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# AGENT-BASED MODELING AND SIMULATION ON RESIDENTIAL POPULATION MOVEMENT PATTERNS: THE CASE OF SEJONG CITY

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## ABSTRACT

An urban simulation is a useful tool for urban administration and policy experiments. Our research goal is composing an agent-based simulation that models the behavioral and movement patterns of the urban population with a real-world city, Sejong in South Korea. Particularly, we modeled the urban dynamics of the city with the size of the real population and with the real-world GIS data. We followed the statistical survey of the behavioral pattern of the population in accordance with a time-use survey data. Lastly, we constructed the public transportation based on bus lines and schedules. Our result shows the initial qualitative validation result of the urban population behavior, specifically on the utilization of the public transportation.

## 1 INTRODUCTION

A city has diverse aspects to model and simulate; and these aspects have interwined effects among themselves. For instance, the traffic infrastructure of a city can be simply modeled from either traffic flow or the traffic entity perspectives, but this sinlge dimensional approach becomes a hurdle in the holistic comprehension of the city population, infrastructure, and their interwined lifestyles; while such a single aspect model becomes a very specific model to calibrate and validate at the engineering or the operational resolutions.

If we are interested in analyzing the holistic aspects of a city, we need to define the modeling scope at the appropriate holistic level. In military domains, the operational success becomes the single most primary objective, so the modeling scope is more easily narrowed down to the operational personnel, environment, equipment, and key expertise, etc. On the other hand, citizens have no such primary objective as in the military domains, so their diversity of everyday lives becomes the modeling scope, which can be very huge and diverse. Given this difficulty in setting the modeling scope, the task of developing a *Digital Twin* of a city is a daunting task, which needs to be mitigated by the elaborated urban modeling objective; a detailed definition of *Digital Twin* is given in subsection 2.2. Also, we would argue that there is no single *Digital Twin*, which is a silver bullet in modeling every aspect of a city, because of this modeling scope problem. Eventually, we conjecture that these *Digital Twin* of cities would be case-by-case with different modeling objectives and scopes.

Hence, this paper presents a case study of urban modeling that focuses on the mixture of population, traffic infrastructure, and urban services, i.e. health care, shopping, education, etc. This case study emphasizes the population's daily behavior so that the simulation can result in the logs of their daily movements and time-use at locations. The final goal of this case study is providing a simulation tool to provide alternative policies on the urban mass-transportation; for example, buses in this model. Our paper

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models the interwined effects between population, service, and traffic; and we assume that this interwined effect is the main dynamics of the potential supplies and demands of transportations.

Due to this microscopic objective of demands and supply on mass transportation, this case study utilizes the agent-based modeling and simulation, or ABM. Our ABM includes the residential agents with several occupations. Additionally, our ABM models the mass transportation resources, i.e. bus, as agents. We model the urban services, which are categorized as public, medical, educational, shopping, dining and residential. Finally, we model the urban area traffic network and its flow level speed factors. We may argue that our ABM is an on-going work of a *Digital Twin* by its scalability because we provide a simulation with near 100% scale of the population of the modeled city.

## 2 PREVIOUS RESEARCH

### 2.1 Traditional Urban Modeling and Simulation

Early researches on urban area builds a theoretical model to understand simple urban structures. Schelling proposed a model that describes population segregation, using a cellular automata (CA) approach (Schelling 1971). In Schelling's model, the segregation is the result of agents' homogeneous preferences, which emphasizes the modeling of population characteristics in the urban context. Batty and Xie modeled the urban growth process using the CA approach (Batty and Xie 1994; Batty and Xie 1997). They showed a variety of urban growth patterns with different assumptions or parameter values. These studies provide an intuition on the formation and the development of cities, but these works remained at the analogical and hypothetical city, which are not real cases.

With the help of the geographic information system (GIS) data, the following urban dynamic researches began to model real cities, not virtual ones. White and Engelen modeled the island of St. Lucia, to predict the future land-use and eventually to gain insights on the climate change (White and Engelen 1997). Similarly, there are land-use application studies for various regions: Cincinnati (White et al. 1997), the Netherlands (White and Engelen 2000), Dublin (Barredo et al. 2003), and etc. Clarke et al. introduced the SLEUTH model which creates the formation of the San Francisco bay area using the CA approch (Clarke et al. 1997; Clarke and Gaydos 1998).

Unlike the previous studies of a single aspect model on urban areas, i.e. the population distribution or land-uses, recent studies combine population and geographic modeling in an integrated setting. These studies use the agent-based modeling (ABM) approach instead of the CA approach because of the ABM's entity-oriented view. Manson modeled land-use changes in the southern Yucatan peninsula of Mexico (Manson 2005). The environment was modeled based on the cellular model, and the heterogeneous actor agents were created using a genetic algorithm. Also, Robinson et al. modeled urban growth in Scio township, in Southeastern Michigan (Robinson and Brown 2009), and Koper, Slovenia (Robinson et al. 2012). They modeled the population with discrete types as households, residential developers, and industrial agents. As a result of Koper case, they confirmed the change of noise pollution according to urban development, and they showed that clustering policies on industrial development help reducing noise pollution. Similarly, Arsanjani et al. modeled Tehran city with heterogeneous agent types: resident agents, developer agents, and government (Arsanjani et al. 2013). They focused on predicting future urban growth patterns.

