Tourist Trip Design Problem considering Fatigue

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\textbf{Abstract:} Inbound tourism has been steadily increasing in Japan and has benefited the country in many ways. To provide newcomers with a more satisfying experience, trip routes can be suggested by solving the Tourist Trip Design Problem (TTDP). However, the traditional TTDP does not consider the tourists’ fatigue level. Hence, the most optimal route may end up not being the most desirable route. Therefore, the goal of this research is to add the fatigue factor into the TTDP and solve the Tourist Trip Design Problem with Fatigue (TTDPF). We analyze how the optimum route changes based on different levels of fatigue sensitivity. For a person with low fatigue sensitivity, it is logical to visit more tourist attractions with less rest in between. Eventually, we aim to provide the tourists with trip routes that are more realistic and directly applicable.

\textbf{Keywords:} Tourism, TTDP, Fatigue, Route, ILS

\section{1. INTRODUCTION}

For many countries, tourism is a very important contributor in their gross domestic product (GDP); for example, in Thailand (10.4\%), France (2.4\%), and the United States (1.3\%) (World Bank, 2017). Tourism and its importance is also increasing in Japan. For example, only in Kyoto, the historical capital of Japan, the number of visitors annually has increased from approximately 39 million to 50 million in the last few decades. A good number of tourists always consist of foreigners, who visit the country for the first time. As in 2017, there were 15.57 million visitors who have spent at least one night in Kyoto. Out of those, 3.53 million people were foreigners (The Japan Times, 2018). Cities are making continuous efforts to make their foreign tourists’ stay more comfortable. For instance, since 2012, Kyoto city has been providing 3 hours of free Wi-Fi to everyone at 649 different bus stops. Also, the city has been running a 24/7 multilingual call center to help tourists that stay at traditional inns, where foreign language services are quite rare. On top of that, they have created an official tourism website, Kyoto Travel Guide, which is available in 8 different languages (The Japan Times, 2014). At the same time, there are still a lot of issues the city has to overcome in terms of tourism. One of the biggest complaints that visitors have is the overcrowding at popular tourist attractions and packed buses.

One of the above-mentioned efforts to improve the tourism experience is to establish tourism websites and suggest itineraries and travel routes to the tourists. In academic research, the subject of trip itineraries has been addressed as the Tourist Trip Design Problem (TTDP) (Vansteenwegen et al., 2007), which is a route-planning problem for tourists wanting to visit multiple Points of Interests (POIs) (Gavalas et al., 2014). Typically, the travel time, travel cost
or a combination of these is optimized in the TTDP.

One might further critically assess the underlying assumption that tourists are optimizing their tours according to such assumptions. It is in some cases the experience of travelling itself and possibly “leisurely strolling” that provide satisfaction. This might be reflected in low (or even negative) costs of specific elements of a tour. Furthermore, touring a city one will want to make breaks and probably ensure that one visits the main POIs before time runs out and tiredness starts to set in. It is this latter point that we aim to include in the TTDP. That is, unfortunately, the existing traditional TTDP does not consider the fatigue level of the individual travelers, who are the ultimate end-users. Therefore, the goal of this research is to formulate a new Tourist Trip Design Problem with Fatigue (TTDPF) model that provides routes that are more suitable and catered towards the users. Additionally, in order to solve this formulation, we have developed an Iterated Local Search (ILS) heuristic. Performances of the proposed TTDPF and the ILS algorithms have been evaluated on a test instance based on the tourist attractions in Kyoto city. The results show that the proposed TTDPF can provide the tourists with trip routes that are more realistic and directly applicable.

2. LITERATURE REVIEW

The TTDP can be solved as a more simplified form of the Orienteering Problem with Time Windows (OPTW), which is a variant of the Orienteering Problem (OP) that in turn is based on the sports game of orienteering (Golden et al., 1987). In the OP, players start from a fixed origin point to visit check points, each associated with a unique score, then return to the origin point within the time limit. The winner of the game would be the one with the highest score. It has also been named as the selective Traveling Salesman Problem (TSP) (Laporte and Martello, 1990), the maximum collection problem (Kataoka and Morito, 1988), and the bank robber problem (Arkin et al., 1998). Since then, the problem has been explored in multitude of different variations.

