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ORIGINAL ARTICLE

An intelligent hybrid scheme for optimizing parking space: A Tabu metaphor and rough set based approach

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Abstract Congested roads, high traffic, and parking problems are major concerns for any modern city planning. Congestion of on-street spaces in official neighborhoods may give rise to inappropriate parking areas in office and shopping mall complex during the peak time of official transactions. This paper proposes an intelligent and optimized scheme to solve parking space problem for a small city (e.g., Mauritius) using a reactive search technique (named as Tabu Search) assisted by rough set. Rough set is being used for the extraction of uncertain rules that exist in the databases of parking situations. The inclusion of rough set theory depicts the accuracy and roughness, which are used to characterize uncertainty of the parking lot. Approximation accuracy is employed to depict accuracy of a rough classification [1] according to different dynamic parking scenarios. And as such, the hybrid metaphor proposed comprising of *Tabu Search* and *rough set* could provide substantial research directions for other similar hard optimization problems.

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1. Introduction

The significant and dramatic increase in demand for parking spaces due to the increase of on the road vehicles in cities and urban areas around the world on one hand and the significant shortage of these parking spaces created a challenging problem for managing these spaces. Although on the road parking spaces in most of the cities are metered, which should reduce the demand, the demand is still significantly high leading also to congested roads and overcrowded transit lines as well as increase in travel time and costs. This demand also leads to economic, social, and environmental losses. And with the continuous increase in the population, the problem becomes more critical. As such parking space optimization and control has become a real challenge for city transportation planners and traffic authority. And despite the fact that most of the modern planned cities provide adequate support and guidance to the drivers about the parking slot selection and effective utilization of parking space, in terms of variable message signs, directional arrows, names of the parking facilities, status, number of available parking spaces, proper entry, exit point of parking, etc. [2], traffic system and drivers face extreme difficulties especially during festival time and in unpredictable situations of traffic congestion.

This paper proposes a novel software interface to guide and assist the drivers for better parking space utilization and to tackle unpredictable congested traffic situation on road. The interface is based on an intelligent hybrid scheme combining a Tabu metaphor and rough set for parking space optimization. The interface could be initially tried as off-line decision support system and subsequently it could be incorporated in an on-line traffic network whereby the delivery of instruction could be mobile phone-based audio instruction. To handle unpredictable situation of traffic and assist the driver with a crisp decision of parking guidance, the proposed model uses a customized *Tabu Search* approach metaphorically constructed and supported by the rough set rules. *Tabu Search* meta-heuristic [3–5] works based on the use of *prohibition-based* techniques and intelligent schemes as a complement to basic heuristic algorithm like local search, with the purpose of guiding it *beyond local optimality*. Subsequently, Rough set is used as a powerful tool for managing uncertainty that arises from inexact, noisy, or incomplete information created due to random traffic conditions. Besides data reduction, rough sets theory [6,30–33] is also suitable for the problems of features dependencies to evaluate the significance of features, deal with data uncertainty and vagueness, discover cause-effect relationships, generate decision algorithms from data, and approximate classification of data. The proposed model was validate and the interface was test using traffic data related to a medium city (the city Mauritius) as a case study. The result of the simulation is also presented.

The rest of the paper is organized as follows: Section 2 presents a brief review of recent literature. Section 3 formulates and defines parking space problem in which Tabu Search and rough set is discussed. In Section 4 results and implications are presented followed by the conclusion in Section 5.

2. Review of literature

Parking space problem has been addressed by many researchers. The following is a review of some of the recent papers.

Caicedo [7] used two different ways to manage space availability information in parking facility within PARC system to reduce search times. Caicedo [15] develops a demand assignment model with the intention of reducing the time and distances involved in finding a parking space. Zhao and Collins [8] developed an automatic parallel parking algorithm for parking in tight spaces using a novel fuzzy logic controller. Space allocation of parking lots was analyzed by Davis et al. [9] to estimate the supply of parking spaces to potential demand. Using a fuzzy knowledge-based Decision Making, Leephakpreeda [10] presented a car-parking guidance. Arnott and Rowse [11] developed an integrated model for curbside parking and traffic congestion control in a downtown area. Shoup [12] presented a model of how drivers choose between cruising for curbside parking or pay for off-street parking. Teodorovic and Lucic [13] proposed an intelligent parking space inventory system. The system is based on a combination of fuzzy logic and integer programming techniques that would allow making online decisions to accept or reject a new driver's request for parking. Benenson et al., [14] presented an agent-based system that simulates the behavior of each driver within a spatially explicit model. The system captures, within a non-homogeneous road space, the self-organizing and dynamics of a large collective parking agents. Estimation of parking lots footprint across a four state region is presented in [16]. Feng et al., [17] designed a combined trip network for congested road-use pricing and parking pricing which was based on Logit. Using a utility function, combining travel time, search time, waiting time, access time, and parking price, a Probit-based parking pricing is formulated for curb parking pricing [18]. Chou et al., [19] presents an intelligent agent system with negotiable parking pricing for optimum car park for the driver.