Finally, there are studies that model population behavior patterns in cities. Compared with urban growth models, the following studies models relatively short time span; i.e. a day or a week. Kaneda and Yoshida modeled the spatial behavioral patterns of customer agents in shopping districts (Kaneda and Yoshida 2012). They modeled a shopping district, which is smaller than a city, but the district model is similar to a city model given that the district model has the interaction of spatial information and population behavior patterns. Lee et al. analyzed the effect of urban demographic changes on the commercial area using an agent-based simulation model (Lee et al. 2015). This study used GIS data from the real-world to build a realistic geographic model. Also, the study applied population census data and time-use survey data to the population behavioral model. Similarily, Beheshti and Sukthankar also used survey data and

GIS data to model student behavior on the university campus (Beheshti and Sukthankar 2015). Our work can also be categorized in this group from the perspective of Table 1 comparing our work to the previous urban simulation studies.

Table 1: Comparison with ABM-based urban behavior pattern simulation studies.

| Literature | Method | Agents | Environments |
|---|---|---|---|
| Kaneda and Yoshida (2012) | ABM | 3,000 agents | Shopping district with 60 shops |
| Lee et al. (2015) | ABM | 1,189 agents | Down-scaled city with 17 buildings |
| Beheshti and Sukthankar (2015) | ABM | 47,000 agents | Actual campus with full scale |
| **Proposed model** | **ABM** | **300,000 agents** | **Actual city with full scale** |

## 2.2 Recent Urban *Digital Twin*

According to Boschert and Rosen's definition, *Digital Twin*, the next wave of simulation technology, means a ”comprehensive physical and functional description” of a subject (Boschert and Rosen 2016). In addition to providing information gathered from the real-world, the goal of the *Digital Twin* is providing the future prediction and the virtual experiment environment for policy development with modeling and simulation. Ultimately, *Digital Twin* aims for the continuous and simultaneous interaction between the real-world and the virtual world. There are a number of on-going projects that applies a digital twin technique to the manufacturing, the building and the city management domains.

If we narrow down the digital twin applications to the urban modeling, one of the well-known urban *Digital Twin* project is *Virtual Singapore* that is a city model with 3D visualization and functions as a collaborative data platform (Government. 2018). Its goal is providing functions such as virtual experiment, planning, and decision-making with hypotheses. Another *Digital Twin* project is *VU.City*, which is modeling several UK cities in 3D objects (Projects. 2019). Our work also follows the direction of the *Digital Twin*. On the contrary to the digital twin examples with urban physical model, our model focuses on the functional model of a city. This paper presents an urban model that reflects the various types of data collected from the real-world, and this work also present a simulation model for experimenting with transportation city policies.