When we maximize the objective function for P number of routes instead of one with the OP, it is called the Team Orienteering Problem (TOP) (Chao et al., 1996). A TOP model can be beneficial when planning for multiple days. For instance, Butt and Cavalier (1994) propose a TOP application of athlete recruitment from high schools. Another application of the TOP is when there are multiple numbers of users. Tang and Miller-Hooks (2005) introduced a technician routing situation. To solve the TOP, some exact approaches and many efficient heuristics have been proposed. Few examples are the branch-cut-and-price algorithm by Pessoa et al. (2008), the Particle Swarm Optimization-inspired algorithm by Dang et al. (2013), and the Pareto mimic algorithm by Ke et al. (2015).

A new problem of OPTW is created by applying time windows to the (T)OP. This means that each node which the user can visit has a specific opening time and closing time. The OPTW was first solved by Kantor and Rosenwein (1992). Later, Gunawan et al. (2015) and Vansteenwegen et al. (2009) solve the (T)OPTW using the Iterated Local Search (ILS) algorithm. Wu et al. (2017) delve deeper into the idea by solving the TTDP including the tourists’ preference of attraction, time, and cost budgets. To achieve this, the study incorporates the utility of edges as well as the utility of nodes into the objective function. Gavalas et al. (2014) provided an extensive literature survey about the TTDP and indicated inclusion of breaks and relaxing spot must in the TDDP as one of the future research directions. Cenamor et al. (2017) presented “PlanTour”, an application that generates tourist routes based on the data from social network sites. Once the POIs are extracted from the social network sites, they are clustered to be visited, one per day based on utility
maximization (the social network website scores). Finally, the routes are generated for each cluster (for each day). They added restaurants for eating stops considering the hunger drive, which is represented by a time window during which a tourist can eat. Li et al. (2018) conducted laboratory tests by showing pictures of four selected Chinese traditional gardens, which were scored by participants, while wearing an electroencephalography (EEG) device. This test is repeated for three times on same sample of photos and it was found that the score values as well as attention levels in EEG are getting reduced with each run (as well as within run). A similar experiment on actual locations also yielded the similar results. It was concluded that aesthetic fatigue is responsible for the reduced attention during the repeated tours and scoring tests. Traditionally, in transportation related studies, fatigue (or loss of concentration of the primary task) has been considered in many accident-related researches with recent emphasize on autonomous driving (Vogelpohl et al., 2019).

From the above literature review, it can be seen that although the consideration of fatigue has been indicated as a future TTDP research (Gavalas et al., 2014)) but it has only been considered passively (Cenamor et al., 2017) and never been considered as loss of utility value in the TTDP optimization. The variants of the orienteering problem as well as the TTDP in previous researches have not exclusively considered the loss of utility value for the end-users (i.e. tourists) for continuous, tiring trips. In order to do so, we looked into studies discussing about accumulating sleep pressure and seek inspiration for the concept of fatigue. The study done by Acherman and Borbély (1994) focuses on the sleepiness of a person during a day and how the sleep pressure can be evaluated. Through simulations of daytime vigilance, they have concluded that sleepiness is determined by two factors, the homeostatic and the circadian process. The homeostatic process is a sleep-wake dependent system that increases its level during waking and decreases it when sleeping. Folkard and Åkerstedt. (1987) show how the sleep pressure of the homeostatic process affects the person’s awareness. When exposed to a long period of waking state, the alertness level decreases as sleep pressure increases. Hursh et al. (2004) examine the effect of sleep deprivation on a soldier’s fatigue level and effectiveness in war fighting. The results indicate that a soldier’s effectiveness graph has the same shape as the reverse of sleep pressure over the course of sleep and wake cycles. Burke et al. (2015) study the influences of sleep inertia, sleep homeostatic, and circadian processes have on higher-order cognitive functions. The research shows that the different systems affect different cognitive functions either independently or interactively. Especially, the sleep homeostatic influences factors such as subjective happiness and motivation. Therefore, we assume here that longer tours will affect the satisfaction of tourists in the same way as he/she will be getting more and more tired. If instead breaks are taken during the journey, one can reduce fatigue and enjoy the subsequent POIs more. We have formalized this idea in the mathematical form in the next section.