3. Problem definition and formulation

A car park consists of n numbered spaces in a line. The drivers of m cars have independently chosen their favorite parking spaces. Each driver arrives at the car park and proceeds to his chosen space, parking there if it is free. If the chosen space is occupied, the driver continues on toward the larger-numbered spaces and takes the first available space if any; if no such space is available, the driver leaves the car park. The probability that everybody parks successfully and number of the n^m sequences of choices by the drivers leading to everyone parking is a mathematical function is known as *parking function* [20].

Hence, for a generalized parking function, the given a sequence $x = x_1, x_2, \ldots, x_n$.

- An x-parking function is a sequence of non negative integers $u = u_1, u_2, \ldots, u_n$,

  such that once sorted as $u' = u'_1, u'_2, \ldots u'_n$ such that $u'_i \leqslant u'_{i+1}$ one has for all i:

  $$u'_i < \sum_{j=1}^{i} x_j$$

- Note that the usual parking functions are (1, 1, 1, …, 1)-parkings.

More recently Stanley and Pitman [21] generalized this notion by introducing what is called (a, b)-parking functions. A (a, b)-parking function of length n is defined as a sequence $p = p_1, p_2, \ldots, p_n$ of non negative integers less than $a + bn$ such that there exists a permutation $\alpha = \alpha_1, \alpha_2, \ldots, \alpha_n$ of G_n such that, for all i we have, pi $< (\alpha_i - 1)b + a$. It is often said that such permutation is a certificate for the sequence p. For instance, 7, 0, 4 is a (4, 2)-parking function, for which 3, 1, 2 is a certificate; but 3, 7, 6 is not. It is easy to check that any sequence obtained by permuting the elements of an $(a, \bar{b})$-parking function is also an (a, b)-parking function. Hence, an easy way to check that a sequence $p = p_1, p_2, \ldots, p_n$ is an (a, b)-

parking function consists in reordering p such that to obtain a weakly increasing sequence.

Drivers around the world pay for using different parking facilities and as such and in some instances, traffic congestion can be significantly reduced as a result of parking price. Hence, different parking pricing strategies could be a part of the comprehensive solution approach to the complex traffic congestion problems [2]. Parking management system must satisfy the flowing constraints [2]:

- Demand for parking should be considered as variable over time;
- Parking spaces should also be booked against advanced payment;
- Parking lot or garage is limited in space and as such cannot support variable demand;
- Occupancy time should be considered as a variable in parking.

3.1. Tabu metaphor and rough set for handling parking function

Initially proposed by Glover in 1989 [3], the Tabu Search method as a technique used in combinatorial optimization problems was adopted later in his work in 1997 [4]. Tabu Search can be defined as a meta-heuristic procedure, which uses a local search subroutine in order to find local optima. Unlike other local search approaches, Tabu Search stores information on the paths that have been previously visited (previous solutions) by using memory structures known as tabu lists, thereby preventing the search from cycling and becoming trapped in a local search. Since the tabu list is a short-term memory of previously visited solutions in the search, its size greatly determines how many iterations cannot be called again in the search (commonly referred to as tabu). This suffices to be one of the limitations of this technique as it may restrict the search too much, thus preventing some promising moves to the most probable solution in the search space. Tabu Search has been applied to a wide range of optimization problems that involve various classes of integer problems.

Using tabu, the simple car parking problem could be presented with the probability that everybody parks successfully and the question of how many of the n^m sequences of choices by the drivers lead to everyone parking remain to be answered [20]. In the following, we elaborate and coined cases, where a simple parking function is introduced and then the problem is further expanded in the context of rough set guided *Tabu Search* process.

Let f be a mapping from cars $\{1, \ldots, n\}$ to parking spaces $\{0, \ldots, n-1\}$ in a one way street. In this case, the situations are:

The cars arrive in order with the ith arrival being assigned position $f(i)$.

If an earlier car already took the spot, then car i will try the next place along until it parks or fails at the last parking space and relinquishes as afterward.

If no car is compelled to relinquish, then the corresponding situation becomes only true for the first four sequential cars numbered accordingly and by Cayleey's formula there are n^{n-2} labeled trees on n vertices. Therefore, the issue of optimizing the parking space arises.

