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A Computational Model For Urban Design: An Amasya Case

Topic: Architecture

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Abstract:

This paper presents a hybrid method for an urban design in an existing city. A city is a complex system which has many forms and structures affecting each other spontaneously. Even if, we shape cities certain areas with laws and planning decisions, through time, it reorganizes its parts and formation with bottom-up forces. Therefore, an urban system which creates the city may seem complicated and hard to understand. In this complex structure, while designing new spaces, designers must understand the inner nature of the city in order to design coherent structures with city's existing culture, social-economic structure as well as its architectural tissue. In this context, this paper proposes Cellular Automata (CA) as a generative urban design tool to create an urban model depending on environmental and urban data in the scope of sustainable design in an existing city.

In the phase of collecting information from the city, Data Mining techniques will be used in the context of Information Technologies in order to investigate and define urban patterns and their relations to each other. Then, we can produce a specific CA rule system for a sample city based on Data Mining results. Cellular Automata may provide a simple rule system that helps us to understand the complex city formation in terms of social, economic and physical way. The data generating the rule system for CA can be produced by Data Mining methods. By doing this, we can not only produce our own rule system for CA but also we can extend the boundaries of CA basic rules according to different urban relations.

In the first phase of the study, the sample city, Amasya, and the selected part of it, Hatuniye Neighbourhood will be identified. After explaining the methodology of the study, the Data Mining concept will be explained in the scope of Knowledge Discovery in Databases. Then, the case study will be presented. In the case study, digital maps are provided by Amasya Municipality and cleaned in AutoCAD in order to get rid of unrelated urban layers. Then, the clean drawing file is exported to ArcMap. Furthermore, Building Info Form is prepared to complete missing information on digital maps. The Data in Info Forms are translated to Arcmap Attribute Table for buildings and prepared for Data Mining software which is RapidMiner- an open source platform. In RapidMiner, different clustering tools and Correlation Matrix are used in order to reveal hidden patterns and relationships in Hatuniye Neighbourhood. The results coming from RapidMiner are interpreted in order to produce a specific CA rule system for this neighbourhood.

In the final section, we produce a model in the neighbourhood to discuss the potentials of this hybrid method in terms of investigating urban patterns and defining their relations to each other for urban design studies embracing locality.

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A COMPUTATIONAL MODEL FOR URBAN DESIGN: AN AMASYA CASE

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1. Introduction

In the last decade, there has been an increasing demand on tourism and construction activities in historic cities in Turkey. Thus, there is a high pressure and treat on the historic parts of cities. In this study, we propose a design method in historic towns with Cellular Automata (CA) by understanding urban dynamics and characteristics with digital tools. Urban system which creates the city may seem complicated and hard to understand. Especially in historic towns it is very important to sustain the tissue of the city. To achieve that, we should understand the system of the city and its independent parts deeply. In 1965, Christopher Alexander published an article named "A city is not a tree" in which he made a distinction between artificial and natural cities. According to Alexander [1], a city is a semi-lattice system. While we plan a new city which is artificial we only copy the appearance of the old one (natural city) and forget the essence which gives life to the old city. To overcome this, designers need to understand the structure of the city and its parts. The city consists of interdependent parts which all work together unconsciously as a whole. In natural cities, parts of the whole usually overlap and fuse with each other and create a complex living system [1]. Therefore, decomposing and realizing these parts are very important to reveal the inner nature of this complex system which gives a characteristic to the city.

– 2. Methodology

For a sustainable design in an urban environment, designers must have strong ideas about architectural, social and economic dynamics of the city in addition to history and local values.

Therefore, design area and its surroundings need to be analyzed with both qualitative and quantitative research methods. The results coming from various analyses may help designers to reveal systems of cities. After, they can clearly see repetitive patterns, random behaviors and different factors affecting each other in the city's structure. Thus, we have to collect as much as information from cities. Then, we need to find appropriate methods and techniques which can resolve the complex structure of urban systems. In this study, in order to compile and collect different sources of information from cities GIS software will be used and in an analysis phase of this information, we will benefit from various Data Mining techniques. For Data Mining studies, Rapid Miner –open-source software- was used. Collecting data for Data Mining was carried out in ArcMap/ESRI and cleaning digital data was done in AutoCAD/Autodesk. After analyzing phase of urban information, we created our local CA rules in Autocad/Maya/Mel according to Data Mining results (Figure 1).

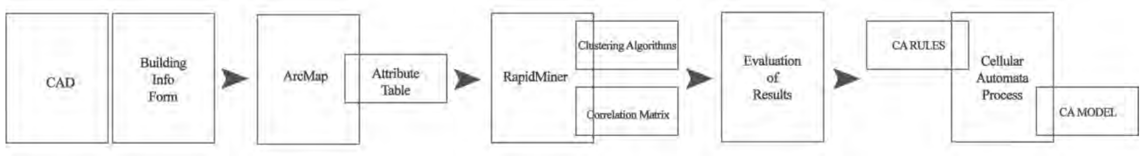


Figure 1: Stages of the Study

– 2.1 Geographic Information Systems

Geographic Information System (GIS) provides visual and non-visual information of spatial locations. GIS tools can collect, store, process and visualize geo-spatial data. Different disciplines take advantage of GIS, such as urban planners, architects, historians, sociologists, economists, cartographers, local governments and so on. In this study, the main point of using GIS software is to collect, store and visualize geo-spatial data. Through a database made by the GIS software, collected information become unique to the neighborhood. There are many open-source and commercial GIS software. Even if they don't have an opportunity for dynamic modeling, they can assist designers to supply, preprocess and transform urban data. In this study, we can create a database through the GIS software and preprocess and visualize this data for Data Mining techniques. Also, GIS software can reveal the formation process of the neighborhood according to a timeline.

