TRANSIT-ORIENTED DEVELOPMENT ASSISTIVE INTERFACE (TODAI)

A Machine Learning-Powered Computational Urban Design Tool to Enhance TOD Planning Processes

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Abstract. Transit-oriented Development (TOD) is widely regarded as a sustainable development paradigm for its sensible space planning and promotion of public transit access. Research in providing decision support tools of TOD may contribute to the Sustainable Development Goals, especially towards sustainable cities and communities (SDG goal 11). While the existing Geographic Information System (GIS) approach may well inform TOD planning, computational design, simulation, and visualisation techniques can further enhance this process. The research aims to provide a data-driven, computational-aided planning support system (PSS) to enhance the TOD decision-making process. The research adopts an action research methodology, which iteratively designs experiments and inquires through situating the research question in real-world practice. A work-in-progress prototype is provided – Transit-Oriented Development Assistive Interface (TODAI), along with an experiment in a newly proposed metro station in Sydney, Australia. TODAI provides real-time visualisation of urban forms and analytical data indicators reflecting key considerations relevant to TOD performance. A regressive machine learning model (XGBoost) is used to make predictions of analytical indicators, promptly producing outcomes that may otherwise require a costly computational operation.

Keywords. Urban Planning; Transit-Oriented Development; Planning Support System; Machine Learning; SDG 11.
1. Background

Against the backdrop of burgeoning urbanisation, cities are becoming packed with people and vehicles. With overpopulation and traffic congestion becoming problems in modern cities, it is increasingly vital to make urban development sustainable. According to the United Nations New Urban Agenda, by 2030, 60% of the world’s population will live in cities, which will be doubled by 2050 (New Urban Agenda, 2016). As is highlighted by the United Nations in its 2030 Agenda for Sustainable Development, it is one of our top priorities to make cities and human settlements inclusive, safe, resilient, and sustainable (goal 11).

Transit-Oriented Development (TOD), a term first coined by Peter Calthorpe (Calthorpe, 1993), is one of the planning paradigms that has gained increasing popularity among many cities worldwide. TOD describes developments near transit hubs, often characterised by compactness, walkability, and mixed usage. Many claims that TOD reduces car reliance by building walkable communities, improving public transit access, and encouraging well-thought-out spaces. There are many convergences between the targets of SDG Goal 11 and aims of TOD, such as providing access to public transits (target 11.2), providing public spaces (target 11.7), providing spaces that support positive social-economical outcomes (target 11. a).

1.1. TRANSIT-ORIENTED DEVELOPMENT (TOD)

Transit-Oriented Development (TOD) has attracted growing attention in academia and practice in the past decades. The development aims to reduce automobile usage by providing higher density in areas with good access to public transport and locating public amenities within walkable distance (Lima et al., 2016, Ibraeva et al., 2020). Implementing TOD to a targeted site often requires thorough site research and analysis and introducing multi-aspect attributes as indexes for factor analysis, and evaluating the potential impacts on local ridership and urban characteristics (Cervero and Kockelman, 1997). Cervero et al. (1997) defined 3Ds in evaluating local travel demand: Density, Diversity and Design. Furthermore, the study established 13 variables related to the 3Ds, analysed them with coefficient values, and concluded that better transportation accessibility, squared urban layout, and concentrated mix-used facilities positively promoted less mobile vehicle usage. Several other researchers have introduced similar indexes (Sung and Oh, 2011, Zhou et al., 2020, Ewing et al., 2017). The evaluation process across these multidimensional aspects will influence the precision and comprehension for the planning, design, and implementation process for a successful application of Transit-Oriented Development (Thomas and Bertolini, 2017).