3. MATHEMATICAL FORMULATION

The mathematical representation of the Tourist Trip Design Problem with Fatigue (TTDPF) is based on the study by Wu et al. (2017). To begin with, the transportation network is considered as a directed graph $G = (V, E)$. Here, $V = \{v_1, v_2, \ldots, v_n, v_{n+1}, \ldots, v_N\}$ is the list of nodes within the system, and the edge set $E$ consists of all feasible edges $(i, j)$, $i, j \in V$. $v_1$ is the origin node as well as the ending node. To consider the concept of fatigue, the nodes are divided into two groups, $v_1$ to $v_n$ are the attraction (fatiguing) nodes and the resting nodes (from $v_{n+1}$ to $v_N$). Visiting a resting node decreases the value of the tourists’ fatigue level, while visiting a tourist attraction increases the fatigue level. We assume that a resting node is not just a single resting spot. Rather, it is cluster of places such as restaurants that are
located around the attraction. Consequently, unlike attraction does, resting nodes are allowed to be visited multiple times (as tourists are unlikely to visit a single place multiple times, but might visit different resting places in the same area). Regardless of the node’s type, they are all given unique opening times \( t_{o_i} \), closing times \( t_{c_i} \), attraction level \( A_i \), service time \( T_i^s \), and cost \( C_i \). Likewise, each edge is given attribute values as well. \( T_{ij}^k \) is the travel time from node \( i \) to node \( j \) using transport mode \( k \), and \( C_{ij}^k \) is the corresponding travel cost on that edge.

The main goal of this research is to integrate the fatigue factor into the trip planning. To do so, we first look into how the trip is originally constructed. First, the time constraints are given by the tourist in the form of start time \( t_{o_1} \) and end time \( t_{c_1} \). The cost budget \( C \) is given as well. Then the tourist starts departing nodes at \( t_{d_i} \) and arriving at nodes at \( t_{a_i} \), meanwhile spending time \( T_i^v \) and money \( C_i \). Eventually, the tourist would return to the origin point before time \( t_{c_1} \). The resulting route would then include all the visited nodes, their chronological order, and the transport method used to move between each pair of the nodes. The goal of the tour route planning would be to choose a set of nodes with their order and travel methods that give the highest utility.

The objective function consists of three parts. First is the utility of traveling through an edge. The formulation is a linear function of time and cost as shown below.

\[
U_{ij}^k = \alpha_1 T_{ij}^k + \alpha_2 \varphi C_{ij}^k
\]  

Where \( U_{ij}^k \) is the utility of traveling from node \( i \) to node \( j \) using transport mode \( k \). \( \alpha_1 \) and \( \alpha_2 \) are parameters based on the tourist choice and sensitivity to its respective factor (i.e. time and cost). \( \varphi \) converts the cost value into time value. The value of \( U_{ij}^k \) is always negative as both \( \alpha_1 \) and \( \alpha_2 \) are negative, meaning traveling from one place to another generates a disutility.

Secondly, we have the utility of visiting a node.

\[
U_i^a = \begin{cases} 
\beta_1 \tau A_i + \beta_2 T_i^v + \beta_3 \varphi C_i & \text{(attraction)} \\
\beta_4 \tau A_i + \beta_5 T_i^v + \beta_3 \varphi C_i & \text{(resting)} 
\end{cases}
\]  

\( U_i^a \) is the utility of visiting the node \( i \). \( \beta_1, \beta_2, \beta_3, \beta_4, \) and \( \beta_5 \) all control the degree of sensitivity to their corresponding factors (i.e. attractiveness of the spot, time spent at the spot and the cost spent at the spot). Both \( U_{ij}^k \) and \( U_i^a \) are based on the study by Wu et al. (2017) except that the values of \( \beta_4 \) and \( \beta_5 \) are assumed to be smaller than those of \( \beta_1 \) and \( \beta_2 \) since they are for visiting a resting node that returns a smaller utility reward. \( \tau \) is the conversion value that transfers the attraction level into time.