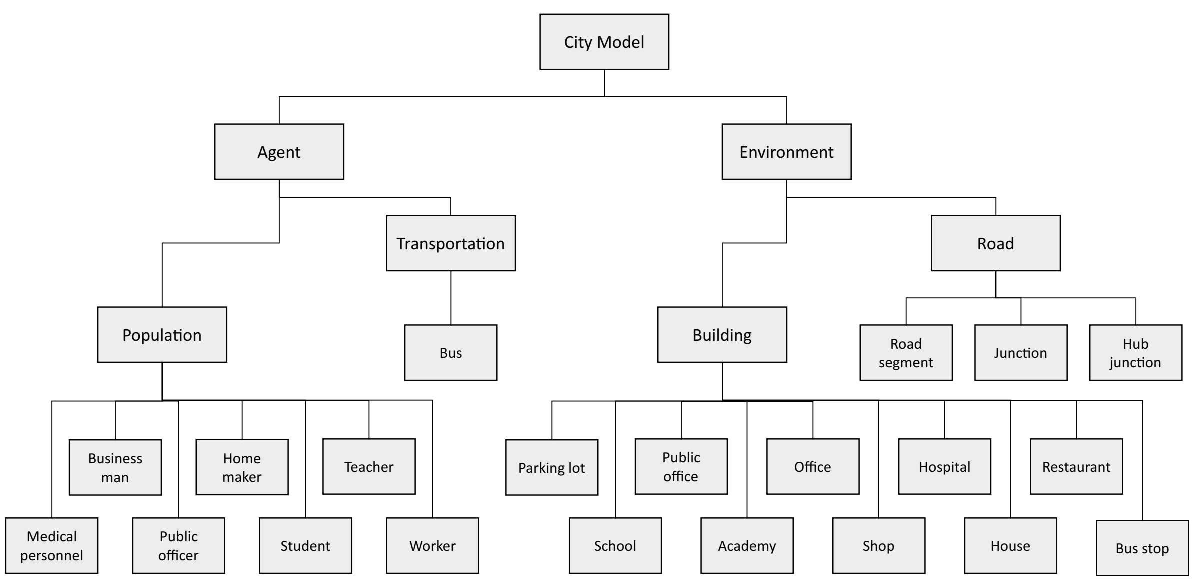


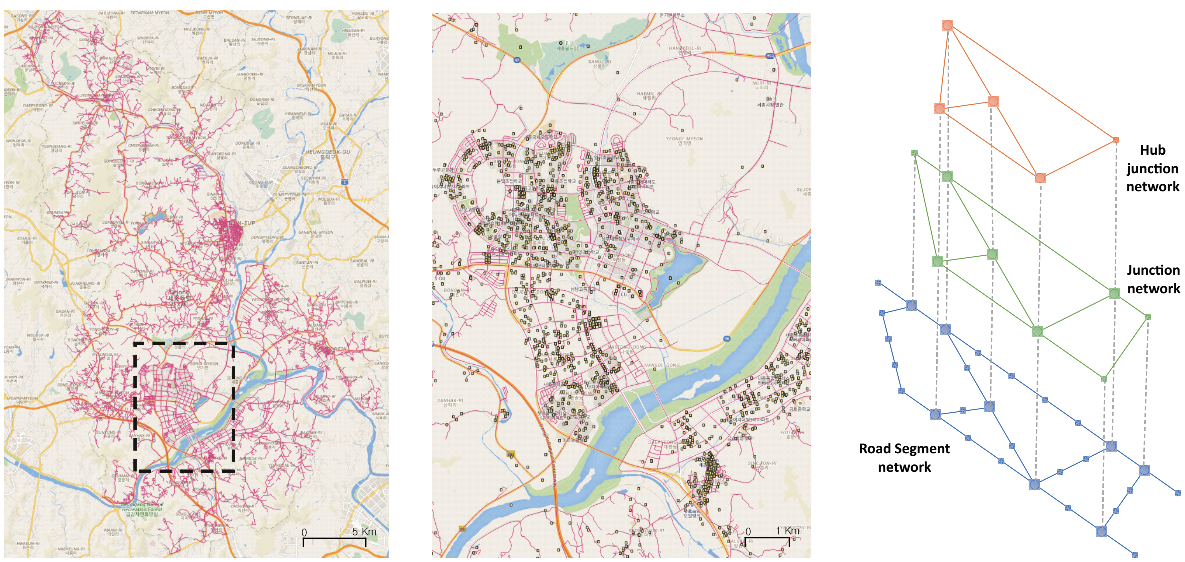

Figure 1: Model structure hierarchy.

## 3 METHODOLOGY

In this section, we describe our model in the following order. First, we explain the urban environment model, which includes roads and buildings. We describe the real-world data used to create each aspect of the urban environment and their functions. Next, we describe the agents in the model: population and transportation. As above, we enumerated the real-world data used to create the agent. In addition, this section illustrates the behavioral patterns of agents. Figure 1 shows the component hierarchy of the model.

### 3.1 Model Environments: Road

We generated the road network using the Sejong city's road shapefile, provided by the Korean government. Figure 2a visualizes the road environment on a Google Maps, with red lines representing the road. We converted the road information into a graph whose nodes are the straight-line end-point coordinates of a road segment. Given the lack of the intersection information in the shapefile data, we connected any road segments within 5m radius from the end-point coordinates.




(a) Full image of the Sejong city. (b) Enlarged image of the center area. (c) Example of road hierarchy.

Figure 2: Model environments visualization on Google Maps and road hierarchy example.

Roads restrict the movement of agents in the model. Agents should move along the roads, except for travel between buildings and nearby roads, which we assume that the agents are walking or driving on a short private lane. We assumed that agents use the shortest distance path to reach their destinations. We implement the Dijkstra algorithm to calculate the shortest path. However, the number of nodes is too large to implement the Dijkstra algorithm on our road segment graph; the number of nodes in the road segment graph is 503,259. In order to solve this computational issue, we created a hierarchical road network structure, as the below.

- We treated the end-point coordinate of the road segments, linked with three or more other road segments, as junctions. From this assumption, we composed a junction graph with 234,171 nodes. The junction graph also has too many nodes to run the Dijkstra algorithm.
- In the same way, we handled junctions, linked with three or more other junctions, as hub junctions. As a result, we devised a hub junction graph with 25,118 nodes. The shortest path is calculated on the hub junction graph.
- Figure 2c illustrates the road hierarchy concept.

### 3.2 Model Environments: Building

We virtually placed a building in our urban model by using the business license data from Sejong City-hall. The business license data is composed of the following data fields: shop name, business type, detailed address, telephone number and etc. We converted the address information into latitude and longitude values, and we used the coordination values to set-up the location of the buildings. Then, we hypothesized the generated building type according to the business type of the license. The utilized license information enumerates the building types: *public office*, *working place (office)*, *hospital*, *restaurant*, *school*, *academy*, and *shop*. In the case of residential *house*s, we created the residential buildings directly using the full-scale residential data of the Sejong city. Table 2 specifies the residential data of the Sejong city, and we turned the residential data into houses by eliminating duplicated entries of the houses. The modeled buildings become a destination of an agents' movement, and the heterogeneity of the building environment invokes the demand of the agent's movement. The residential agents need to move to the appropriate type of building to perform a particular action, whose details are illustrated in the next subsection. Figure 2b is an enlarged image of the center of Sejong city, and the small squares on the image represent the buildings.