The bi-jection paradigm could also be correlated.

Considering nine cars in a single situation, the following scheme is derived as also shown in Fig. 1.

Nine cars are not placed in a sequence; therefore, this could be one possible combination:

$A_0 = \{2, 5, 7\}$, $A_2 = \emptyset$, $A_3 = \{4\}$, $A_4 = \emptyset$, $A_5 = \{1, 6, 8\}$, $A_6 = \emptyset$, $A_7 = \{9\}$, $A_8 = \emptyset$, $A_9 = \emptyset$; where, A denotes car number and $\emptyset$ indicates empty set.

Here, we formulate a proposition, where car number 6 is occupying less time in parking zone and it is about to leave, whereas, car number 9, is just entering into parking queue and it may occupy car number 6's position. Theoretically, an order $(n + 1)$ labeled tree could be obtained, which is also a connected graph with set of vertices $\{0, 1, 2, 3, \ldots, n\}$, and with n edges.

In this context, we have been motivated by reactive search [22–24] and introduce a rough set guided Tabu Search, which slowly but steadily improves the solution and could bypass the local minimizer. The typical feature of the proposed model is

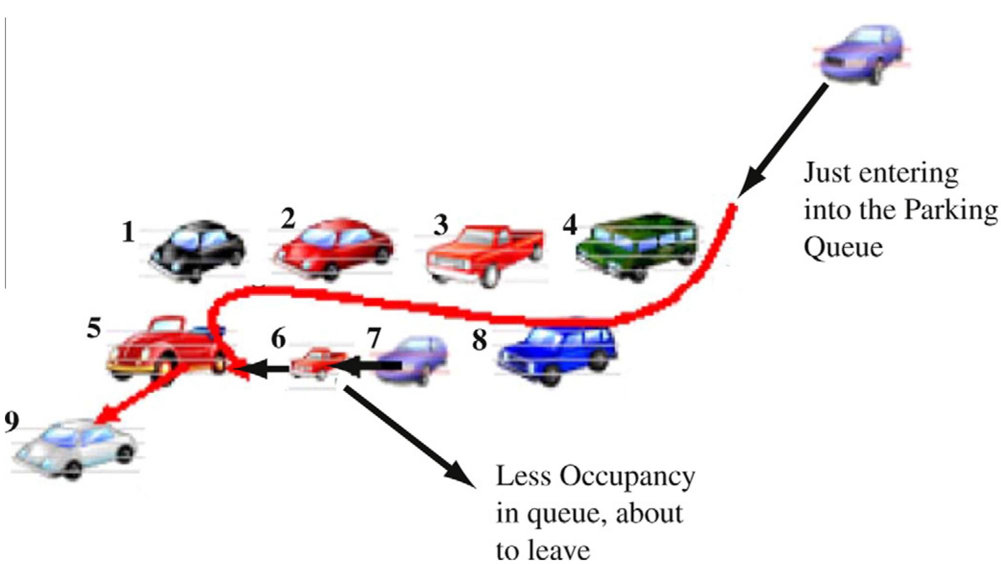


Figure 1 Parking function thematic illustration.

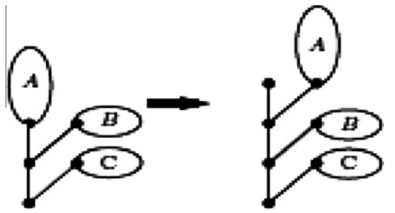


Figure 2 Proposed polytonic positions of parking spaces A, B and C – with different edge length.

to consider all real time attributes related with data assisted by rough set to quantify parking space search process. It has been also suggested to develop control panel software to find out optimum parking space and establish the polytonic attributes in our proposed parking model, where parking function has been kept generalized. Therefore, the sub graph on original parking space, has been defined in the form of di-graph. Finally the searching on di-graph for best or optimum edge is accomplished with the help of rough set rules.

If A, B and C are three interchangeable parking spaces, their arrangements could be made polytonic with different positional digraph orientations with different edge length as shown in Fig. 2.

Similarly, once the different positing of parking spaces have been identified, the other toll rough set is introduced to improvise the marginal parking scenario and thus lead toward better optimization.