2.2 Data Mining

Data Mining is an important part of the process called Knowledge Discovery in Databases (KDD). KDD process "makes sense of the data [4]" stored in digital Databases. Every day, heavy load of information is uploaded into Databases and this raw data cannot be analyzed with manual methods. KDD gives us computational techniques and tools to evaluate, interpret this data and construct meaningful hypotheses according to our interest. This process of transformation from raw data to knowledge helps us to analyze the current situations, make predictions and decisions for the future. Data Mining is the main part of this process which is "the application of specific algorithms for extracting patterns from data [4]". Data Mining contains different mathematical techniques for producing patterns from transformed data in databases for further interpretation and evaluation. If we consider the city as a large database collecting raw data, we can use Data Mining techniques in order to produce knowledge by collecting, selecting and evaluating data in order to produce useful patterns and structures focusing on our design problems in cities. Our aim of this study is to use Data Mining methods in a similar manner. For this purpose, in Amasya, we chose historic Hatuniye Neighborhood and started creating a Database for this neighborhood with GIS software. After having a large collection of information about this neighborhood, we can use Data Mining techniques in order to see a complex structure of this part of the city. We can detect interesting or dominant patterns, relationships between city elements and evaluate these results to find the essence of the Hatuniye Neighborhood which gives form to it.

2.3 Cellular Automata

The generative design model proposed in this paper, is based on Cellular Automata (CA) developed by John von Neumann [9] in 1940s. CA is a mathematical approach where simple forms follow neighborhood relations as rules in order to be arranged and produce complex systems. CA can produce highly complex behaviors from simple rule sets [7]. Therefore, it has been used in different disciplines where complex phenomena are studied, such as physics, geography, urban studies and so on [5]. Batty [2] states that rule based procedures like CA can reveal how complex systems work and which conditions they are dependent. Similarly, according to Wolfram [10], people usually assume that the underlying system of complex structures should be as complex as the structure itself. But as we seen in CA, very simple rules can effect simple forms inside a primitive grid and produce highly intricate structures. In a basic CA world, there are 5 major components: transition rule, time, lattice (or grid), neighborhood and cell state [6]. The most important component is the transition rule, because it determines cells that stay alive or die in the next generation and designates the general form of the cells. Thus, in order to produce a sustainable and regional design method for Hatuniye Neighborhood, construction of transition rules are very crucial. In this study, CA will be used to generate an urban design model based on environmental and urban data coming from GIS database and Data Mining techniques. The database will be composed in GIS software and consists of various data from the Neighborhood. Data Mining techniques will help us to understand raw data by turning them into useful knowledge about the underlying structure of this urban unit. After analyzing and interpreting the raw data we can produce our own-local CA rules and construct a method to produce new areas in Hatuniye Neighborhood.

3. Case Study

Figure 2-3: Location of Amasya and view from Hatuniye Neighborhood [8].

Amasya is a historic city in the Black Sea Region, Turkey (Figure 2). It is located in a valley created by Yeşilırmak (Iris) River and between the Kırklar and Sakarat Mountain. A Case study is carried out in Hatuniye Neighborhood which is situated along the river and leans its back to the Kırklar Mountain. At the peak of the mountain, Harşena Castle, above it 5 Pontic tombs and the urban structure of the neighborhood with the river create "a poetic urban experience [3] " (Figure 3,4). The neighborhood has 4 bridges and two of them draw the periphery of the neighborhood. We chose this neighborhood for a case study, because it has clear geographic borders and has a unique urban form despite changing social, economic and cultural dynamics. The neighborhood consists of 14 street blocks, 204 parcels, and 206 buildings in total. Most of the waterfront houses in the Neighborhod are from the Ottomans in the 19th century. There are also few houses and monuments built in the 18th and the 17th century.

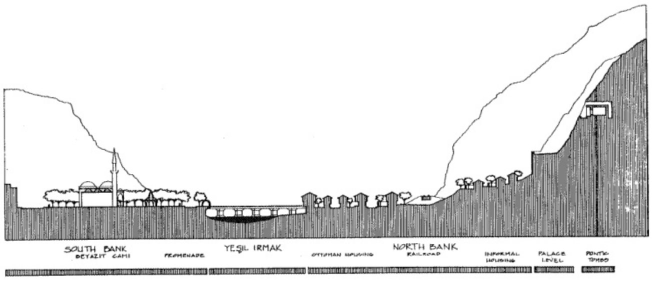


Figure 4: Diagrammatic Section of Amasya, Hatuniye Neighborhood contains the Ottoman Housing [3].

Until recently, most of the houses were neglected in the neighborhood, but still you could have an idea about how the Ottoman town looks like in terms of urban character, scale and environment [3]. Today, some of the buildings contain the remains of older ones and in the urban layout, the roads of the old town is still protected [3]. Amasya exists in a very narrow valley, therefore, the city forms as a linear structure parallel to the river. Unlike the modern urban areas in the city, old settlements were built in sloping areas in order to give space for agricultural activities and to have a protection from floods. Nowadays, the city is evolving through flat agricultural areas [11]. Also, all historic neighborhoods of the city are under the pressure of the high demand of tourism and construction activities. Thus, there is an urgent need for a design method to produce new spaces in historic parts of the city in order to protect the city's self-evolved structure through time respecting local climate, topography and culture.

Figure 5: Google Earth image of Hatuniye Neighborhood.