Also, there are building environments related to the transportation infrastructure in the model. The first type of the transportation infrastructure is a parking lot. We generated parking lots with the real-world data of Sejong city. The parking lot plays an important role in determining the route of agent's movement by driving. The parking availability is also considered in the utility calculation of nearby shops and restaurants. The next type of the transportation infrastructure is a bus stop. We used the actual Sejong city's bus line information to make the bus stop. Bus agents travel between bus stops by following the real-world bus lines, and the residential agents can only get on and off buses at the bus stops when the buses are arrived.

### 3.3 Model Agents: Residential Population

We explain the modeled residential population in two folds: how to instantiate the population and how to implement the population behavior.

#### 3.3.1 Population Instantiation with Micro Census Data and Anonymized Residential Information

The proposed model implements a full-scale of the Sejong city population with heterogeneous residential agents, using two real-world data sets. Table 2 lists the two real-world datasets, used in residential agent generation process, and a brief summary of the datasets. Instantiating an individual requires determining two different attributes, which are the residence location and the individual occupation. The location and the occupation are provided in the aforementioned two datasets, but the two assignments should be embodied to a single individual. Therefore, we require a mapping between the residence dataset from the Sejong city and the occupation dataset from MDIS.

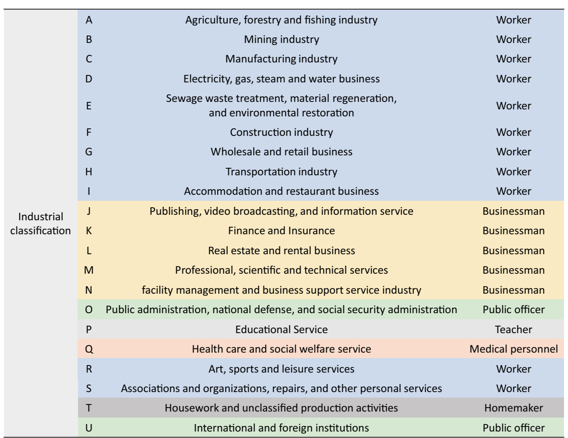
**Dataset Matching Mechanism** We matched the residential data and the occupation data through the following two steps. First, we assumed an occupation industial classification distribution of the occupation data as multinomial distribution: $Multi(\phi_{ic}^{n,g})$, and $\phi_{ic}^{n,g}$ indicates the multinomial distribution parameter whose occupation industrial classification is *ic*, when age and gender are given as *n* and *g*, respectively. $\phi_{ic}^{n,g}$ is calculated through $\frac{\sum_i \mathbf{1}_i(ic,n,g)}{\sum_i \mathbf{1}_i(n,g)}$, where $\mathbf{1}_i(condition)$ is the indicator function returns 1, when an individual *i* in the occupation dataset satisfies the conditions in the parentheses. Then, we assigned the occupation industrial classification attribute to populations of the residential data as a sampled value from the obtained multinomial distribution, with the same age and gender.

**Population Instantiation Sequence** By following the matching mechanism, we enumerated individuals that embody the residence location and the occupation with the fitted distribution of two separate datasets. While the mechanism explains the underlying statistical charateristics of the match, we perform the population instantiation by following the below sequence. The first step is allocating a new individual to a new residential house, which was closely located to the latitude and the longitude from the city dataset. The second step is filling the attribute of the individual, so we determine the individual's gender and

Table 2: List of used data sets in agent generation process.

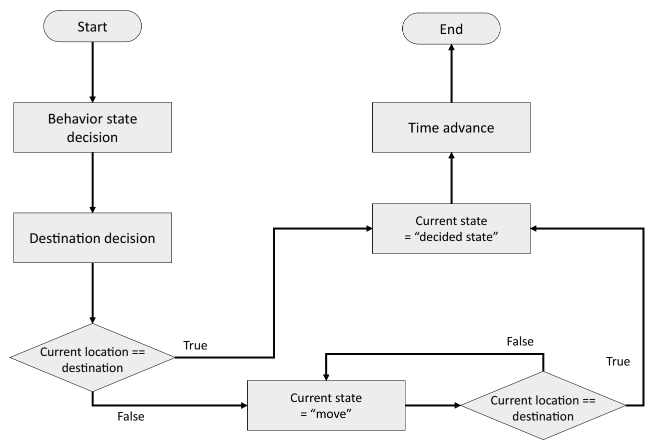
| Dataset | Properties | Values |
|---|---|---|
| Residential data of the Sejong city (anonymized to comply Korean regulation) | Data source | Sejong City-hall (anonymized, yet government proprietary) |
| | Number of samples | 306760 (full-scale) |
| | Sampled period (Year) | 2018 |
| | Provided data fields | Age, gender, residential house's latitude / longitude value |
| Occupation MDIS data of the Sejong city (Micro-Data Integrated Service) | Data source | Statistics Korea |
| | Number of samples | 5220 (2% of full scale) |
| | Sampled period (Year) | 2015 |
| | Provided data fields | Age, gender, occupation industrial classification, commuting status, etc. |

age by the city dataset. The third step is allocating the occupation to the individual by following the matching mechanism. We regarded agents who are younger than 24 years old as students. The rest of the residential agents, whose ages are older or equal to 24, are hypothesized to have an occupation by the industry classification of the MDIS data. Figure 3a shows the corresponding agent occupation by the MDIS industrial classification category.