There are two general kinds of decisional rules in classic rough set theory [25]. The first is the *exact decisional rule*, named also deterministic, where the decisional set (the cost) contains the conditional attributes (area or other features). The second is the *approximate decisional rule* in which only some conditional attributes (area or other features) are included in the decisional set (price) [5,26]. In this case of parking function, the causal relationships between the property features and its value are appraised without any uncertainty. The logical prepositions *if…then* allow the user to create a preferential system based on the property market data. The *granularity* of the system, its uncertainty can be increased in case the information is based on a few observations [5]. An example [26] of rule that may be used for valuation purposes is indicated below:

If near_ parking_dist = $x \wedge$ time_occupancy = "LESS" $\wedge$ Date $\wedge$ YEARS = Z $\rightarrow$ cost of parking is high)

//Sample Parking Map Rule 1
If arrival_time = y (not peak hour), then $y \vee Z \wedge$ probability of available parking space $\rightarrow$ cost of parking is less with high probability of parking space
//Sample Parking Map Rule 2

Let A = (U, IND (B)) be an approximation space. A pair $(L,U) \in P(U) \times P(U)$ is called a rough set in A, where $L = A(X)$, $U = A(X)$ for some $X \subseteq U$ and $P(U)$ is the power set of U. Due to the granularity of knowledge, rough sets cannot be characterized by using available knowledge. Therefore, for every rough set X, we associate two crisp sets, called lower and upper approximation. Intuitively, the lower approximation of X consists of all elements that surely belong to X, the upper approximation of X consists of all elements that possibly belong to X, and the boundary region of X consists of all elements that cannot be classified uniquely to the set or its complement, by employing the available knowledge [33]. In the following, the measure proposed for the parking information system has been simplified, where $U = \{u_1, u_2, u_{24}\}$ and $A = \{a_1; a_2; a_3; a_4$ with a_1 = effective parking slot, a_2 = average numbers of vehicle to be parked on a day, a_3 = duration and a_4 = different parking probabilities for drivers. Let R be an equivalence relation defined on U and let $R_1 = \{a_1, a_2\}$ and $R_2 = \{a_1; a_2; a_3\}$ [1].

Let $S = (U, A)$ be an information system and $U = A = \{X, X_2, \ldots, X_m\}$

A knowledge granulation of A is given by:

$$\mathrm{GK}(A) = \frac{1}{|U|}\sum_{i=1}^{m}|X_i|^2$$

By computing, we have GK (R_1) = 0:132 and GK (R_2) = 0:090. It is the difference between the knowledge of granulation of R_1 and that of R_2. In fact, $U/R_1 \subseteq U/R_2$ i.e. R_2 is finer than R_1.

Let, $X_1 = \{u_4; u_5; u_6; u_{17}; u_{23}\}$,
$X_2 = \{u_1; u_2; u_3; u_8; u_{11}\}$,
$X_3 = \{u_8; u_{11}; u_{12}; u_{15}\}$,
$X_4 = \{u_1; u_4; u_5; u_9; u_{14}; u_{19}; u_{21}; u_{22}; u_{23}\}$ and
$X_5 = \{u_6; u_7; u_{11}; u_{12}; u_{15}; u_{17}; u_{18}; u_{21}; u_{24}\}$.
$X_6 = \{u_{25}; u_{26}; u_{27}; u_{28}; u_{31}\}$.

Apart from five sets (that follows standard lower and upper approximation similar to [1], (Table 3a), the sixth is a different one, which comprises overlapping parking events (event u_{29} and u_{30}. However, these sets may have different Roughness (X) (Table 3b), which has been adopted from [1]. After following the roughness table from [1], the model identifies the ambiguous parameters.

This is caused by the fact that R_1 and R_2 have different knowledge granulations. Thus, under the measure proposed in this paper, the uncertainties of X with respect to different equivalence relations are well characterized [1].

Rough set system helps us determine in real time for every parking tariff class, the time moment after which there are no longer vacant parking spaces for the drivers requesting it. In any time moment t, we will know the remaining time interval $T_{(t)}$ for selling parking spaces to a particular parking tariff class. It is clear that $T_{(t)}$ depends on the cumulative numbers of drivers requesting a particular tariff class $D^i(t)$, (i = 1, 2, 3, ...). The cumulative numbers of driver requests are antecedents, while remaining time period for selling the parking spaces $T_{(t)}$ is the consequence [2,27]. As such a parking information system is a pair $S = (U; A)$, where,

- U is a non-empty finite set of objects which is the number of cars C here to be under queue of parking; n are the parking slots and k are un-parked drivers if any.
- For every $a \in A$, there is a mapping a, a: $U \rightarrow V_a$, where V_a is called the value set of a. Each subset of attributes $P \subseteq A$ determines a binary indistinguishable relation *Opti(Park)* as follows:

$$Opti(Park) = \{(u, v) \in U \times U | \forall a \in P, a(u) = a(v)\} \quad (1)$$

It can be easily shown that *Opti(Park)* is an equivalence relation on the set U [28]. Similarly, to formulate the μ, this

Table 1 Parking slot distribution in Mauritius.

