T	R	E	R
1	10	1.0	E	R	T	R	R	R
1	11	1.1	E	R	T	R	R	R
1	14	1.2	E	R	T	R	R	R
2	3	1.0	E	R	T	R	T	E
2	4	24.0	E	R	T	R	T	E
2	5	0.8	E	R	T	R	T	E
2	7	14.0	E	R	T	R	T	R
2	9	1.2	E	R	T	R	T	R
2	10	1.4	E	R	T	R	R	R
2	19	6.9	E	R	T	R	R	R
3	6	2.2	E	R	T	R	R	T
3	9	3.2	E	R	T	R	R	T

3	10	3.9	E	R	T	R	R	E
3	14	13.0	E	R	T	R	R	T
3	19	14.0	E	R	T	R	R	T
4	5	1.1	E	R	T	T	R	R
4	6	5.7	E	R	T	T	R	R
4	7	7.5	E	R	T	T	R	R
4	9	2.3	E	R	T	R	R	R
4	12	1.4	E	R	T	T	R	R
4	18	1.5	E	R	T	T	R	R
4	19	16.0	E	R	T	E	E	R
5	7	2.3	E	R	T	R	E	R
5	8	1.4	E	R	T	R	E	R
5	10	1.6	E	R	T	R	E	R
5	15	1.4	E	R	T	R	E	R
6	7	6.2	E	R	T	R	R	E
6	12	0.5	E	R	T	R	R	E
6	18	1.1	E	R	T	R	R	E
7	8	24.0	E	R	T	R	T	R
7	10	1.9	E	R	T	R	E	R
7	14	1.0	E	R	T	R	R	R
7	18	1.7	E	R	T	R	T	R
7	20	3.8	E	R	T	R	T	R
8	13	0.6	E	R	T	R	R	E
8	19	7.5	E	R	T	R	R	E
8	20	33.0	E	R	T	R	R	R
9	14	7.5	E	R	T	R	R	R
9	17	7.5	E	R	T	R	R	R
10	11	0.4	E	R	T	E	R	R
10	12	12.0	E	R	T	E	R	R
10	14	19.0	E	R	T	E	R	R
10	15	1.9	E	R	T	E	R	R
10	19	5.3	E	R	T	E	R	R
11	12	2.3	E	R	T	T	R	R
11	14	3.0	E	R	T	T	R	R
11	15	1.0	E	R	T	T	R	R
11	16	23.0	E	R	T	R	R	R
12	15	1.7	E	R	T	R	T	R
12	17	15.0	E	R	T	R	T	R
12	19	8.4	E	R	T	R	T	R
13	14	8.0	E	R	T	E	R	T
13	15	1.0	E	R	T	E	R	T
13	16	6.0	E	R	T	E	R	T
14	15	9.8	E	R	T	R	R	E
14	18	0.9	E	R	T	R	R	E
15	17	5.3	E	R	T	R	R	R
16	17	12.0	E	R	T	R	R	R
17	19	7.5	E	R	T	R	R	R
18	19	4.7	E	R	T	R	E	R

Table A2. Flows for original Armour and Buffa (1963) test problem and distance metrics for test problems.

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