Finally, we have the fatigue factor that will be subtracted from the utility to represent loss of utility due to tiredness of a tourist.

\[
F_i = R_i \gamma (\tau A_i + T_i)
\]

\[
R_i = \begin{cases} 
1 - e^{-\Delta t / \tau_r} (1 - |R_{i-1}|) & \text{(attraction)} \\
-e^{-\Delta t / \tau_d} |R_{i-1}| & \text{(resting)} 
\end{cases}
\]
Here, $F_i$ is the fatigue value at node $i$; $\gamma$ is the fatigue sensitivity value for the attraction level and time. As mentioned earlier, $\tau$ is the conversion value from attraction level to time. $R_i$ is what we define as the rest pressure a tourist experiences after visiting the node $i$. Equations (3) and (4) are modified version of the sleep pressure suggested by McCauley et al. (2008).

With these three utility factors, we can formulate the Tourist Trip Design Problem with Fatigue (TTDPF) as below.

\[
\max U = \max \left( \sum_{k=1}^{m} \sum_{i=1}^{n-1} \sum_{j=2}^{n} x_{ij}^k U_{ij}^k + \sum_{i=2}^{n-1} \delta_i U_i^g - \sum_{i=2}^{n-1} \delta_i F_i \right) 
\]

\[
\sum_{k=1}^{m} \sum_{i=1}^{n} x_{i1}^k = \sum_{k=1}^{m} \sum_{j=1}^{n} x_{1j}^k = 1 
\]

\[
\sum_{k=1}^{m} \sum_{i=1}^{n} \sum_{j=1}^{n} x_{ij}^k = 1 
\]

\[
t_{d1} = t_{\text{start}} 
\]

\[
t_{si} + T_i^p = t_{di} 
\]

\[
t_{di} + T_{ij}^k = t_{aj} 
\]

\[
\sum_{k=1}^{m} \sum_{i=1}^{n-1} \sum_{j=2}^{n} x_{ij}^k T_{ij}^k + \sum_{i=2}^{n-1} \delta_i (t_{di} - t_{ai}) \leq t_{\text{end}} - t_{\text{start}} 
\]

\[
\sum_{k=1}^{m} \sum_{i=1}^{n-1} \sum_{j=2}^{n} x_{ij}^k C_{ij}^k + \sum_{i=2}^{n-1} \delta_i C_i \leq C 
\]

\[
x_{ij}^k = \begin{cases} 
1 & \text{if going from node } i \text{ to node } j \text{ using } k \text{ mode}; \\
0 & \text{otherwise} 
\end{cases} 
\]

\[
\delta_i = \begin{cases} 
1 & \text{if node } i \text{ is selected}; \\
0 & \text{otherwise} 
\end{cases} 
\]

\[
t_{si} = \begin{cases} 
t_{ai} & \text{if } t_{ai} \geq t_{oi} \\
t_{ai} + t_{wi} & \text{if } t_{ai} < t_{oi} 
\end{cases} 
\]

\[
t_{wi} = \begin{cases} 
t_{oi} - t_{ai} & \text{if } t_{ai} < t_{oi} \\
0 & \text{otherwise} 
\end{cases} 
\]

\[
\sum_{i=2}^{n-1} \delta_i F_i = \begin{cases} 
0 & \text{if } \sum_{i=2}^{n-1} \delta_i F_i < 0 \\
\sum_{i=2}^{n-1} \delta_i F_i & \text{otherwise} 
\end{cases} 
\]

The objective function (5) maximizes the tourism utility considering tourist fatigue. Constraint (6) ensures that the route starts from Node 1 and ends at Node 1. Constraint (7) makes sure that no attraction node is visited more than once. However, in our case, resting nodes are allowed for multiple visits. Constraint (8) determines the tour start time. Constraints (9) and (10) calculate the departure time and arrival time at a node. Constraint (11) and (12)
make sure the time and budget constraints are met. Constraints (14) and (15) define the binary variables. Constraints (16) and (17) define the starting time and wait time at a node. Constraint (18) prevents the fatigue factor from ever increasing the utility.