Name of parking area	Actual parking slots available
Port Louis	1598
Curepipe	170
Rose Hill	230
Quatre Bornes	127

Data provided by Department of Public Infrastructure, Land and Transport, Govt. of Mauritius.

is the valid move for parking car, we can define a decision table as an information system $S = (U, C \cup D) with C \cap D = \emptyset$, where, an element of C is called a condition attribute, an element of D is called a decision attribute [1]. Table 1 demonstrates the parking area assigned in a small city e.g. Mauritius and their actual capacity defined in terms of parking space. Depending on the data provided in Tables 1 and 2 present the effective and functional parking slots available.

Table 2 Statistical snapshot about car parking in Mauritius (weekly data).

Day	Effective parking slots available	Avg. No. of vehicles on a day	No. vehicle parked	Duration (min./max.)
1	1590	988	923	30 min/4 h
2	1582	1005	910	15 min/3 h
3	1587	990	934	30 min/4 h
4	1584	885	780	45 min/3 h
5	1591	1021	990	311 min/5 h
6	1576	940	880	15 min/3 h
7	1588	970	905	30 min/4 h

Table 3a Parking problem parameters against different ambiguous parameters.

Parking events	Effective parking slot	Average density of vehicle to be parked	Duration	Parking probabilities
u_1	Available	High	Long	Neal
u_2	Not available	High	Short	May vary
u_3	Available	Medium	Moderately short	Very high
u_4	Not immediate	Moderately med.	Normal	Medium
u_5	Not available	Moderately avg.	Avg.	May vary
u_6	Available normal	Highly dense	Long	Neal
u_7	Not immediate	Moderately high	Timely	Low
u_8	Available with time limit	High	Avg.	Very high
u_9	Available	Very high	Moderately short	Neal
u_{10}	Not available in time	Low	Normal	Very high
u_{11}	Not immediate	Moderately low	Long	High
u_{12}	Available normal	Very low	May vary	Very high
u_{13}	Available	High	Short	May vary
u_{14}	Not available in time	Normal	Long	Medium
u_{15}	Available	Not exactly known	May vary	Low
u_{16}	Not immediate	High	Long	Low
u_{17}	Not available in time	Moderately medium	Timely	Neal
u_{17}	Available	High	Long	Neal
u_{18}	Not available in time	Normal	Long	Medium
u_{19}	Available with time	High	Avg.	Very high
u_{20}	Available with time limit	Not exactly known	May vary	Low
u_{21}	Not available in time	Low	Normal	Very high
u_{22}	Not immediate	Moderately low	Long	High
u_{23}	Available	Medium	Moderately short	Very high
u_{24}	Available	Very high	Moderately short	Neal
u_{25}	Not immediate	Moderately low	Long	High
u_{26}	Available with time limit	Not exactly known	May vary	Low
u_{27}				
u_{28}	Available	Medium	Moderately short	Very high
u_{31}	Overlapping	Not defined	Not defined	Not defined

Table 3b Lower and upper bound of the proposed rough model

X	$R_1X = R_2X$	$\bar{R}_1X = \bar{R}_2X$
X_1	$\{u_4, u_5, u_{23}\}$	$\{u_4, u_5, u_6, u_7, u_{17}, u_{18}, u_{23}, u_{24}\}$
X_2	$\{u_1, u_2, u_3\}$	$\{u_1, u_2, u_3, u_8, u_{10}, u_{11}, u_{12}\}$
X_3	$\{u_{11}, u_{12}\}$	$\{u_8, u_{10}, u_{11}, u_{12}, u_{15}, u_{16}\}$
X_4	$\{u_4, u_5, u_9, u_{21}, u_{22}, u_{23}\}$	$\{u_1, u_2, u_3, u_4, u_5, u_9, u_{13}, u_{14}, u_{19}, \ldots u_{23}\}$
X_5	$\{u_6, u_7, u_{11}, u_{12}, u_{17}, u_{18}, u_{24}\}$	$\{u_6, u_7, u_{11}, u_{12}, u_{15}, u_{16}, u_{17}, u_{18}, u_{21}, u_{24}\}$
X_6	$\{u_{25}, u_{26}, u_{27}, u_{28}, u_{31}\}$	Marginal resultant of $R_1X = R_2X$ *With overlaps*

- Statistics of car parking (mostly taxi) of seven continuous days have been recorded (Table 2).
- Day 5th and 6th (Bold part in Table 2) envisage high density of car arrived and least parking spaces available, respectively.
- The duration of parking varies from minimum 15 min to 5 h in a particular day.
- Statistically, it is also observed that for each day the parking space is not adequate except the day 5th when only 31 cars did not get appropriate available parking space in the city.
- The statistical data are used for the proposed simulation for finding the optimal space of through intelligent methodology.

