

Mathematical Modelling and Optimization for Efficient Parking Space Allocation - MISG 2024

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Background

- ▶ Many cities are experiencing rapid growth, leading to an increased number of vehicles in urban areas.
- ▶ The increasing gap between the number of vehicles and available parking spaces leads to parking scarcity.

Problem Statement

The Parking Space Allocation (PSA) problem is centred on the efficient distribution of available parking spaces among users. Models for PSA can be categorized based on user class (single or multi-class) and the type of community (open or closed) they serve. The primary objectives are:

- ▶ Minimizing parking space misuse - ensuring optimal utilization of available spaces.
- ▶ Reduce the walking distance for each user from their parking spot to their destination.

There is a significant imbalance between the high demand for parking and the limited availability of spaces.

A balanced parking policy is essential: allocating permanent spaces to some, while others share or face variability in availability.

The Objectives

Our goal is to develop an optimization model that maximizes the efficiency of existing parking spaces in a competitive, policy-driven university environment.

- ▶ Explore different models for formulating parking space allocation policies.
- ▶ Focus on minimizing parking space misuse to ensure optimal utilization.
- ▶ Prioritize reducing the walking distance for each user from their parking spot to their destination.

Aims

Develop and solve the parking space allocation problem for a campus environment.

- ▶ Study the existing parking space allocation model.
- ▶ Formulate a mathematical optimization model for the problem.
- ▶ Develop an appropriate solution approach to the model.

Variables and Parameters

- ▶ D_{ij} → Distance from parking space i to j
- ▶ N_{jk} → Total number of individuals from building j belonging to class k
- ▶ M_i → The number of parking spaces in the parking lot i
- ▶ I → Total number of parking space(s), $i = 1, \dots, I$
- ▶ J → Total number of building(s), $i = 1, \dots, J$
- ▶ K → Class and/or category associated to each individual, $k = 1, \dots, K$
- ▶ X_{ijk} → Individual from building j belonging to class k assigned to parking space i

Objective function

$$\min z = \sum_i^I \sum_j^J \sum_k^K D_{ij} X_{ijk} \quad (1)$$

subject to

$$\sum_i^I X_{ijk} = N_{jk}, \quad \forall j, k \quad (2)$$

$$\sum_j^J \sum_k^K X_{ijk} \geq M_i, \quad \forall i \quad (3)$$

$$X_{ijk} \geq 0, \quad \text{and integer.}$$

Objective and Constraints

- ▶ The objective function in Equation (1) minimizes the total distance walked by all the individuals from each parking space to their respective buildings.
- ▶ The constraint (2) ensures that the total number of individuals belonging to a class type in each parking space must equal the sum of the parking allocations in each parking space.
- ▶ In constraint (3), the sum of the allocations for all individuals must be greater than or equal to the number of parking spaces available.

Major Difference of our Model

- ▶ The author in the thesis used the number of reserved and unreserved spaces in the parking lot. He was only trying to solve the problem of assigning users to already marked parking spaces. But our model consider a case where it is the mathematical model that will assign different classes of users to the parking lots.
- ▶ The author also considered only two classes (reserved and unreserved) excluding the handicapped population. But our model consider four classes - reserved normal, reserved handicapped, unreserved normal and unreserved handicapped.

Data 1

- Data was sourced and modified to cater for more than two classes from the thesis "Model and Solutions to Campus Parking Space Allocation Problem" LO Joel (2013)

A	B	C	D	E	F	G	H	I	J	K	L	M
	Building 1	Building 2	Building 3	Building 4	Building 5	Building 6	Building 7	Building 8	Building 9	Building 10	Building 11	Building 12
Parking lot 1	79	108	182	57	143	97	183	48	168	94	189	136
Parking lot 2	160	86	100	170	128	187	55	116	15	53	45	95
Parking lot 3	26	196	56	125	85	24	67	159	80	83	26	123
Parking lot 4	143	62	83	156	13	147	157	93	66	169	106	196
Parking lot 5	183	146	152	191	80	97	184	161	77	81	143	58
Parking lot 6	93	170	15	15	48	151	145	85	126	58	63	58
Parking lot 7	141	43	176	183	11	26	78	43	11	109	60	61
Parking lot 8	195	147	125	59	152	69	155	163	124	93	55	169