The rest pressure is the main determining factor as to how much fatiguing or relaxing a node visit will be. Each $R_i$ is dependent on the previous $R_{i-1}$ and therefore, dependent on every value of $R$ that comes before. If many attractions were visited in a sequence, the rest pressure would be high and the next attraction visit will be even more fatiguing. At the same time, if the same person were to visit a resting node, the rest will be that much sweeter and will reduce the fatigue level by quite a bit. On the other hand, if a tourist visits many resting node only, the next visit to a resting node won’t be much satisfying. In this scenario, visiting a tourist attraction would yield a very high utility as it will add a relatively low fatigue value.

4. SOLUTION HEURISTICS

The proposed TTDP is an NP-hard problem as it is a variant of the OP, which is proven to be a NP-hard problem. Therefore, in order to obtain the approximate optimal solution for our problem, we developed an iterated local search (ILS) heuristic. It is a basic form of the ILS and consists of two steps, “Insertion” and “Shake”.

4.1. Insertion

The first part of the ILS is the insertion step that adds new visits to the route, one node at a time. First, it creates a subset of unvisited potential candidate nodes. The nodes are then tested for their feasibility in every possible insert position. If feasible, the utility is calculated and compared with the others. The best node is the one that returns the highest utility when added to the solution. This process is repeated until there is no possible addition of a node at any position that will increase the utility of the solution. Then, the solution is declared as a local optima and the insertion step ends.

4.2. Shake

The shake step is a much simpler step that is designed to escape the local optima. In this step, a certain number of visits will be deleted from the solution. The number of visits that gets deleted is denoted by $R$. The starting node for the deletion is denoted by $S$. After the visits are deleted from the trip, the disconnected visits of $S$ and $S + R$ are connected with the best travel mode for the route.

4.3. ILS for Tourist Trip Design Problem with Fatigue (ILS-TTDPF)

As initial solution, the heuristic is given a route that goes from the origin point to a random node within the system. Then, the initial solution is thrown into a loop. The loop continues until the solution receives no improvement for more than 50 iterations. During the loop, the solution first goes into the insertion step. Here, the insertion heuristic would add the best possible visit to the route one by one until the local optima is reached. Once the insertion is over, the current solution would be compared to the best solution there was. Since this is the first iteration, the best solution would be an empty one with zero (0) utility. Therefore, the best solution would be updated and the current solution would enter the shake step. Next, the values of $S$ and $R$ are chosen at random within the possible space (i.e. the length of the current route). Once the values are set, the shake step deletes visits starting from visit $S$ by $R$.
number of visits. Then the loop starts from the top again. The flowchart of the ILS is shown in the Figure 1.

5. PERFORMANCE EVALUATION

5.1. Sample case based on Kyoto city

In order to test our formulations, we use a sample network based on Kyoto city as shown in Figure 2.
The network includes 10 of the most popular tourist attractions in the city (according to japan-guide.com) and an origin point, a hotel, located at Karasuma station. The origin point is marked by number 1, and the tourist attractions are marked by number 2 to 11. Next to each one of these nodes are the resting nodes marked by numbers 12 to 22. Again, these resting nodes do not represent a single resting spot but rather a group of places that form a cluster. Every test has been carried out with a cost budget of 10,000 JPY. Time starts from 6AM and is calculated in minutes. Attraction of a POI is rated from 1 to 5 on a continuous scale based on user ratings from japan-guide.com. Table 1 shows the assumed factors at the attraction nodes. The cost of attractions is the entrance fee and their service times were assumed proportional to the physical size of the attraction. For resting nodes assumption of a “basic meal break” are made. In Japan simple lunches can be obtained for less than 1000 Yen. Clearly a tourist might spend more time and money on food. In that case we suggest that the break starts to become an attraction itself. This could be reflected by user defined attraction ratings of attraction and resting nodes. In other words, the resting nodes could also become attraction nodes itself.
Although not shown on the map, every single node of the network is connected to another node through an edge. In this sample case, there are two travel modes ($k = 2$), bus/subway and taxi. Due to its scarcity, subways are considered with the bus system and not as a separate mode. All travel times and costs were obtained through Google Map. When traveling from any non-resting node to an adjacent resting node, the travel time is assumed as 10 minutes with the cost of 0. This represents that the tourist is walking to the destination. Similarly, when consecutively revisiting the same resting node, meaning that the tourist is moving to another resting place within the same area, the person is assumed to walk there, hence, the time is taken as 10 minutes with the cost of 0 again.