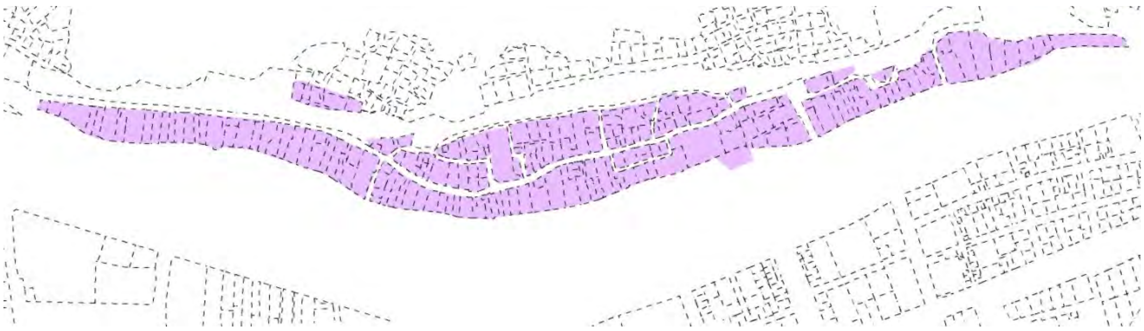


Figure 6: ArcMap Visualization of Hatuniye Neighborhood. Pink areas represent street blocks, Dashed lines represent parcels

Figure 7: ArcMap Visualization of Hatuniye Neighborhood. Pink areas represent street blocks, Blue represents buildings

Figure 8: ArcMap Visualization of Hatuniye Neighborhood. Pink areas represent street blocks, Blue represents buildings and marked areas are courtyards

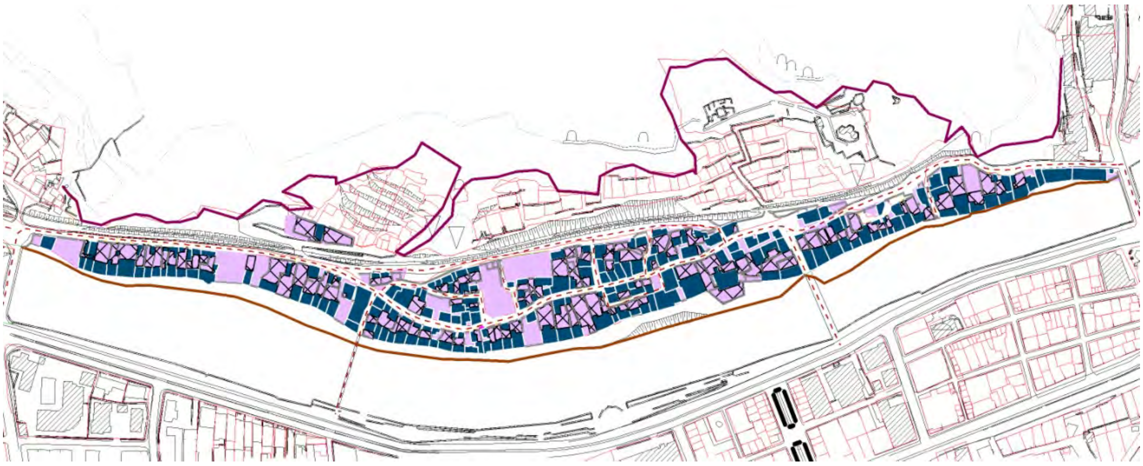


Figure 9: ArcMap Visualization of Hatuniye Neighborhood contains all urban entities.

3.1 Application of Data Mining Techniques

Digital data is provided by Amasya Municipality and cleaned in AutoCAD. This available data was poor, so that for every building in the area, a Building Info Form is filled. In total, 21 attributes were determined as a start. Also, numeric values for blocks, parcels and buildings were automatically calculated in GIS. In Table 1, we can see all attributes in the data set and their numeric and nominal values. Also, in Figure 10, we find a schematic explanation of some attributes.

Table 1: Attribute Table shows attribute types and values

	Name	Type	Value
1 (id)	*Block_ID (Ada_Kimlik)*	Polynominal	A,A1,B,C,D1,D2,E,E1,F,G,J,H
2 (id)	*Building_ID (Bina_Kimlik)*	Polynominal	Building Numbers
	Attribute_Name	Value_Type	Attribute_Value
1	Ground Floor Area (Taban_Alani)	Numeric	
2	*Conservation (Koruma_Durumu)*	Binominal	Registered, NotRegistered
3	*Building Function (BinaFonk)*	Polynominal	Residential, Accomodation,Empty, Governmental,Leisure, Mixed-used, Social, Education,Monumental
4	*Ground Floor Function (ZeminKatFonk)*	Polynominal	Residential, Accomodation,Empty, Governmental,Leisure, Mixed-used, Social, Education,Monumental
5	*First Floor Function (1KatFonk)*	Polynominal	Residential, Accomodation,Empty, Governmental,Leisure, Mixed-used, Social, Education,Monumental
6	*Basement (Bodrum)*	Binominal	Exists, NoBasement
7	*Floor (KatSayisi)*	Numeric	1,2,3,4,5
8	*Building-Street Relation (Yapi_Sokak_iliski)*	Polynominal	Building_Entrance, Courtyard_Entrance, AdditionalBuilding_Entrance
9	*Building-Parcel Relation (Yapi_Parsel_Durumu)*	Polynominal	DetachedHouse, CornerBuilding , AttachedHouse
10	*Courtyard (Avlu)*	Binominal	Exists, NoCourtyard
11	*Courtyard Location (Avlu_Konum)*	Polynominal	FrontCourtyard, SideCourtyard, BackCourtyard, MiddleCourtyard, Front/BackCourtyard
12	*Orientation (Yapi_GirisKapisinaGore_Oryantasyon*	Polynominal	N_S, E_W, NW_SE, NE_SW
13	*View Area (Bina_Bakis_Yonu)*	Polynominal	River, Mountain, Street
14	*AdditionalBuilding (EkYapi)*	Numeric	0,1,2
15	*Building_Width (Bina_en)*	Numeric	
16	*Building_Height (Bina_boy)*	Numeric	
17	*Courtyard_Area (Avlu_Alan)*	Numeric	
18	*Building_Form (Bicim)*	Binominal	L-Shape , Rectangular
19	*Distance_to_Center (Meydan_Mesafe)*	Numeric	0-100, 100-200, 200-300, 300-400, 400-500, 500,600
20	*Material_(Malzeme)*	Polynominal	Wood/Brick, Concrete, StoneMasonry
21	*Construction (Yapım_Teknigi)*	Polynominal	WoodFrame, Concrete, StoneMasonry

Information coming from the Building Info Form and cleaned digital data from AutoCAD is transformed into GIS software (ArcMap) to produce a map for all urban attributes. In this map, all quantitative and qualitative data can be joined together and represented both cartographically and in a database form. After creating this data set, we can export it for Data Mining studies to Rapid Miner (an open-source data mining software). In the mining stage of this raw information, the main aim is to identify clusters and groups, find out the dependency of urban attributes to each other and look for significant patterns in the urban tissue. The process of gathering information and creating a database is still running so that some initial studies are made at this stage to test the Data Mining methodology of the study.

