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Self-Aware Autonomous City: From Sensing to Planning

Bo-Wei Chen, Muhammad Imran, Nidal Nasser, and Muhammad Shoaib

***Abstract*—This article presents a knowledge mining model, where a city can plan its development based on existing knowledge during city expansion, for example, telecommunication resource allocation and crowd forecasts in a new region. Unlike most works that focused on Internet-of-Things (IoT) sensing, this study is aimed at urban planning by using harvested data, from the perspective of city architects. For large-scale metropolitan areas, a massive amount of data is generated every day, either from static surveys or dynamic IoT sensing. For urban planners, data collection is not their prior concerns. How to transfer harvested knowledge from exiting parts of the city to suburban/rural/ untapped areas is a new challenge. This is because those areas still lack sufficient statistics, and the density of IoT deployment is low. Therefore, development is risky and uncertain. To exploit new regions requires knowledge inference. Such a transition needs data interpretation from historical city dynamics, involving sensor deployment, human activities, and resource allocation in the vicinity. With the proposed model, a city can estimate the requirement for resources when the peripheral areas on the outskirts of a city develop. The same model can be applied to enterprises for resource deployment, and applications are not merely limited to governments.**

***Index Terms* — Knowledge mining, crowd forecast, crowd modeling, crowd intelligence, data inference, city dynamics, city economics, city decay, city resilience, city monitoring, nonnegative matrix factorization, self-organizing sensing, self-organizing map, resource allocation, resource planning, mobile edge computing, smart city**

I. Introduction

City economics, or urban economics, discusses the interplay between various crowd behavior and living environments, e.g., populations, house prices, and communication coverage, in an urban spatial structure. Usually, the methodology for city economics involves two parts. One is detection of urban dynamics, and the other is prediction of urban growth/decay. For detection, typical approaches rely on static surveys, such as questionnaires and household statistics. Today, ever since cyber-physical systems arise, modern city economics no longer passively depends on static data but proactively collects them by leveraging the various Internet of Things (IoT). With advances in miniaturization of electronic circuits, the IoT can be deployed almost in every corner of a city. For example, generic IoT devices like particulate matter sensors and carbon dioxide meters can be installed outdoors to measure the air quality of a city. Gaseous and pH sensors can be respectively placed underground or underwater to monitor sewage.

More recently, as artificial intelligence technology has made considerable progress, it subsequently empowers edge computing. Edge computing is an architectural shift from clouds to terminals. Such a shift involves comprehensive technical changes in computation, communications, middleware, and hardware. Edge devices can provide basic functionalities, such as identification and encoding, to alleviate computational loads and constrained bandwidth of cloud sides. When edge computing gradually evolves into mobile edge computing, the IoT no longer stays fixed in one place as before.

For mobile edge devices, heterogeneous sensors are simultaneously installed in carriers, like autonomous multirotor drones (i.e., unmanned aerial vehicles) and self-driving cars (i.e., unmanned ground vehicles), to capture various data. These carriers can provide high mobility for city monitoring by forming a fluid, movable, and wireless sensor network. The number of participatory carriers can also be adaptively readjusted anytime. For instance, if city regions have high population densities, new carriers join the network to handle more samples. Sensing therefore becomes more dynamic, and the immersion of IoT sensing can deeply fuse into daily life. Among all types of IoT sensing, drones particularly attract significant attention in recent research. Compared with ground vehicles, drones are capable of adapting to various terrains that are inaccessible to ground vehicles due to aviation capabilities. Sensing coverage is therefore largely enhanced. In addition to sensing, telecommunication can also be attached to a fluid mobile network, and this establishes an ad hoc net, such as Mobile Ad Hoc Networks (MANETs). MANETs are fluid, movable, wireless networks that focus on decentralized communications by leveraging ubiquitous mobile devices. In Vehicle Ad Hoc Networks (VANETs) and Flying Ad Hoc Networks (FANETs) [1, 2], vehicles and drones become telecommunication nodes — A major carrier of communications in a fluid network. At present, a great deal of effort has been devoted to urban sensing, for instance, [3-7]. Apart from IoT approaches, urban monitoring based on crowdsensing [8] and satellite remote sensing is also another widely used method for detection of urban dynamics [9, 10]. As a whole, city dynamics can be captured from different perspectives with the state-of-the-art IoT. The point is how to utilize and convert these harvested data into knowledge, especially when a city expands. How many base stations are required for new regions when telecommunication service providers operate? What is the influence of crowd activities?

B.-W. Chen is with National Sun Yat-Sen University (email: bo-wei.chen@mail.nsysu.edu.tw)
M. Imran and M. Shoaib are with King Saud University
N. Nasser is with Alfaisal University

Do crowd activities cause migration of current arrangement? A key to the above problems resorts to crowd prediction.