Table 1: Details of the nodes in the test instance

<table>
<thead>
<tr>
<th>S. No.</th>
<th>Name</th>
<th>Open (0=6AM)</th>
<th>Close</th>
<th>Time (minutes)</th>
<th>Cost (JPY)</th>
<th>Attraction</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Hotel(Karasuma Station)</td>
<td>0</td>
<td>1020</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>Nijo Castle</td>
<td>165</td>
<td>660</td>
<td>50</td>
<td>600</td>
<td>1.9</td>
</tr>
<tr>
<td>3</td>
<td>Kyoto Imperial Palace</td>
<td>180</td>
<td>660</td>
<td>40</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>4</td>
<td>Kiyomizudera</td>
<td>0</td>
<td>720</td>
<td>50</td>
<td>400</td>
<td>4.6</td>
</tr>
<tr>
<td>5</td>
<td>Gion</td>
<td>120</td>
<td>840</td>
<td>40</td>
<td>0</td>
<td>1.9</td>
</tr>
<tr>
<td>6</td>
<td>Ginkakuji</td>
<td>150</td>
<td>660</td>
<td>50</td>
<td>500</td>
<td>2.3</td>
</tr>
<tr>
<td>7</td>
<td>Heian Shrine</td>
<td>0</td>
<td>660</td>
<td>50</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>8</td>
<td>Philosopher's Path</td>
<td>120</td>
<td>1080</td>
<td>20</td>
<td>0</td>
<td>1.9</td>
</tr>
<tr>
<td>9</td>
<td>Fushimi Inari Temple</td>
<td>120</td>
<td>1080</td>
<td>60</td>
<td>0</td>
<td>5</td>
</tr>
<tr>
<td>10</td>
<td>Kinkakuji Temple</td>
<td>180</td>
<td>660</td>
<td>40</td>
<td>400</td>
<td>3.7</td>
</tr>
<tr>
<td>11</td>
<td>Ryonanji Temple</td>
<td>120</td>
<td>660</td>
<td>30</td>
<td>400</td>
<td>2.3</td>
</tr>
<tr>
<td>12</td>
<td>Resting node</td>
<td>120</td>
<td>960</td>
<td>30</td>
<td>800</td>
<td>1</td>
</tr>
<tr>
<td>13</td>
<td>Resting node</td>
<td>120</td>
<td>960</td>
<td>30</td>
<td>800</td>
<td>1</td>
</tr>
<tr>
<td>14</td>
<td>Resting node</td>
<td>120</td>
<td>960</td>
<td>30</td>
<td>800</td>
<td>1</td>
</tr>
<tr>
<td>15</td>
<td>Resting node</td>
<td>120</td>
<td>960</td>
<td>30</td>
<td>800</td>
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<td>18</td>
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<td>120</td>
<td>960</td>
<td>30</td>
<td>800</td>
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<tr>
<td>19</td>
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<tr>
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<td>960</td>
<td>30</td>
<td>800</td>
<td>1</td>
</tr>
<tr>
<td>21</td>
<td>Resting node</td>
<td>120</td>
<td>960</td>
<td>30</td>
<td>800</td>
<td>1</td>
</tr>
<tr>
<td>22</td>
<td>Resting node</td>
<td>120</td>
<td>960</td>
<td>30</td>
<td>800</td>
<td>1</td>
</tr>
</tbody>
</table>

5.2. Parameter Settings

Many parameters used in this research are directly borrowed from previous literature. Meanwhile, some parameters were modified to suit our case and one was newly introduced.