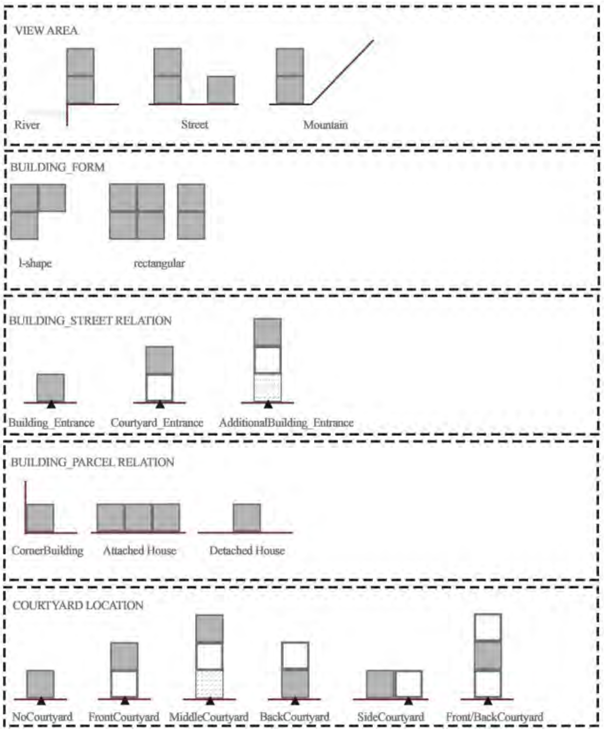
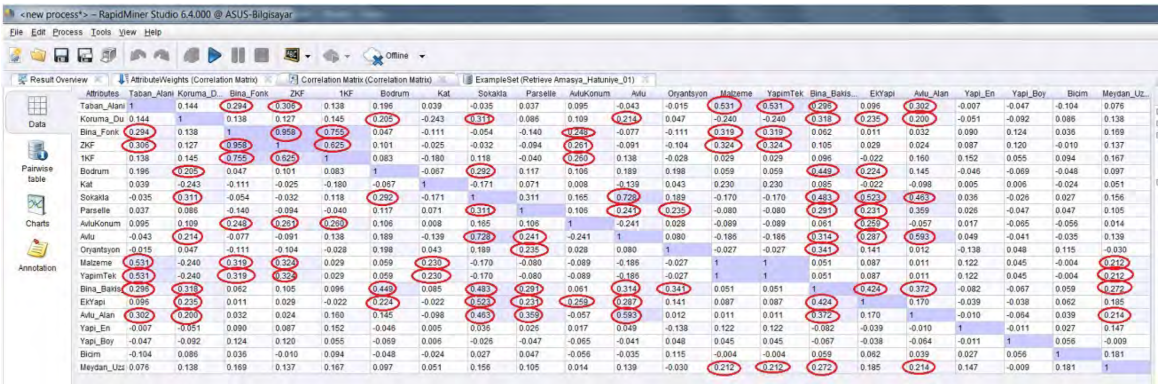


Figure 10: Diagrammatic representations of urban attributes and their values

3.2 Data Mining Results

The data table from ArcMap is imported in a data mining application software-Rapid Miner as an Excel sheet. Before doing anything, the software analyzes numeric values such as parcel and building areas in terms of maximum, minimum and average values. According to this analysis, while the smallest street block is 66,468 m², the biggest one is 9144 m². The difference between these blocks can be clearly seen from the map (Fig.6). For the size of parcels, while the smallest one is 19,591 m², the biggest one is 946,342 m². The average value of parcels is 153,646 m². Monumental buildings also added into the calculation, therefore, their influence on the average should be considered during design experiments. Similarly, the smallest building size is 21,196 m² while the biggest one is 336,655m² with average 86,634 m². In this way, Rapid Miner can give us statistical results about maximum, minimum and average values for the building envelopes and open spaces for further design studies. Next, 170 main buildings were classified with K-means clustering algorithm according to the building area. K-means clustering was chosen because of the small size of the numeric data. 5 groups of buildings emerged due to building size: [1] 21-58 m² [2] 59-94 m² [3] 96-130 m² [4] 150-203 m² [5] 253-336 m². The first group of buildings mainly contains additional structures and the fifth group contains monumental ones such as mosques and baths. In the data table, there are mainly nominal values for attributes. In order to find out their dependency to each other, Correlation Matrix was used. In Correlation Matrix, dependency is computed between -1 and 1. If an attribute has a negative effect on the other, the result appears as -1. 0 means no relationship at all between clusters and 1 means an attribute meets itself in the matrix. The table below represents results generated through Correlation Matrix (Table 2).