1.2. PLANNING SUPPORT SYSTEM (PSS) FOR TOD

PSS describes the integration of Geographical Information System (GIS) with the specific use in modelling for different planning schemes (Harris and Batty, 1993). Researchers had started implementing such a system in TOD and generated concrete presentations in visualising and optimising urban forms and layouts. Lima et al. (2016) explored the TOD urban generation process with Rhino and Grasshopper, employed the TOD attributed into the optimising algorithm and provided a clear visualisation for
the audience to understand urban optimisation outcome based on the theory of TOD. This interface transformed what Cervero had discussed in the 1990s, which only provided a complex and extensive number of figures into a state-of-the-art planning interface while also can be easily altered and reconstructed based on different inputs. Similarly, Pettit (Pettit, 2005) had also implemented PSS in a case study scenario to link and predict land-use relationships with the algorithms in predicting potential local growth with GIS data. In such a way, PSS enables planners to not only integrate data but also work collaboratively with the stakeholders.

1.3. MACHINE-LEARNING-POWERED TOD

Machine learning techniques are applied in various TOD and urban planning researches. Machine learning improves the ability to optimise and predict potential input attributes and outcomes. In the project named CityMatrix, Zhang et al. (2018) produced an interactive block model for an indicative urban layout, which adapts the user input with a slider that controls the overall height of the building and population density simultaneous visual feedback for building ratings and city performance. Machine learning was used to make city performance predictions based on previous agent-based simulation data. However, CityMatrix was based on an orthogonal grid urban layout, which may not be sufficient for representing cities where existing urban fabrics are organic. A similar approach has also been used by Lima et al. (2016), who used a genetic algorithm to relocate amenities, resulting in better walkability performance. However, the research focused on factors related to accessibility. Other factors related to TOD, such as development area, population, the urban form, can also be included in such PSS.

In summary, there was abundant research in evaluating and optimising for part of the process of TOD. However, there is not yet a dedicated computational design tool to reflect on several features of the TOD, especially urban density, mixed-use conditions, and improved walkability. Our research will test the possibility of using machine learning algorithms to provide an advanced TOD assistive interface.

2. Methodology

In this research, the action research methodology is applied along with the design research method. A thorough iterative design process is framed to experiment with urban geographical information data. Such methodology aims to generate TODs outcomes with the appropriate datasets to encompass the research aim as mentioned and develop a planning support system that reflects key TOD features.

The 'key infrastructure' within the action research process is that the 'research scientist' work collaboratively with the 'practitioner that oriented to the practical problems as the 'organisational scientists' (Baskerville and Wood-Harper, 1996). Therefore, this research is partnered with industry practice HDR inc. to investigate real-world problems when developing the TOD interface.
The plan to be conducted as ‘action taking’ is within the cycle of the action research process (Susman, 1983). Moreover, while designing out the features in Grasshopper, the industry partner HDR inc. also proves both technical and industry realised issues during the development process during the meeting where the early prototypes are presented. The prototype is tested with a real-world metro location located in Five Dock, Sydney, as one of the newly proposed Sydney metro stations.

After defining the research aim, we seek to plan the actions for developing the back-end design and development workflow, which includes the study of the previous TOD principles as identified in other research papers; the features of TODs to develop on; and the primary Grasshopper processes for realising such features. The plug-in Urbano is also used for importing GIS data from OpenStreetMap as well as the tool to analyse some features of TODs such as walkability (walkability score) and amenity popularity (amenity score), Galapagos is used for improving the urban forms and amenity locations for better walkability and all to be visualised by using Human UI as the plug-in for developing the TOD assistive interface.

3. Transit-Oriented Development Assistive Interface

3.1. DATA COLLECTION

The foremost step in developing the TOD model is to collect useful geographical data with embedded metadata. The geographical data is used as we are only redeveloping the urban forms in this research rather than taking away the street layouts.

As shown in Figure 1, the three primary geographical datasets are acquired. Street networks, existing amenity locations, and their metadata are acquired from OpenStreetMap. The cadastre boundaries are stored as Esri shapefiles, made available from the government’s open data platform. Planning constraints, such as zoning and building height limits, are processed and made publicly available from the AURIN platform.

3.2. TOD SITE ANALYSIS
Two TOD-specific analyses of the existing urban fabric are conducted when developing the TOD urban forms. In such a manner, the improvements of the urban forms would be generated based on the identified existing urban issues. With the reallocation of amenities and transit-centred development, TOD seeks to promote better walkability to transit stations and local amenities. Hence, less auto-mobile usage is needed, and the primary transportation method will be transformed to walking. This section elaborates the analysis based on urban walkability, urban density, and urban design.