| | | | |
|---|---|---|---|
| Industrial classification | A | Agriculture, forestry and fishing industry | Worker |
| | B | Mining industry | Worker |
| | C | Manufacturing industry | Worker |
| | D | Electricity, gas, steam and water business | Worker |
| | E | Sewage waste treatment, material regeneration, and environmental restoration | Worker |
| | F | Construction industry | Worker |
| | G | Wholesale and retail business | Worker |
| | H | Transportation industry | Worker |
| | I | Accommodation and restaurant business | Worker |
| | J | Publishing, video broadcasting, and information service | Businessman |
| | K | Finance and Insurance | Businessman |
| | L | Real estate and rental business | Businessman |
| | M | Professional, scientific and technical services | Businessman |
| | N | facility management and business support service industry | Businessman |
| | O | Public administration, national defense, and social security administration | Public officer |
| | P | Educational Service | Teacher |
| | Q | Health care and social welfare service | Medical personnel |
| | R | Art, sports and leisure services | Worker |
| | S | Associations and organizations, repairs, and other personal services | Worker |
| | T | Housework and unclassified production activities | Homemaker |
| | U | International and foreign institutions | Public officer |

(a) Agent occupation by the industrial classification.





(b) Agent behavior pattern modeling flowchart.

Figure 3: Figures related to the residential agent modeling.

### 3.3.2 Population Behavior Implementation by Assigned Occupation

The residential agents have different behavior patterns depending on their occupations. Each agent make a transitions toward the next behavioral state through the steps of Figure 3b. As the first step, the agent determines the next action state and its duration based upon the time-use survey data from the Korean national statistical office. Table 3 denotes the data field of the time-use data. We created a probability $P^{J,t}(state) \sim Multi(\phi_s^{J,t})$, and $\phi_s^{J,t}$ indicates the parameter of the multinomial distribution modeling the agent, whose occupation is $J$, to perform a certain behavior $s$ at time $t$. $\phi_s^{J,t}$ is calculated through $\frac{\sum_i \mathbf{1}_i(J,s,t)}{\sum_i \mathbf{1}_i(J,t)}$, where $\mathbf{1}_i(condition)$ is the indicator function returns 1, when population $i$ satisfies the conditions in the parentheses. The next state of an agent is determined by the sampling on $P$. Additionally, the state duration is sampled from $N(\mu_{J,s,t}, \sigma_{J,s,t})$: $\mu_{J,s,t}$ is calculated from $\frac{\sum_i [D_i(t) \times \mathbf{1}_i(J,s,t)]}{\sum_i \mathbf{1}_i(J,s,t)}$, where $D_i(t)$ is the state duration from the time $t$ of population $i$; $\sigma_{J,s,t}$ from $\frac{\sum_i [D_i(t)^2 \times \mathbf{1}_i(J,s,t)]}{\sum_i \mathbf{1}_i(J,s,t)} - \hat{\mu}^2_{J,s,t}$.

Table 3: Data field summary table of the time-use data.

| Data category | Name | Description |
|---|---|---|
| Demographics | Gender | Gender of surveyee |
| | Age | Age of surveyee |
| | Job status | The employment situation |
| | Industrial classification | Industrial classification of surveyee's occupation |
| Time-use | Date | Target day of the survey |
| | State | Surveyee's state information during the target day (The data collects for every 10 minutes, 144 length) |
| | Location | Surveyee's location information during the target day (The data collects for every 10 minutes, 144 length) |

Table 4: Behavior state and corresponding building pair.

| | | | | | |
|---|---|---|---|---|---|
| State | Sleep | Rest at home | Keep house | Dining | Go leisure |
| Building type | *House* | *House* | *House* | Restaurant | Shop |
| State | Go hospital | Work | Go shopping | Go school | Go academy |
| Building type | Hospital | *Working place* | Shop | *School* | Academy |

Afterwards, the agent determines the destination building corresponding to the action state, previously defined. Table 4 summarizes the behavior state and its corresponding building type pairs. The building types, written in *italic*, means a predesignated building for each agent at the initialization stage, i.e. the resident house or apartment for an residential agent, which is a different location selection mechanism that is transident over the simulation executions. An agent's working place is determined by the agent's pre-selected occupation, such that medical personnel agents select their working places to be one of the hospital buildings. For a transient destination choice, an agent sets an arbitrary building as the destination for shopping or dining. In the random selection, the distance to the building from the agent's current location and the amount of parking space around the building are considered as utility elements. Mathematically, the location selection from the candidate set follows $\frac{exp(-\alpha \cdot dist_j/max_j(dist_j))}{\sum_j exp(-\alpha \cdot dist_j/max_j(dist_j))}$, where $\alpha$ is a weight parameter of distance information; $dist_j$ denotes the distance to the building $j$ from the agent's current location.

If the selected destination building is the same as the current location, the agent starts the state immediately; otherwise, the agent starts the state after the arrival at the destination. The state lasts for the duration, sampled previously. When the state is over, the agent repeats the behavior pattern flowchart.