Table 2: Correlation Matrix shows dependent and independent urban attributes



Attributes	Taban_Alani	Koruma_D...	Bina_Fonk	ZKF	1KF	Bodrum	Kat	Sokakla	Parselle	AvluKonum	Avlu
Taban_Alani	1	0.144	0.294	0.306	0.138	0.196	0.039	-0.035	0.037	0.095	-0.043
Koruma_Du	0.144	1	0.138	0.127	0.145	0.205	-0.243	0.311	0.086	0.109	0.214
Bina_Fonk	0.294	0.138	1	0.958	0.755	0.047	-0.111	-0.054	-0.140	0.248	-0.077
ZKF	0.306	0.127	0.958	1	0.625	0.101	-0.025	-0.032	-0.094	0.261	-0.091
1KF	0.138	0.145	0.755	0.625	1	0.083	-0.180	0.118	-0.040	0.260	0.138
Bodrum	0.196	0.205	0.047	0.101	0.083	1	-0.067	0.292	0.117	0.106	0.189
Kat	0.039	-0.243	-0.111	-0.025	-0.180	-0.067	1	-0.171	0.071	0.008	-0.139
Sokakla	-0.035	0.311	-0.054	-0.032	0.118	0.292	-0.171	1	0.311	0.165	0.728
Parselle	0.037	0.086	-0.140	-0.094	-0.040	0.117	0.071	0.311	1	0.106	0.241
AvluKonum	0.095	0.109	0.248	0.261	0.260	0.106	0.008	0.165	0.106	1	-0.241
Avlu	-0.043	0.214	-0.077	-0.091	0.138	0.189	-0.139	0.728	0.241	-0.241	1
Oryantsyon	-0.015	0.047	-0.111	-0.104	-0.028	0.198	0.043	0.189	0.235	0.028	0.080
Malzeme	0.531	-0.240	0.319	0.324	0.029	0.059	0.230	-0.170	-0.080	-0.089	-0.186
YapimTek	0.531	-0.240	0.319	0.324	0.029	0.059	0.230	-0.170	-0.080	-0.089	-0.186
Bina_Bakis	0.296	0.318	0.062	0.105	0.096	0.449	0.085	0.483	0.291	0.061	0.314
EkYapi	0.096	0.235	0.011	0.029	-0.022	0.224	-0.022	0.523	0.231	0.259	0.287
Avlu_Alan	0.302	0.200	0.032	0.024	0.160	0.145	-0.098	0.463	0.359	-0.057	0.593
Yapi_En	-0.007	-0.051	0.090	0.087	0.152	-0.046	0.005	0.036	0.026	0.017	0.049
Yapi_Boy	-0.047	-0.092	0.124	0.120	0.055	-0.069	0.006	-0.026	-0.047	-0.065	-0.041
Bicim	-0.104	0.086	0.036	-0.010	0.094	-0.048	-0.024	0.027	0.047	-0.056	-0.035
Meydan_Uza	0.076	0.138	0.169	0.137	0.167	0.097	0.051	0.156	0.105	0.014	0.139

Attributes	Oryantsyon	Malzeme	YapimTek	Bina_Bakis...	EkYapi	Avlu_Alan	Yapi_En	Yapi_Boy	Bicim	Meydan_Uz...
Taban_Alani	-0.015	0.531	0.531	0.296	0.096	0.302	-0.007	-0.047	-0.104	0.076
Koruma_Du	0.047	-0.240	-0.240	0.318	0.235	0.200	-0.051	-0.092	0.086	0.138
Bina_Fonk	-0.111	0.319	0.319	0.062	0.011	0.032	0.090	0.124	0.036	0.169
ZKF	-0.104	0.324	0.324	0.105	0.029	0.024	0.087	0.120	-0.010	0.137
1KF	-0.028	0.029	0.029	0.096	-0.022	0.160	0.152	0.055	0.094	0.167
Bodrum	0.198	0.059	0.059	0.449	0.224	0.145	-0.046	-0.069	-0.048	0.097
Kat	0.043	0.230	0.230	0.085	-0.022	-0.098	0.005	0.006	-0.024	0.051
Sokakla	0.189	-0.170	-0.170	0.483	0.523	0.463	0.036	-0.026	0.027	0.156
Parselle	0.235	-0.080	-0.080	0.291	0.231	0.359	0.026	-0.047	0.047	0.105
AvluKonum	0.028	-0.089	-0.089	0.061	0.259	-0.057	0.017	-0.065	-0.056	0.014
Avlu	0.080	-0.186	-0.186	0.314	0.287	0.593	0.049	-0.041	-0.035	0.139
Oryantsyon	1	-0.027	-0.027	0.341	0.141	0.012	-0.138	0.048	0.115	-0.030
Malzeme	-0.027	1	1	0.051	0.087	0.011	0.122	0.045	-0.004	0.212
YapimTek	-0.027	1	1	0.051	0.087	0.011	0.122	0.045	-0.004	0.212
Bina_Bakis	0.341	0.051	0.051	1	0.424	0.372	-0.082	-0.067	0.059	0.272
EkYapi	0.141	0.087	0.087	0.424	1	0.170	-0.039	-0.038	0.062	0.185
Avlu_Alan	0.012	0.011	0.011	0.372	0.170	1	-0.010	-0.064	0.039	0.214
Yapi_En	-0.138	0.122	0.122	-0.082	-0.039	-0.010	1	-0.011	0.027	0.147
Yapi_Boy	0.048	0.045	0.045	-0.067	-0.038	-0.064	-0.011	1	0.056	-0.009
Bicim	0.115	-0.004	-0.004	0.059	0.062	0.039	0.027	0.056	1	0.181
Meydan_Uza	-0.030	0.212	0.212	0.272	0.185	0.214	0.147	-0.009	0.181	1

Due to interesting dependency results, some questions were asked to find out patterns in the urban tissue. Therefore, DBSCAN algorithm was used for classification on nominal attributes dependent to each other.

- Does having a courtyard/or not determine the relationship between the building and the street?