3.2.1. Walkability Analysis

The process of generating the walkability calculation is by calculating the distance from the locations of the local amenities to the transit centre / local amenities; this character has also been discussed in the past decade (Lamour et al., 2019, Singh et al., 2017, Sung and Oh, 2011). It is generally encouraged to locate residential buildings near where the walkability score is high (Hall and Ram, 2018, Dogan et al., 2018). Hence, the initial step in the analysis process is to calculate the walkability in the case study site. The calculation of walkability can be seen as calculating the average of the networked distance between origins (residence) and destinations (amenities), weighted by the possibilities of visiting each amenity during the week (amenity index).

To further realise the result from the walkability score, the overall visualised result is completed, the Grasshopper process is shown in Figure 2.

![Figure 2. Left: Existing Site Walkability Score Visualisation](image1.png)

![Figure 3. Right: Existing Building Height Limit](image2.png)

3.2.2. Building Height Limit Analysis

Zoning requirements under the New South Wales legislation of Local Environmental Plans (LEP) directly relate to the building height limits and building types to build on different land lots. The zoning revitalisation under the principle of TODs is also a crucial element in providing various housing types for different income groups, and essentially, is linked to the local real estate value (Ibraeva et al., 2020). The regeneration of the land zoning could enhance the densification and mix-used zone around the transit centre while providing affordable housing around the rear area to the transit centre (Ibraeva et al., 2020). This definition of zoning has also been discussed in the previous sections.
To compare the existing zoning and the TOD featured redevelopment on the case study site. An analysis of the existing zoning condition has been visualised using the dataset imported from the LEP data source. Furthermore, the height limits on the current conditions of building lots have been visualised. This building height limit data is also visualised and compared in the interface. The height limit visualisation is shown in Figure 3.

3.2.3. TOD Based Urban Redevelopments

Based on the two analyses completed, a TOD based generation process is followed. In this section, two improvements will be discussed: relocation of the amenities and the extra amenity types added for a better walkability score; redevelopment on local land zoning and building forms generation. The systematic improvements can build an overall TOD improved local blueprint and operated as part of the final assistive interface.

3.2.4. TOD height zoning and Building forms generation

The existing urban fabric at the study site exhibits small and segregated building lots due to historic settlement. Building sites are first amalgamated algorithmically before further process.

After the amalgamated land parcels are generated, an optimisation process is developed to minimise the overall shadow casting by the generated built forms using a genetic algorithm through Galapagos. This optimisation reduced the shadow area in the study area, especially around the high-density development areas, so that residents and workers may have adequate access to sunlight for wellbeing. (Figure 4).

3.2.5. Relocation of amenities for better walkability score

Further optimisation of the walkability is conducted by relocating the amenities using genetic algorithms inspired by (Lima et al., 2016). The objective function minimises the networked distance between residential buildings and public amenities. After the walkability score analysis, an overview of the existing situation is visualised.

There were 39 different amenities on the original site. In this step, some more amenities are added to improve the walkability performance. Moreover, in the end, 55 amenities are located on the TOD enhances the site. The final 'walkability score' has also been increased due to such an event. (See Figure 6)
TODAI - A MACHINE LEARNING POWERED COMPUTATIONAL URBAN DESIGN TOOL TO ENHANCE TOD PLANNING PROCESSES

3.2.6. Assistive Interface

Finally, an interface with user input and a data dashboard is developed to reflect on the TOD planning and development indicators discussed in Section 3.2, including zoning, density, and walkability score. The interface is developed using HUMAN UI in Grasshopper. All passive factors for changing the building forms and amenity locations are integrated into the interface to manipulate the TOD redevelopment process as desired. At the same time, the geometries will also be visualised in the Rhino preview window (Figure 7 and Figure 8).