During city development, different types of crowds may gradually form, and crowds may vary from street to street and from block to block, depending on crowd types. Herein, crowds refer to all the activities generated by humans, e.g., data traffic and subscribers. Each type of crowd has its own characteristic. Not every region has the same statistic. When more activities occur, crowds and flows become larger, subsequently forming hotspots. Crowd activities are usually volatile and fluctuate over time. Beside, different types of crowds are highly diversified.

In practice, it is impossible for a city to grow infinitely when new immigrants keep moving in. Resources could be depleted, and living quality may degenerate. When parts of a city decay or oversaturate, expansion or crowd relocation occurs on the outskirts of a city. Flows may be diverted from existing regions to suburbs. For these peripheral suburban/rural areas, the sampling data of the previously mentioned IoT methods for crowd detection are quite limited. Thus, knowledge inference for those areas may be inaccurate, and development is full of uncertainty. For city planners and enterprises, uncertainty means risks. How to effectively predict the demand of those new regions is of prior concerns.

Take telecommunication networks for example. The statistic of data flows is a good indicator during deployment of base stations. They are built to balance communication loads and to provide access points for End Users (EUs). In a metropolitan area, site selection should consider both service coverage and maintenance costs while constrained communication resources are satisfied at the same. An equilibrium is reached after a long period of adjustment. When a city expands, suburban/rural areas gradually evolve. The scale of the city increases, but original resources no longer support the new scale. With those developing areas, the equilibrium and activity hotspots may shift. To evaluate the influence of newly emerged crowds and manage crowd activities in advance is highlighted herein.

In this study, crowd management is fulfilled by autonomous deployment of each edge device in the proposed fluid mobile array. Since each edge device is responsible for sensing and communications (i.e., data from crowds), devices have to provide services for crowds in a balanced way and cover crowd requests. To this end, swarm intelligence-enabled fluid mobile arrays are proposed. The capability of autonomous deployment in such an array is empowered by Self-Organizing Maps. The array has capabilities to dynamically adapt to crowd changes, e.g., an increase or a decrease in crowds. This allows every part of crowds to be serviced by an edge device. No edge devices are overloaded or underloaded. Demands from crowds are balanced out.

The innovative contributions of this study can be divided into two parts. One is autonomous sensing, and the other is autonomous planning. Herein, sensing aims for the current observed data, and planning means prediction for the future. Two parts affect each other.

- For autonomous sensing, this study proposes swarm intelligence-enabled fluid mobile edge arrays. ***i***) The proposed array can resolve topological reconfiguration problems in MANETs by providing an automatically learning mechanism. Such a mechanism can dynamically change the topology of the array based on sensed data, e.g., EU requests. MANETs can self-adapt to environments. ***ii***) The proposed array supports an incremental scheme that allows new mobile devices to join the current formation without reorganizing the entire array. ***iii***) The proposed array has the capability of providing isolated subnetworks by using a logically hierarchical structure. Thus, heterogeneous subnetworks can coexist.
- Regarding autonomous planning (including crowd management), harvested data are fed into the planning model to predict the arrival of new data. Subsequently, the existing data along with the predicted data are input to the proposed array. As swarm intelligence can adapt to changes, the fluid array uses the new topology for future deployment, e.g., site selection and array expansion. Requests of new crowds can be satisfied.

The rest of this paper is organized as follows. Section II details city sensing based on fluid mobile arrays. Section III then describes city management. Next, analytic results are discussed in Section IV. Conclusions are finally drawn in Section V.

II. Fluid Mobile Sensing Based on Self-Organizing Swarm Intelligence

To be self-aware, the first step is to collect as many data as possible before the self-reasoning process is performed. The following sections introduce a swarm intelligence-enabled sensing technique for mobile edge devices. Swarm intelligence is a bionically inspired subject that studies collective behavior of decentralized individuals [11, 12]. Such a swarm of individuals can present collaborative intelligence to tackle a difficult problem that is beyond the capability of any individual. Earlier research like Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO) focused on finding the best path among the search space by simulating social behavior. Nowadays, such technologies have been used in robots, drones, and satellites for sensing, such as Swarmanoid projects (sponsored by the European Commission), Swarm MANETs, and Microsatellite Swarms by Bluetronix. However, neither ACO nor PSO supports incremental and hierarchical mechanisms at the same time. Thus, Self-Organizing Maps along with incremental and hierarchical mechanisms are introduced.

A. *Self-Organizing Mobile Edge Array*

The Self-Organizing Map (SOM) is a type of neural network. A typical SOM consists of only two layers of neurons. One is the input, and the other is the visual map space. Neurons between layers are interconnected by edges. The input layer is used to perceive outside data, whereas the map space reflects the input by changing the topology or appearance.

Unlike neural networks with multilayered perceptrons that use both feedforward and backpropagation algorithms, SOMs adopt merely the former one. This means changes of the topology in the map space do not loop back to affect the input layer or weights. It is worth noting that each neuron in the map space is fully connected with all of the neurons in the input layer. To reflect strength of connectivity, a value is assigned to each connection. Such a value is the weight between two connected neurons. No weighted edges exist in the same layer.