Parameters used in Eq. (1) and (2) to define travel and node utilities are $\alpha_1, \alpha_2, \beta_1, \beta_2, \beta_3$ are adopted directly from Wu et al. (2017) (-0.5, -0.5, 0.3, 0.4, and -0.3 respectively). $\beta_4$ and $\beta_5$ are sensitivity parameters for attraction and time when visiting a resting node. Therefore, it’s logical to think that they should resemble $\beta_1$ and $\beta_2$ but have smaller values of 0.03 and
0.04 respectively. The value of $\varphi$ set by Wu et al. (2017) was based on CNY and has been converted to 0.0062 in order to match JPY. The value of $\tau$ was set very low by Wu et al. (2017). When ran with the value provided, the attraction level would have very little impact on choosing which node to visit. In our case if attractions do not have a distinct advantage over resting places, the heuristic would never add them to the route. Therefore, we have increased the value of $\tau$ to 40. The value of $\gamma$ is the sensitivity for the fatigue factor and is set to 2. This value has been decided based on the sensitivity analysis that will be discussed in more details in section 5.4.1. Lastly, the values of $\tau_r$ and $\tau_d$ are doubled and halved respectively into 2184 and 126. This change was made so that the rest pressure increases faster and decreases slower than the sleep pressure suggested by Acherman and Borbély (1994). We assume that traveling through attractions is a tiring act that would cause more fatigue then a daily routine. Also, resting at a restaurant is assumed to be not as refreshing as getting a good sleep at a bed.

5.3. Algorithm Evaluation

5.3.1. Insertion Process

In this section, we demonstrate the impact of resting places and attractions on total utility. We explain using the insertion iterations of the insertion part of the heuristics. The heuristic starts with the initial solution of 1-7-1 and after inserting a visit 9 times, reaches the local optima of 1-4-15-16-9-16-5-8-18-7-12-1.

The total fatigue value as the solution develops has been given in Figure 3. Each line shows the change of total fatigue as a tourist travels through the trip. Iterations 1 to 4 were removed from the figure for the sake of visibility. As expected, whenever an attraction node is inserted into the solution, every visit following the insertion has its accumulated fatigue value increased. Likewise, a resting node will lower the total fatigue value of all subsequent visits. Also, when a resting node is added to the route, and then an attraction is visited, the fatigue acquired at that attraction is lower than it would have been before. For instance, iteration 5 visits node 5 after node 9, both of them attractions. The fatigue increases from 56.01 to 79.24, with an increment of 23.23. Then, node 16, a resting node, is inserted in between. The total fatigue is now 56.01 at Node 5, then 47.71 after visiting Node 16 and 66.12 after Node 9. The increments are hence -8.30 and 18.47 respectively. Hence, we can observe that inserting the resting node 16 not only decreased the total fatigue at a subsequent attraction, but also the individual fatigue gained at said node.

Figure 4 shows the corresponding values of total utility at each iteration. As mentioned earlier, the insertion heuristic only adds Nodes with the highest positive increment in the utility, therefore, the total utility value is increasing as the solution developed. Once there are no Nodes with positive increment in utility (due to fatigue), the insertion heuristics stops as further continuation of the tour will not add any further satisfaction to the user.
Figure 3: Total fatigue values during the insertion heuristic iterations

Figure 4: Total utility during the iterations of the insertion heuristic

5.3.2. ILS

Figure 5 shows a detailed progression of the heuristic. We observe that there is very little chance of a breakthrough after about 50 loops without an improvement. Therefore, we conclude that a limit of 50 loops without an improvement is sound. The computation time approximates to 30 seconds per run with an Intel Core i7-4720HQ with 8GB of RAM, which is reasonable.
1.4 Sensitivity Analysis

We remind, that parameter $\gamma$, which is the sensitivity value of fatigue, is a new idea that we have introduced in the TTDPF formulation. It represents how easily a person would get fatigued. A person with a very small value of $\gamma$ would be able to visit attraction after attraction without losing a lot utility. On the other hand, a person with a higher value of $\gamma$ might need to seek a resting place after just one or two attractions. This may represent elderly people, larger families, or someone with a physical condition.