3.2.7. XGBoost - Regressive machine learning

Regressive machine learning models learn the numeric representation of the given dataset and make predictions based on input values by mapping the data domain.
Compared to complex simulations like Walkscore, making predictions through a trained machine learning model is often more streamlined and takes significantly less time to compute. XGBoost (short for eXtreme Gradient Boosting) is an ensemble learning algorithm and is a tree-boosting technique (Chen & Guestrin, 2016). XGBoost ensembles many smaller learning models with parallelisation, gradient boosting, sparse awareness. These features make XGBoost one of the more popular machine learning algorithms for regression with less requirement in data quality. A low-code XGBoost implementation named H2O is selected for our machine learning training.

Firstly, a training dataset is collected. By enumerating all possible user inputs in Grasshopper, a training dataset is automatically captured in a CSV file, including its resultant indicators corresponding to each possible input combination. Secondly, the CSV file is consumed by using H2O. Each feature column is labelled with input (input features) or output (targets) for training. A trained XGBoost model is produced after the dataset is fitted. The trained model is loaded in H2O and ready to predict by giving new input.

In the end, a socket script is set up for bi-directional communication with the H2O platform. Grasshopper sends the input data to the H2O platform for prediction upon the new user input. The H2O predicts based on the given values and returns a numeric result. This result is sent back to TODAI and is presented to the user in near real-time. This process has significantly reduced the time required to show the result for TODAI. However, it is noted that further work is required to produce a robust prediction model.

4. Discussion

This research proposes a framework to provide a data-driven, computational planning support system for Transit-oriented Development. This framework contains the following steps: data collection through publicly available sources, rule-based urban model generation, simulation and analysis, scenario testing and optimisation, and visualisation through a user interface. The simulation and optimisation are further enhanced using the machine learning technique in order to provide prompt user feedback.

The research showcased an early prototype based on existing urban conditions in the Five Dock area in Sydney to test hypothetical TOD and its potential outcome by the proposed metro station. The urban form with optimised amenity allocation and data dashboard has been reflected in TODAI, giving insights on the TOD planning and development process by providing real-time feedback from given planning input.

However, there are also limitations to this research. First, the walkability score analysis’s accuracy relies on a clean street network dataset, and a 5 to 10% margin of error is assumed with current crowd-sourced OSM data quality. This issue can be overcome by using a manually cleaned street network dataset suitable for walkability analysis.

Moreover, more features can be included to build a comprehensive TOD model, such as the street widths, local transportation big data, intercity public transport connectivity, and vegetation, instead of solely street network, amenity and planning constraint.

The interface is still under development. Future studies can engage with various
computational algorithms within this framework to expand the TODAI interface. Such as optimising the TOD automatic form generation with a convolutional neural network for translating the data to a systematic dataset and reducing the computation power needed for the later form optimisation process than the current genetic algorithm. Cellular automata can generate optimised zoning by integrating the TOD feature and indexes for amenities allocations and building types of automation. Further studies can also cover a variety of data sources that may be relevant to TOD development.

5. Conclusion

The exploration of TODAI has indicated the potential of studying TOD's features and characteristics using computational design tools. By using Rhino + Grasshopper, TOD redevelopment algorithms are capable of processing a large dataset and urban geometries and producing an ideal TOD urban optimisation and the outcome.

The research also contributes to planning support systems through computational tool development and machine learning techniques. The interface provides visualised outcomes of the TO development and encourages public participation by enabling non-expert users to explore different input combinations and interactively navigate different scenarios. This tool can also aid application for sustainable future developments in the Architecture, Engineer, and Construction (AEC) professionals to work cooperatively in the feasibility stage of a single project and a masterplan overview.

Two types of machine learning algorithms enhance the process: 1. evolutionary solvers optimise local decisions, where amenity location affects walkability, and built form affects solar access; 2. The regressive ensemble learning model provides an "instant" prediction of the outcome, making real-time feedback in TODAI possible.

By exploring the possibilities of applying the TOD paradigm into a real-world scenario, not only can we promote such tools to more fields and markets, but we can also integrate more urban planning concepts into the same project and produce urban development outcomes on the fly.

References