In correlation matrix, this dependency measured as 0.728. After clustering analysis, the biggest cluster consists of 88 entities which have a courtyard and one main entrance to it. The second biggest one was with 52 buildings with no courtyard and have a direct entrance to the building hole from the street. Thus, if a building has a courtyard, second entrance usually doesn't exist. And most of the buildings have a direct relationship with the public street.

-Is there a relationship between view area and building-street Relation?

DBSCAN algorithm was applied because the correlation matrix result was 0.483. DBSCAN gives us 7 clusters. The most crowded one was with 52 buildings looking through River and have a courtyard between the building entrance and the street. Other 6 clusters were not well decomposed, but still we identified riverside buildings with a courtyard and without an additional entrance.

- Can Building Function and Courtyard Location be related (Figure 11)?

In Correlation Matrix, dependency between building function and courtyard location measured as 0.265. Although this number means there is a weak dependency, we still applied DBSCAN algorithm due to find out the obvious pattern seen from the visual map which consists of houses with a front courtyard. Indeed, clustering algorithm shows us there are 73 urban entities which represent houses with a front courtyard. Another 2 clusters contain 16 entities which are neglected houses with front courtyard and 16 entities are empty buildings with a front courtyard. The algorithm produces another 9 clusters, but they are not decomposed very well. From these numbers, we can say that in the neighborhood majority of the buildings are originally houses with a front courtyard.

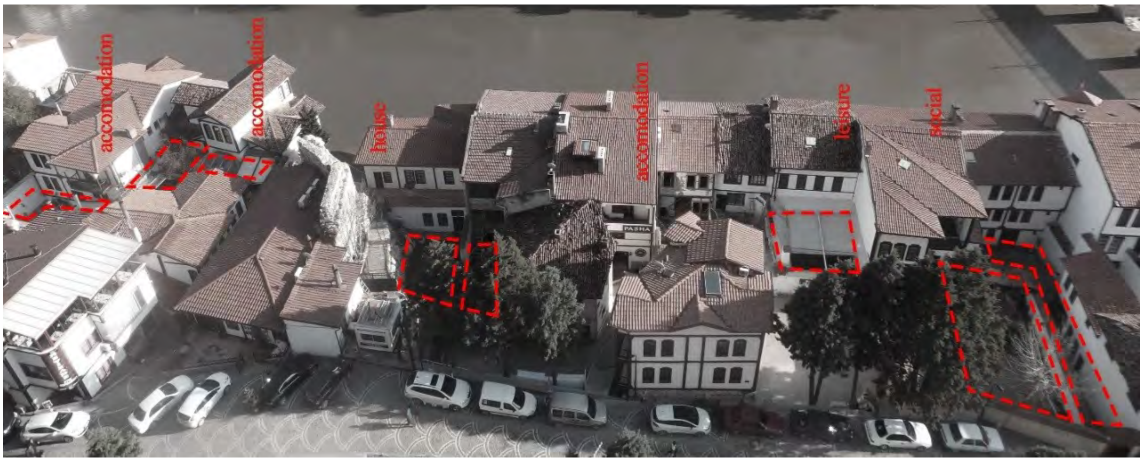


Figure 11: View from Hatuniye Neighborhood. Courtyards and Buildings with different functions

- Does having an additional building/or not determine the relationship between the building and the street?

The result was 0.523. After DBSCAN algorithm for these two attributes, we found 2 major clusters with 68 entities. One was without an additional building and one entrance to the courtyard from the street, and the other one was without an additional building and one direct entrance to the building hole from the street. So, there is no obvious pattern of having an additional structure. Even houses have a big courtyard; they usually don't have an addition. According to Building Info Form, additional buildings are usually used for toilet, store and kitchen. This means that they probably built in recent times in the courtyards for extra functions.

-Can we tell whether or not a building has a basement according to its view (Figure 12)?

The result was 0.449. Therefore, having a basement and view area seem related to each other. DBSCAN algorithm for only these two attributes shows that there are 51 entities which have not a basement and look through the Street. Another cluster contains 29 entities with no basement and in the Mountain area. Other 44 entities look through River and have a basement. Another 3 clusters have small numbers of members which are not well decomposed. According to these results, it is clear that if a building has a view through the river, it has a basement, otherwise, with a high probability it does not.

Figure 12: View from Hatuniye Neighborhood. Basements and the Pontic Wall which creates a base for riverside buildings

-Does view area determine the situation of the building on the parcel?

The result was 0.291. So we can say that there is very weak dependency between these attributes and no need for DBSCAN. But, there is a strong visual pattern seen in the map so that we applied DBSCAN algorithm and find an important pattern which has 67 attached buildings with river view.

Therefore, we can say that at the riverside majority of the buildings are attached houses. Here, also we can detect few detached buildings which break the monotony in the block structure.

- Is there a relationship between view area and building orientation?

The result is 0.341. As in the previous paragraph, there is 1 cluster out of 7 with obvious structure which has 72 entities oriented towards North-South on the riverside. Similar to previous analysis we can say that if a building is situated on the riverside, this building should be orientated towards North-South.

-Is there a relation between having an additional building and the distance to the center of the neighborhood?

Throughout the study there is no obvious cluster for having an additional building. But, according to neighborhood map, we can see that most of the additions are far from the neighborhood center. Therefore, we applied DBSCAN to see results. At the end, only 6 out of 39 buildings which are 100 meters away from the center have an addition. Similarly, only 2 out of 45 buildings which are 200 meters away from the center have an additional building. We can say that because of the smaller parcels near to the neighborhood center, buildings usually don't have any additional buildings.