The available number of parking spaces must be updated every time a driver is accepted for parking. The algorithm describes the rough set guided *Tabu Search* engine for parking space optimization and control in the following steps:

Step 1: Record all cumulative $R_i(t)$ that are based on a large number of driver requests for parking in the parking slot in a particular area. Similarly, establish an objective function based on the constraints.

Step 2: Analyze the area, where the parking slot is located and the following parameters are recorded:

- the asymptotical behavior of the parking slot distribution;
- limiting probability that all parking spaces are occupied;
- let $a(r,s,k)$ denotes the numbers of choices for which r spaces remain unoccupied, s spaces are occupied at the end, and k people drive home [20];

$$a(r,s,k) = \begin{cases} 1 & if r = s = k = 0, \\ a(r-1,s,0) + \sum_{i=0}^{k+1} \binom{s+k}{k+1+i} \cdot a(r,s-1,i) & if k = 0 and (r > 0 or s > 0), \\ \sum_{i=0}^{k+1} \binom{s+k}{k+1+i} \cdot a(r,s-1,i) & if k > 0. \end{cases} \quad (2)$$

- this also leads to the fact that there are $n = r + s$ spaces in total, and that $m = k + s$ drivers arrive [20].
- Hence, *Opti(Park)* is recursive in nature and may be expressed as follows [2,20]:

Note: This will not be true when the uncertain distribution is involved.

Step 3: Formulate a corresponding optimization problem [according to $Opti(Park) = \{(u, v) \in U \times U | \forall a \in P, a(u) = a(v)\}$] and find the optimal parking move μ, for each generated drive's assignment for parking comprising of asg_d (n, m, k).

Step 4: Based on the statistical data resulting from Steps 1 and 2, use some of the existing algorithms [1] to generate the rough set as upper and lower approximation.

3.2. Stopping criteria and measurement of optimal parking

Various stopping conditions can be applied to the proposed algorithm. The algorithm may stop when a maximum number of evaluations; a minimum value of the weighted variance or a maximum number of iterations (without any significant improvement in the objective function) is reached. During any iteration for searching optimal parking space, the length of the Tabu list is calculated as half of the smallest distance between the Tabu points and the marginal points and could be represented as [24]:

$$v_t = u_{k_{(0-1)}} \left[\frac{1}{2} L_{\min} = \frac{1}{2} \min_{j=1}^{k} \|x_t^j - x_u^j\| \right. \quad (3)$$

Where, subscripts u and t represent the promising points and the Tabu lists, respectively. The parameter $_t$ specifies the minimum Euclidean distance that must exist between each random point and Tabu points. It is important to note that using this scheme, the size of the Tabu list dynamically changes based on the distribution of the uncertain and the Tabu points in the parking solution space [24].

Thus, Eq. (3) is a measurable point to analyze the proposed algorithm and differs from [24] by a coefficient multiplication factor $u_{k_{(0-1)}}$, which considers all the marginal and near conditions evolved in real parking scenario. The range of this varies from 0 to 1 units of near ness.

4. Result and implications

The proposed model rough set guided Tabu hybrid metaphor has been implemented on a test data using within MS Windows environment using C+ +. The simulation is supported by 3D plot demonstrating as followings:

- initial parking space 1 against gradient and number of Tabu iterations;
- parking space 2 against gradient and number of Tabu iterations;
- identifying extreme parking space, when the uncertainty distribution in parking function becomes high.

The three parameter sets help to investigate the performance of the proposed algorithm.

In the post implementation phase of the proposed algorithm, a 3D plot is prepared in Fig. 3, which comprises a number of iterations. This plot demonstrates availability and probability of parking space in the first set of iterations. The gradient value is considered under rough set rule. It implies that, in the first set of search optimization, parking space becomes stiffer and most of the cars were un-parked (similar to the statistics of 4th day given in Table 2 where 105 cars remained un-parked). Only gray colored portion in the plot was facilitated (0.2–0.3 units of parking space 1) with proper parking space. Similarly, the value of gradient becomes stiffer but covers wider parking space. Still the convergence is not able to cover the uncertain and extreme conditions. Therefore, plot of parking space 2 against gradient and Tabu iterations shown in Fig. 4 offers > 1.2 units of space in parking slot. This case is analogous to Cayleey's formula and there are nn^{-2} la-