### 3.4 Model Agents: Transportation

We modeled the bus agent as a method of utilizing the public transportation. The bus agent loads and unloads passengers as they pass through the designated bus stops. We used Sejong city's bus line and bus schedule information to setup the route and the departure time of the bus agent in the model. The availability of the public transportation impacts the residential agent's daily life. For example, if the agent is waiting for a bus agent at a bus stop, the agent cannot spend enough time in the designated state activity by wasting time at the stop. Also, the agent considers and being affected by the transit time that is induced by the distribution of the urban services of buildings.

### 3.5 Model Parameters

Table 5 summaries the model input data, the model outputs, and the model parameters. Fundamentally, our input deck consists of the population data from MDIS, the population behavior from the time-use, the urban structure from GIS, and the public transportation from the city management. Our output emphasizes the utilization of the public transportation as well as the agent's motivation of such utilization.

Table 5: List of input variables, output variables, and parameters of the model.

| Type | Name | Implication |
|---|---|---|
| Input | Residential data | Input data used to set residence location of residential agents. (Source: Sejong City-hall) |
| | MDIS data | Input data used to set demographics and type of residential agents. (Source: Statistics Korea) |
| | Time-use data | Input data used to model agent's behavior pattern. (Source: Korea National Statistical Office) |
| | GIS data: Road | Information of Sejong city's road network. (Source: Korean ministry of land, infrastructure and transport) |
| | GIS data: Building | Information of Sejong city's business license. (Source: Sejong city's Public Data Service) |
| | Bus route and schedule data | Routes and departure time information of buses. (Source: Sejong city's Public Data Service) |
| Output | Agent log | residential agent's action and location information for one day |
| | Bus log | Information of the residential agent who has boarded the bus. (Boarding point, get off point, final destination, etc.) |
| | Bus stop log | Bus stop usage record of the residential agents |
| | Parking lot log | Usage information and parking residential agent information of the parking lot. |
| Parameters | Number of agents | Actual population scale of Sejong city (default = 300,000) |
| | Simulation time | Total simulation time (default = 24 hours) |
| | Initial position and state of agent | Initial position of the agent is their residential house building, and initial state is *sleep* |
| | Transportation speed | Simply, we assumed as walking speed is 1, the bus speed is 3 and the car driving speed is 4. |
| | Alpha($\alpha$) | Distance information weighting parameter in the destination determination process (default = 3) |

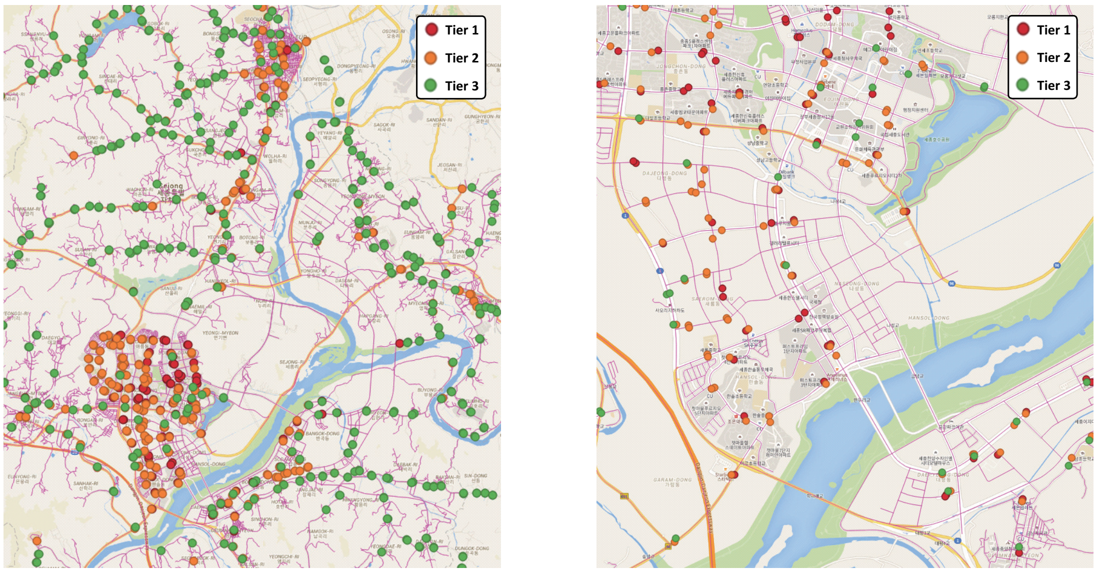
## 4 RESULT

We reproduce the movement patterns of the residential population with the proposed model. The movement patterns are represented by 1) summarized data, such as building visitor data, road usage data, public transportation usage data, and etc; as well as, 2) an individual travel timeline across the city over a single day. These summarized and individualized data provide the virtual status-quo on their city for administrators and policymakers. This section particularly illustrates the examples on the utilization of the public transportation, which we modeled the urban area with an emphasis. We provide the below result to demonstrate the capability of the proposed simulation, not to statistically analyze the data.