4. Designing CA Model

In the designing phase with CA, we have to create our rules from Data Mining results. For this study, Autodesk Maya/Mel is used to generate a design procedure based on local CA rules. A design procedure (Figure 13) should follow this order: Firstly, we should model our neighborhood according to GIS database. Then, the CA procedure in Maya should read the database, create attributes and assign attributes values to the buildings on the scene automatically (ideally). Secondly, we need to construct our CA rules for the Neighborhood according to Data Mining results. In this stage of the study, we should find an empty parcel for implementation of the procedure. CA procedure should calculate the 8 closest neighbors of the empty parcel and carry on procedure by considering only these 8 closest neighbors. The Mel procedure should group values of the same attribute for 8 neighbors in an array for further array evaluations and operations. Before evaluation phase, we should also evaluate attribute arrays to find out which attribute element is the most and the least repeated according to a specific rule. By doing this, rules can work by taking information from attributes array. Finally, we should animate the system in order to freeze different building forms emerging as a result of the CA procedure.

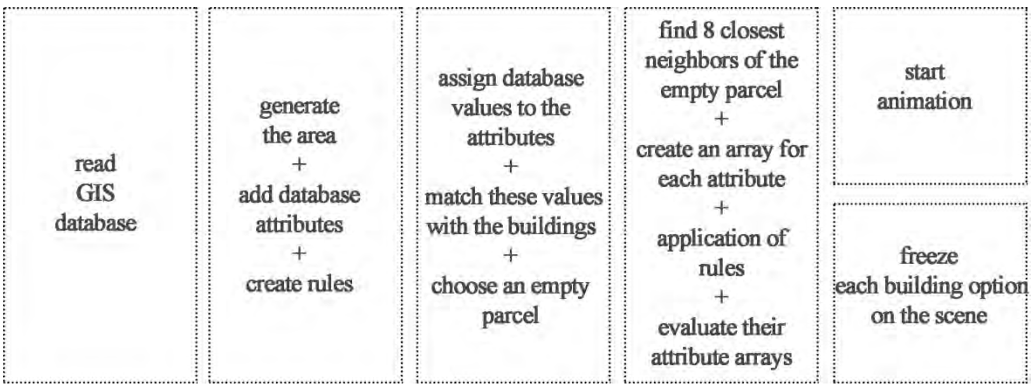


Figure 13: Flow of the Mel Procedure

As a start, we choose a small part of the neighborhood (Figure 14) and try to construct our CA world. This area contains 9 buildings with different functions and an empty parcel locating at the riverside.

Figure 14: Chosen Area

In this stage of the ongoing study, we could not read values from GIS database automatically in Maya; thus, we simply modeled the area and added 15 attributes and their values by hand. Then, we constituted arrays to hold information about 15 attributes for further CA rules operations. For an initial test, we assigned some attribute values before the procedure starts. For instance, for the empty parcel, viewArea is “river” and we’ve already known its parcel area and distance to the Neighborhood Center. Other attributes are left empty, because Mel procedure should find out these values according to CA rules (figure 16). In this phase Data Mining results are mixed with CA rules. Therefore, we have 9 rules in total but only one of them (Floor) is randomly working because of limitations of Data Mining results (Figure 15).

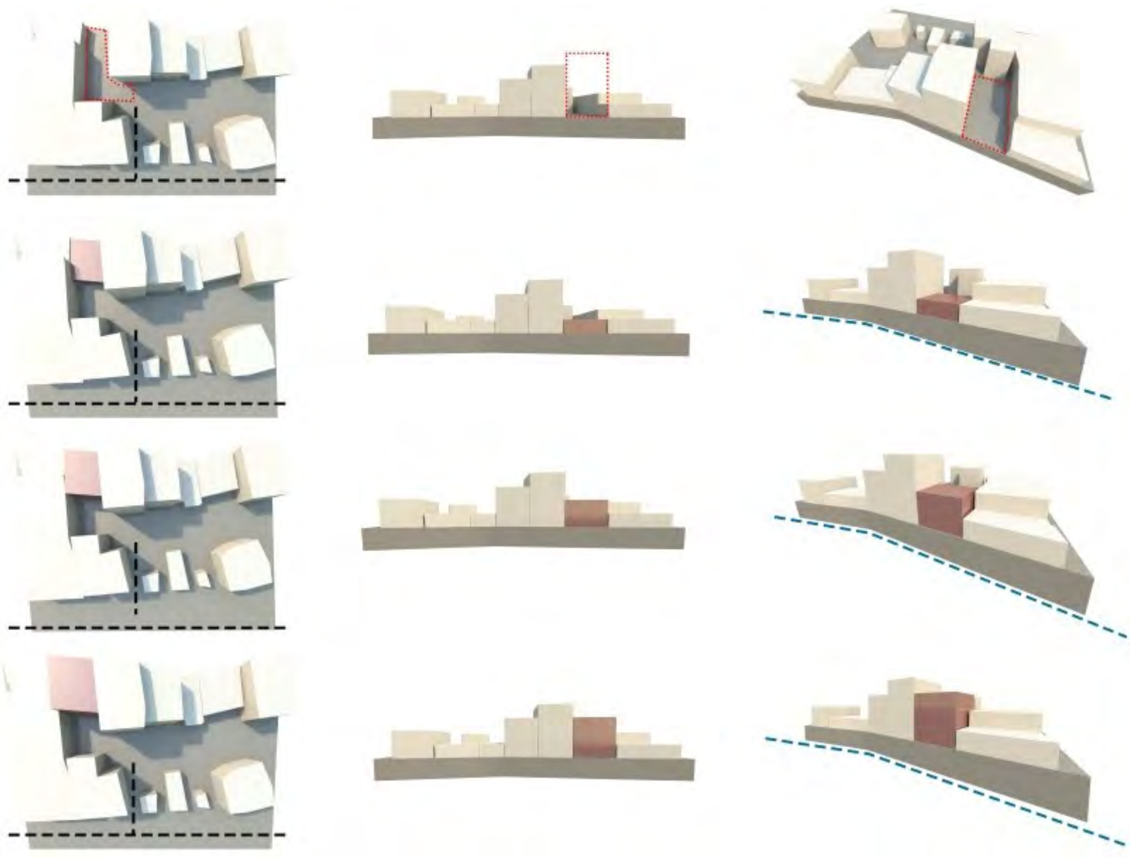


Figure 15: Above we can see an empty parcel at the top and different floor options below, but other 8 attributes values are same for each option.