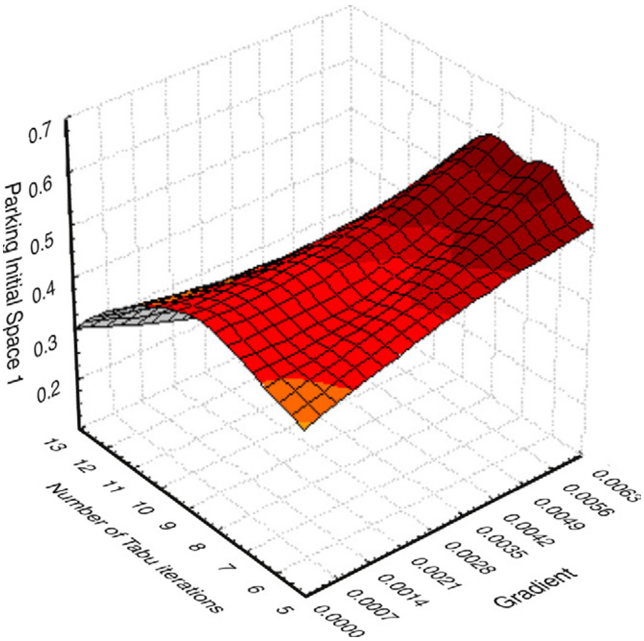


Figure 3 Initial parking space and gradient value (under rough set).

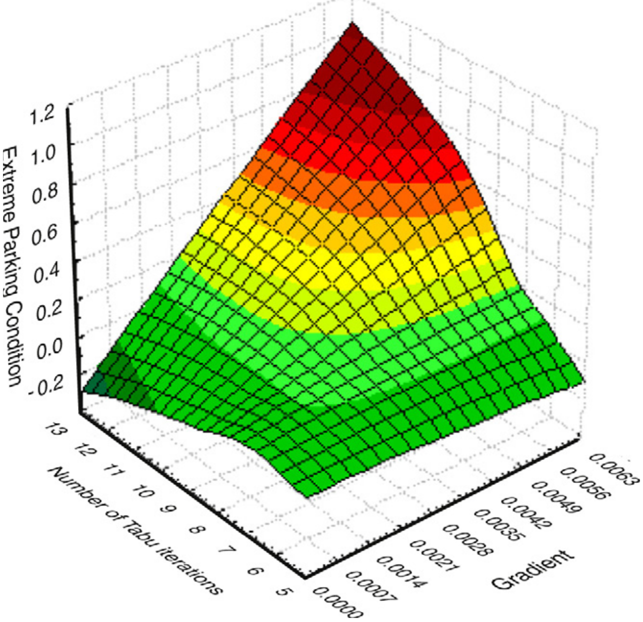


Figure 4 Intermediate parking space and gradient value – marginal parking.

beled trees on n vertices, where car number 9 is just entering into parking queue expecting car number 6 is coming out of the queue (Fig. 1 in Section 3.2). Hence, it is an example of marginal parking condition.

In Fig. 5 extreme car parking criterion is presented through proposed rough set guided Tabu Search. The performance is satisfactory and covers more confident parking space till 0.4 unit space and still maintains a straight gradient irrespective of uncertain conditions. The uncertain conditions encompass

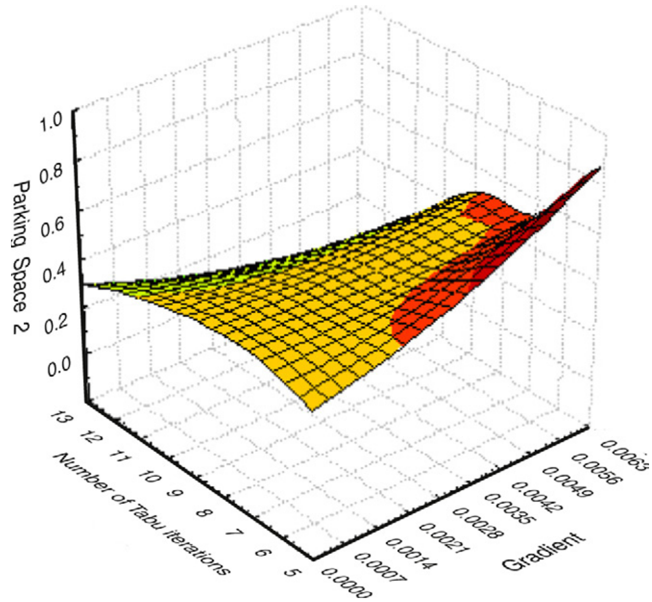


Figure 5 Plot of parking function using hybrid metaphor in uncertain and extreme condition.