Table 6: Bus stop classification summary.

| Bus stop tier | Description | Proportion (%) |
|---|---|---|
| Tier 1 | Number of passengers per day $> 3000$ | 8.19 % |
| Tier 2 | $300 <$ Number of passengers per day $\leq 3000$ | 23.03 % |
| Tier 3 | Number of passengers per day $\leq 300$ | 68.78 % |

The first result is the bus stop classification. We classified bus stops into three tiers, based on the number of passengers per day. Table 6 illustrates the classification criteria and the proportion percentage information for each tier. As the criteria values for the tier classification of bus stops, the values of 1% and 0.1% of the total population of the Sejong city were used. Figure 4 is the result of colorizing the bus stops by tiers and visualizing them on the map. Figure 4a shows that bus stops in areas, where populations or urban services are concentrated, tend to be used by many passengers, which means that our simulation can indicate the place of interests in terms of such services. If we take the story toward the microscopic dimension, there are some cases of the bus stops, facing each other across the road, which have a large difference in the number of passengers; see Figure 4b. This unbalanced utilization of crossing bus stops is induced by the difference in the bus route (i.e. route direction) assigned to the stop. This result implies that the public transportation usage data is not simply a result of the GIS environments, but a result of the interaction of population behavior patterns and public transportation policies within the GIS environments.




(a) Full image of the Sejong city.

(b) Enlarged image of the center area.

Figure 4: Bus stop classification visualization on Google Maps.

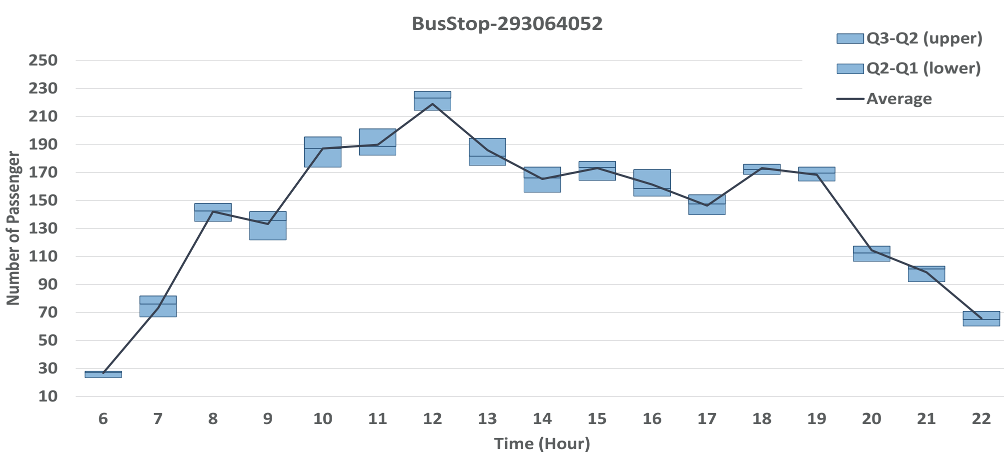



Figure 5: Average number of passengers by time.

The second result is the passenger profiling for a single bus stop. Figure 5 shows the number of passangers by time for an arbitrary bus stop. The line graph illustrates the average number of passengers with ten repeated experiments, and the box-plot illustrates the value of the top 25% and 75%, respectively. The result shows that the number of passengers at the bus stop has peaked on both sides of 12:00 and 18:00. This behavioral pattern is similar to the real-world where people move actively before and after dining times. Figure 6 shows the occupation distribution of passengers by time. The result illustrates that the worker agents account for almost all proportion of occupation distribution, in the earliest hour. As time passed, the businessman agents and the student agents appear in the job distribution, in sequence. This result is produced by our modeling of different behavior patterns according to the residential agent occupation. In the time-use data, the worker agent has an early wake-up time distribution compared to agents with other jobs.

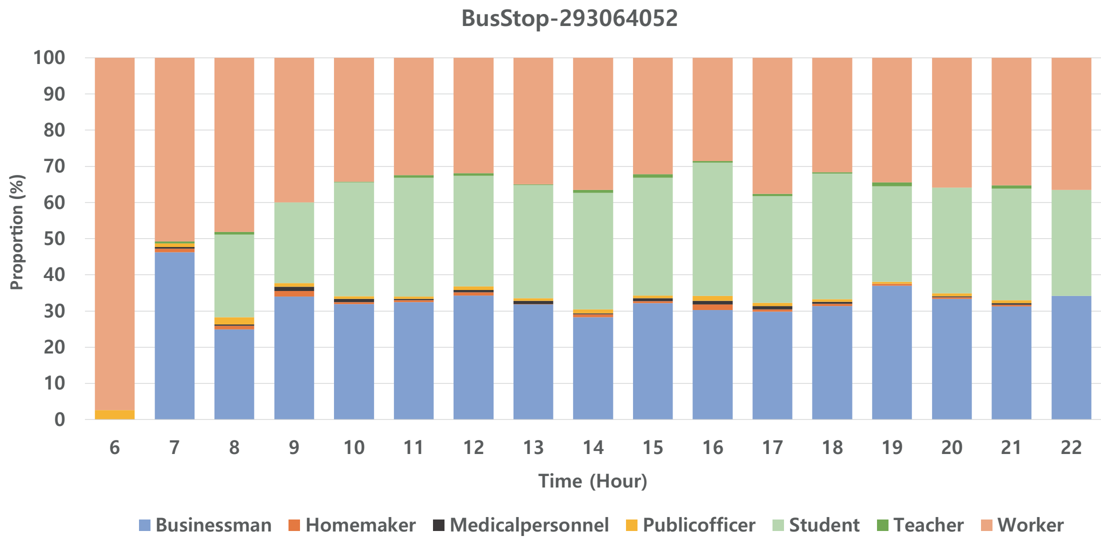



Figure 6: Distribution of passenger occupations by time.