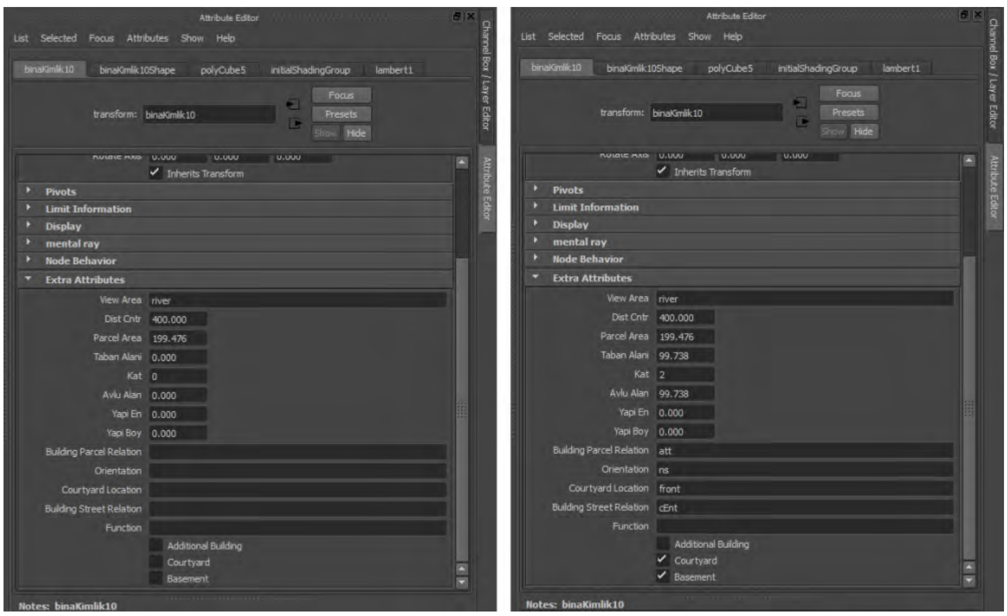


Figure 16: An attribute editor of the Empty Parcel // before and after the Mel procedure.

– 5. Conclusion

This study presented an approach for a generative design model based on CA with the help of data mining techniques and GIS tools. Experiments carried out in this paper are preliminary for further studies, therefore, a small part of the Hatuniye Neighborhood- was chosen for CA application. In the framework of the study, first, a database was prepared in GIS tools by getting information from Amasya Municipality and Building Info Form by visiting the area. After, this data set was used for Data Mining to investigate patterns and relationships among urban entities. Through this, we aimed to transform raw data in our data set into knowledge about urban characteristics. Finally, CA rules were determined according to Data Mining results and an initial model was generated in Autodesk/Maya. The process of construction the building database is still running, but obtained results in this paper showed that Data Mining presents various useful techniques to analyze raw urban information. For instance, numeric attributes can be classified according to its function and we can determine lower and upper size limits of urban entities. The most important pattern emerged at the riverside contains attached houses oriented towards North-South with a front courtyard and a basement. Therefore, houses use a fortress wall for a base, create a semi-private area to protect privacy and have a river view from the South façade. Another finding is about additional buildings. Having an additional structure seems like an independent choice of users, however, far buildings from the neighborhood center are more likely to have an additional building due to larger parcels in that area. In the Street and Mountain area buildings usually don't have a basement and again, they turn their façade to the North-South orientation. Most of the buildings having a front courtyard don't need an extra entrance to the building. These results can be promising for understanding the nature of the neighborhood structure and designing a CA model for a start, but still we need to collect more information and expand our data set to find more intricate relations between urban entities in the scope of further design studies. Additionally, procedure in CA model should allow for designers to enter some pre-existing information with a user interface and calculate more relations determined by CA rules automatically. By doing so, we can achieve our ultimate aim that is to generate a design procedure with digital tools to let designers generate sustainable and regional new designs in historic towns.

– References

[1] ALEXANDER, C., 2013. A City is Not A Tree. in LARICE, M. & MacDONALD (eds.), The Urban Design Reader. New York: Routledge, pp. 152-166.

[2] BATTY, M., 1997. Cellular Automata and Urban Form: A Primer. APA Journal, spring, 63(2), pp. 266-274.

[3] BECHHOEFFER, W., YALÇIN, A.K., 1991. Amasya, Turkey: Lessons in Urbanity. Mimar 40: Architecture in Development. September 1991, London, Concept Media Ltd., pp. 24-29.

[4] FAYYAD, U., PIATETSKY-SHAPIRO, G., SMYTH, P. 1996. From Data Mining to Knowledge Discovery in Databases. American Assos. for AI, Issue Fall, pp. 37-54.

[5] HERR, C.,M. & KVAN, T. 2005. Using Cellular Automata Generate High Density Building Form. CAAD Futures Proceedings Book 2005, pp. 249-258.

[6] JIAO, J. & BOERBOOM, L., 2006. Transition Rule Elicitation Methods for Urban Cellular Automata Models. In J. P. v. Leeuwen & H. J. P. Timmermans, Innovations in Design&Decision Support Systems in Architecture and Urban Planning. Netherlands: Springer, pp. 53-68.

[7] KRAWCZYK, R. J., 2002. Experiments in Architectural Form Generation Using Cellular Automata. Warsaw, eCAADe 20th.

[8] TÜRKOĞLU, E. 2006. The Analysis and Evaluation of Amasya, Hatuniye Neighborhood and the Preservation / Rehabilitation Proposals for the Traditional Settlement. M.Sc. Thesis. Gazi University, Architectural Faculty. Ankara, Institute of Science and Technology.