Figure: Distance from Buildings to Parking Lots

Data 2

	A	B	C	D	E
		Class 1	Class 2	Class 3	Class 4
Building 1		25	2	61	4
Building 2		9	0	28	0
Building 3		26	1	61	5
Building 4		48	3	94	8
Building 5		49	1	90	10
Building 6		41	2	83	6
Building 7		25	0	58	4
Building 8		27	3	61	9
Building 9		26	2	62	5
Building 10		32	1	70	5
Building 11		27	2	64	4
Building 12		36	3	75	9

Figure: Classes of Users for parking

Data 3

A	B
	Capacity of each parking lot
Parking lot 1	72
Parking lot 2	186
Parking lot 3	110
Parking lot 4	198
Parking lot 5	147
Parking lot 6	104
Parking lot 7	160
Parking lot 8	141

Figure: Capacity of each parking

Exact Method

Background:

- ▶ The simplex algorithm is a popular algorithm in optimization techniques for linear programming.
- ▶ The algorithm is used to determine the feasible solution space of a given linear programming problem, which helps to identify the optimal point from the solution.
- ▶ The simplex method uses a search process to find the intersections of constraint equations, called corner points, to find optimal points through the boundary of feasible space.

Optimization Process:

- ▶ Standardize to LP problem, and generate an initial feasible solution, called a basis.
- ▶ Test the solution for optimality, if optimal, stop the process.
- ▶ If the solution is not optimal, generate an improved solution, if optimal, stop the process, otherwise improve the solution for optimal results.

Exact Allocation for Class 1

Allocation for Class 1								
	P1	P2	P3	P4	P5	P6	P7	P8
Building1			25					
Buidling2				9				
Building3						26		
Building4						4		44
Building5				49				
Buidling6							41	
Building7		25						
Building8	13						26	
Building9							26	
Building10		32						
Building11								27
Building12					36			

Figure: The Allocation for Class 1

Exact Allocation for Class 2

Allocation for Class2								
	P1	P2	P3	P4	P5	P6	P7	P8
Building1			2					
Buidling2								
Building3						1		
Building4						3		
Building5				1				
Buidling6							2	
Building7								
Building8							3	
Building9							2	
Building10		1						
Building11								2
Building12					3			

Figure: The Allocation for Class 2

Exact Allocation for Class 3

Allocation for Class3								
	P1	P2	P3	P4	P5	P6	P7	P8
Building1			61					
Buidling2				28				
Building3						61		
Building4						94		
Building5				90				
Buidling6			63				20	
Building7		58						
Building8	50			11				
Building9		10					52	
Building10		51			19			
Building11								64
Building12					75			

Figure: The Allocation for Class 3

Exact Allocation for Class 4

Allocation for Class4								
	P1	P2	P3	P4	P5	P6	P7	P8
Building1			4					
Buidling2								
Building3						5		
Building4						8		
Building5				10				
Buidling6			6					
Building7		4						
Building8	9							
Building9		5						
Building10					5			
Building11								4
Building12					9			

Figure: The Allocation for Class 4

Simulated Annealing

Background:

- ▶ Simulated Annealing (SA) is a probabilistic optimization algorithm inspired by the annealing process in metallurgy.
- ▶ This technique is loosely based on metallurgical annealing, in which metals are heated beyond their critical temperature and cooled according to a specific schedule until they reach their lowest energy state.
- ▶ In this manner, the material is treated in a controlled manner to obtain unique properties that are useful in specific applications.

Optimization Process:

- ▶ SA searches for the global optimum by exploring the solution space through a series of random moves.
- ▶ At each step, the algorithm accepts moves that improve the objective function, but also allows for accepting worse moves with a decreasing probability over time.