The last result is a simulation log of a residential agent behavior and moving paths during the day. Table 7 summarizes the behavior and the location information during the day, for the residential agent, whose occupation is a public officer. In addition, Figure 7 illustrates the residential agent's destinations and several moving paths on the map. These results show that the simulation replicates population behavior patterns similar to reality. However, the agent's moving speed seems to be set faster than in reality. This problem will be solved later by parameter calibration regarding agent movement speed.

Table 7: Daily behavior patterns of the public officer.

| State | Start time | End time | Moving path | Current location |
|---|---|---|---|---|
| *Sleep* | 00:00 AM | 07:55 AM | - | Home |
| *Rest at home* | 07:55 AM | 08:22 AM | - | Home |
| *Breakfast* | 08:27 AM | 08:46 AM | Route 1 (red in Figure 7) | Restaurant 1 |
| *Work* | 08:56 AM | 12:02 PM | Route 2 (yellow in Figure 7) | Working place |
| *Lunch* | 12:11 PM | 12:23 PM | Route 3 | Restaurant 2 |
| *Home making* | 12:40 PM | 13:17 PM | Route 4 | Home |
| *Work* | 13:29 PM | 18:00 PM | Route 5 (blue in Figure 7) | Working place |
| *Home making* | 18:12 PM | 18:44 PM | Route 6 | Home |
| *Dinner* | 18:48 PM | 19:12 PM | Route 7 | Restaurant 3 |
| *Shopping-1* | 19:16 PM | 19:52 PM | Route 8 (green in Figure 7) | Shop 1 |
| *Shopping-2* | 19:55 PM | 20:27 PM | Route 9 (purple in Figure 7) | Shop 2 |
| *Work* | 20:36 PM | 21:20 PM | Route 10 | Working place |
| *Rest at home* | 21:32 PM | 23:06 PM | Route 11 | Home |
| *Sleep* | 23:06 PM | - | - | Home |

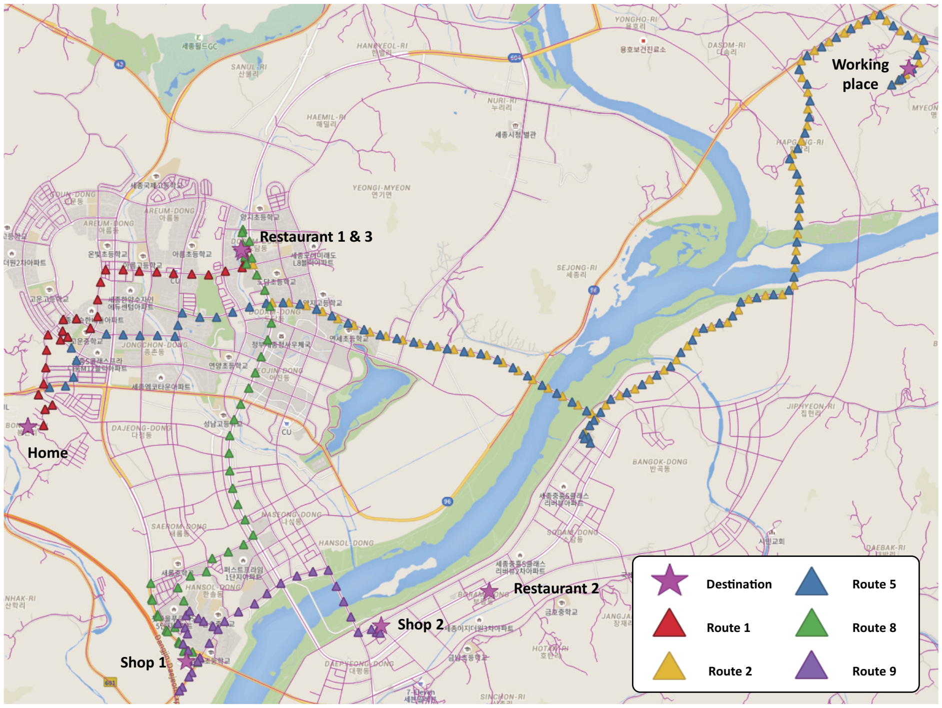



Figure 7: Destinations and moving paths of the public officer.

## 5 CONCLUSION

To sum up, we proposed an urban dynamic ABM model that replicates the residents' movement in Sejong city. Our work provides an implementation approach of the road network modeling adopting a road hierarchy structure. Also, we model the behavior pattern using the time-use survey data. As a result, we verify that there is an interaction between the components of the proposed model: residential agents, model environments, and public transportation policies. Also, the results imply that the model replicates some stylized facts on the population behavioral patterns. This large scale city model requires the validation on the utilization aspect. If a simulation were to be used for a traffic policy, the simulation is required to generate the close approximation to the status-quo of the target city. This study is an on-going project, and therefore we left policy experiments as further work after we conduct the simulation validation, quantitatively.

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