Figure 6 depicts the utility obtained by the solution algorithm at each value of $\gamma$. The utility decreases as the value of $\gamma$ increases. This is because a tourist with a high $\gamma$ needs to fit more resting nodes into the route. Figure 7 demonstrates the number of attractions and resting nodes at each level of $\gamma$. It shows a trend of decreasing number of attractions and an increasing number of resting nodes as $\gamma$ increases. The exception is at the change from gamma 1.5 to 2 where the number of visited resting nodes decreases. This is because instead a different tour is suggested for these two different gamma values.

Returning to Figure 6, the straight line gives the utility value obtained when a person travels through the route of $\gamma = 0$ (i.e. without considering the fatigue factor at all (TTDP)) with a higher value of $\gamma$. The values for this line decrease at a rapid rate which indicates the fact that tourist trips designed with a traditional TTDP would give a very low utility in real life as fatigue and getting tired is inevitable in human beings. Also, it shows that a person with a higher $\gamma$, someone who is more easily fatigued, should not take the same trip as a person with a lower $\gamma$, someone who does not get fatigued easily.
Figure 6: Tour utility for different fatigue sensitivities (gamma parameter)

Figure 7: Attraction-Rest ratio for different fatigue sensitivities (gamma parameter)
Figure 8 shows the highest rest pressure of the routes obtained with each values of $\gamma$, meaning that it is the rest pressure at a single visit. Because the fatigue value is calculated by multiplying the rest pressure by $\gamma$, a high rest pressure does not necessarily mean a high fatigue. In fact, a person with a low value of $\gamma$ can afford to have a high rest pressure by visiting many attractions. Even under the same pressure, this person could withstand it better than others, meaning that his satisfaction would not decrease as much. Hence, at a lower $\gamma$ value, this person will have a higher utility but also a higher rest pressure.

![Figure 8: Highest rest pressure within a trip for different fatigue sensitivities](image)

6. CONCLUSIONS

Traditional TTDP solutions do not consider the fatiguing human nature of the tourists. This can lead to resulting routes that are somewhat infeasible and undesirable in real life. Ergo, we introduce a problem solution that incorporates such factors into the utility. For this concepts from literature on sleep pressure are borrowed. We suggest the analogy sleep pressure to rest pressure is intuitive, though acknowledge that there are also some limitations, particular with regards to parameter estimation. Fatigue levels are depending on a wider range of issues, not only physical condition, fitness and type of activity but also be influenced significantly by external factors such as weather or crowding. This does make parameter estimation a complex issues. We suggest though that some insights could be gained by analysing tour tracking data of tourists to observe when and how often they make breaks. Furthermore, we suggest that the general formulation of the TTDPF as formulated in this paper might be transferable.

The trip route that it provides might be less satisfying at first glance due to fewer attraction visits. However, it eventually can give more time with a positive experience in real life, and is more satisfying. In the future, we hope this idea of Tourist Trip Design Problem with Fatigue Factor is implemented on websites such as the official Kyoto Travel Guide to provide visitors with satisfying trip plans or within mobile phone applications. Applications such as “Stroll” already exist that provide tour suggestions, but, to the best of our knowledge, do not explicitly consider the desire to have breaks. On the websites or within an app tourists would be able to input their own preferences that could further help one estimating parameters related to fatigue sensitivity, willingness to spend time for rest as well as attractiveness of specific locations. Once a large number of tourists have given their input and trips have been observed, one could combine our approach presented here with learning algorithms to better
suggest appropriate parameter ranges. Another future research option could be to conduct interview/questionnaire survey on a sample of tourists population and estimate the parameters based on the stated preferences of the tourists. Finally, we note, that ultimately we hope the work here is not only useful for the travellers themselves but also for urban planning as a better understanding of desired and realistic routes will help to better predict tourist flows and to facilitate the provision of sufficient resting facilities in tourist areas.

REFERENCES