Simulated Annealing

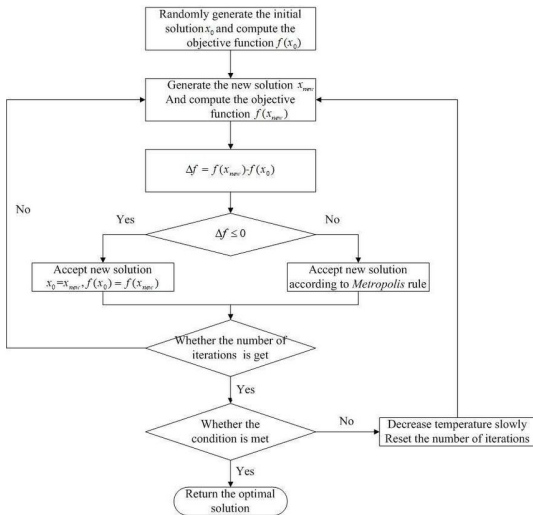


Figure: Flowchart explaining the structure of a Simulated Annealing

Simulated Annealing

Temperature Parameter:

- ▶ SA uses a temperature parameter that controls the probability of accepting worse solutions.
- ▶ Initially high, the temperature decreases over time, allowing the algorithm to explore globally at the beginning and gradually refine the search locally.

Algorithm Steps:

- ▶ Initialization: Start with an initial solution.
- ▶ Iterative Exploration: Move to a neighboring solution based on a defined perturbation, and accept or reject the move based on probability.
- ▶ Temperature Cooling: Gradually decrease the temperature over iterations to reduce the probability of accepting worse solutions.
- ▶ Termination: Stop when a stopping criterion is met, such as a specified number of iterations or a target temperature.

Simulated Annealing

Advantages:

- ▶ Versatility: Applicable to a wide range of optimization problems.
- ▶ Global Search: Can escape local optima due to the acceptance of worse solutions.
- ▶ No Derivatives: Suitable for problems where derivatives are unavailable or expensive to compute.

Applications:

- ▶ Traveling Salesman Problem, Job Scheduling, Network Design, and other combinatorial optimization tasks.
- ▶ Often used in machine learning for hyper-parameter tuning.

Simulated Annealing Allocation for Class 1

Allocation for Class1								
	P1	P2	P3	P4	P5	P6	P7	P8
Building1			21					
Building2							9	
Building3			18			16		
Building4	20					26		11
Building5				19		25	18	
Building6			14				14	
Building7		14						
Building8	27						21	
Building9		18					20	
Building10		16				15		
Building11		13	16					16
Building12					22	11		

Figure: Simulated Annealing Allocation for Class 1

Simulated Annealing Allocation for Class 2

Allocation for Class2								
	P1	P2	P3	P4	P5	P6	P7	P8
Building1			2					
Buidling2								
Building3			1			1		
Building4	3					3		3
Building5				1		1	1	
Buidling6			2				2	
Building7								
Building8	3							3
Building9		2					2	
Building10		1				1		
Building11		2	2					2
Building12					3	3		

Figure: Simulated Annealing Allocation for Class 2

Simulated Annealing Allocation for Class 3

Allocation for Class3								
	P1	P2	P3	P4	P5	P6	P7	P8
Building1			14					
Buidling2							20	
Building3			18			19		
Building4	68					48		42
Building5				77		17	19	
Buidling6			20				13	
Building7		44						
Building8	10						14	
Building9		24					14	
Building10		26				45		
Building11		17	20					18
Building12					25	19		

Figure: Simulated Annealing Allocation for Class 3

Simulated Annealing Allocation for Class 4

Allocation for Class4								
	P1	P2	P3	P4	P5	P6	P7	P8
Building1			4					
Buidling2								
Building3						5		
Building4						8		
Building5				10				
Buidling6			6					
Building7		4						
Building8	9							
Building9		5						
Building10					5			
Building11								4
Building12					9			

Figure: Simulated Annealing Allocation for Class 4

References

- ▶ **Joel, L. O. (2013).** Model and solutions to campus parking space allocation problem (Masters Thesis).
- ▶ **Joel L. O., Adewumi A. O. and Sawyerr B. A. (2013).** An Exact Solution for Allocating Car Parking Spaces on Campus. Proceedings of the International Science, Technology, Education, Arts, Management and Social Science (iSTEAMS) Research Nexus Conference. University of Ibadan, Ibadan, Nigeria, volume III, pp 463-472
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Thank you!

Questions