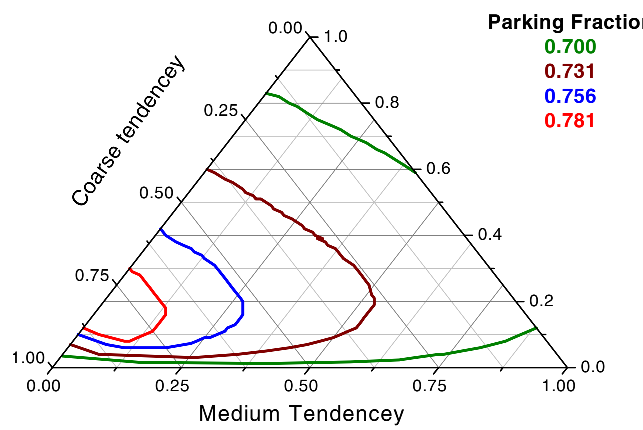


Figure 6 The snapshot of parking slot under medium and coarse tendency.

mainly occupancy time and variable size of parking space and vehicles.

Fig. 6 presents a plot which establishes that real attribute of parking under rough set guided Tabu Search condition could be different under slight variations and could be a prominent examples of *Marginal Set and near set* paradigm. While varying parking fraction from 0.7000–0.781 units, the plot changes and optimum contour of plot is achieved (marked in Red). This also defines the minimum accuracy of $\{u_{25}, u_{26}, u_{27}, u_{28}, u_{31}\}$ under the decision variables and co-multiplication factor defined in Eq. (3).

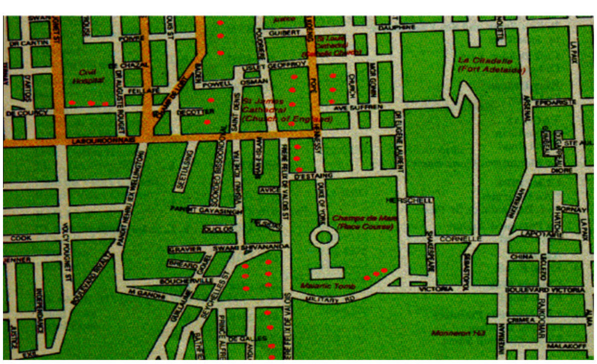
5. Conclusion

In the given optimal parking problem, the problem size is directly correlated with the number of vehicles to be parked. Since large number of vehicles in parking lot usually need large initial tabu privileges, the initial tabu structure is defined as the total number of vehicle multiplied by a coefficient. In the research documented here, a coefficient has been selected based on empirical tests [29]. The upper bound and lower bound of the tenure is set to the maximum of initial tabu space and has been further tuned with rough set rule set. Thus, the upper bound and the lower bound are proportional to the problem size and stay within a reasonable range [29].

Reactive Tabu Search was used and the memory structure of the tabu was extensively used to control the search and to adjust the search parameters based on the quality of the search [29]. The quality of the search is determined by the frequency of revisiting previously visited solutions and the simplest way to identify the solution is to compare the routes with routes of all previously visited solutions. In order to identify previously visited solutions efficiently, a two-level comparison mechanism was used. The solution history is composed of solution-identity information and visit information. The solution identity information includes the objective function value and its hash value [29].

In contrast to conventional optimization of Tabu Search, in the proposed hybrid intelligent scheme of car parking a rough set methodology is incorporated to tackle the uncertainty prevailing in parking function. The asymptotic enumeration behavior of parking function is also studied and most importantly, the nature of traffic for the development of the model has been considered as bi-directional (whereas mostly it refers to unidirectional in recent literature [20]). The intelligent scheme proposed could provide substantial research directions for other similar hard optimization problems.

A software interface for car parking inventory, encapsulating the above mentioned intelligent hybrid scheme was developed that could subsequently be used as an intelligent automation for queuing applications. The uncertainty and extreme conditions of car parking have been modeled through *rough set assisted Tabu Search techniques*. With the initial parameters, simulation produces a satisfactory result. The intelligent hybrid scheme was validated using traffic data related to a small city and the software interface was tested with the thematic map of a city parking as shown in the Appendix.



Appendix A. Appendix

Partial Traffic thematic map of the capital of Mauritius, *Port Louis* is presented with red dots where parking slots are provided. The simulation of the proposed model has been accomplished on the sample traffic map. The database is supported through Microsoft SQL Server and front end is developed using C++ within MS Windows environment.

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