As a visualization tool where high-dimensional data are transformed into the topology of neural connections, the intuition behind SOMs is simply based on the law of attraction. The map space of SOMs is like an elastic grid net. The node on the net represents a neuron, and the edge denotes the distance between neurons. At first, the neuron on this grid net is uniformly distributed, with a fixed separation between neighbors. Every time when stimulation inputs, only one neuron on this net is selected. Subsequently, this neuron attracts its neighbors, and the proximal neighbors move closer to the selected neuron. Edges may become shorter or longer. Shorter edges represent higher similarities between two adjacent nodes, whereas longer edges denote lower ones. In brief, SOMs work as follows.

Step 1: Stimulation enters a SOM
Step 2: Similarity is compared between the stimulation and all the neurons in the map space
Step 3: Most similar neuron in the map space is selected
Step 4: Selected neuron attracts neighbors
Step 5: Loop continues until no stimulation enters

Attraction assimilates neighbors. This reveals that the selected neuron does not differentiate neighbors, but makes them similar to itself. After self-organizing mapping, like attracts like. Groups of similar neurons gather together.

In the applications of mobile edge devices, the internal mechanism is still the same. The difference is that the neurons in the map space are replaced by an array of devices. The input layer becomes a communication layer that receives requests from EUs and commands from dispatch centers (if scenarios in telecommunications are used as an example). Whichever device receives a request, it broadcasts to the entire array. The array can dynamically modify its topology to fit the area of interest (i.e., the target area) and the density of requests.

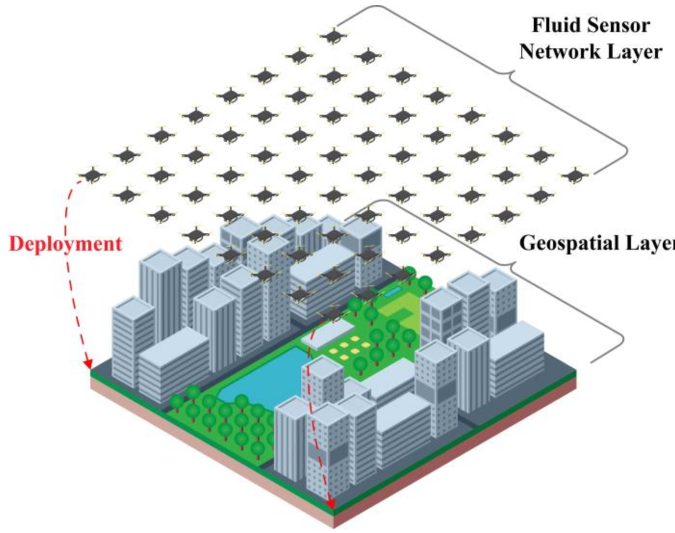

Fig. 1. Self-organizing mobile edge array, where the topology can be dynamically changed based on crowds. The mobile edge array is composed of mobile edge devices, each of which is connected to proximal devices. The sensor array is deployed in the city

Fig. 1 shows city sensing based on a swarm intelligence-enabled fluid mobile array. This figure displays two layers. One is the geospatial layer, and the other is the fluid sensor network layer. The former represents the physical environment, and the latter denotes the proposed self-organizing mobile edge array. Such an array uses swarm intelligence to dynamically change the topology of the array. This further empowers MANETs to own a self-organizing capability. When data enter the array, Fig. 1 becomes Fig. 2.

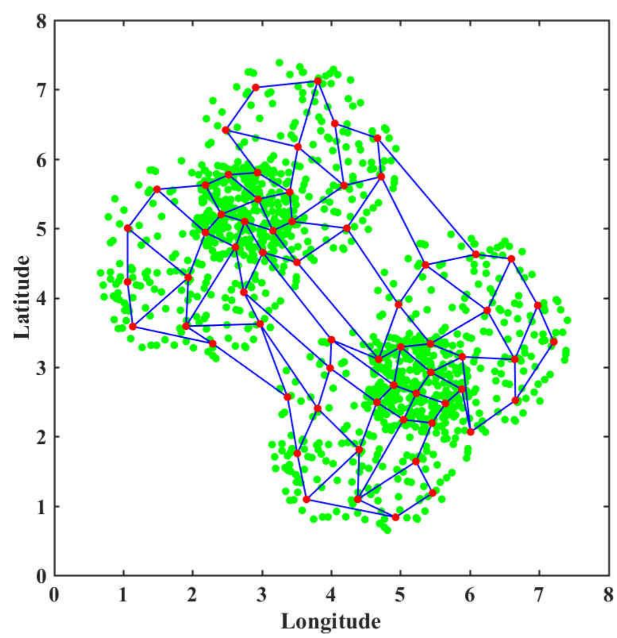

Fig. 2. Self-adaptation of an 8×8 mobile edge array to various EU requests based on the initial formation in Fig. 1. Red dots are mobile edge devices, and blue lines are connections between devices. Green dots represent EU requests.

Fig. 2 is an example of the mobile edge array powered by self-organizing swarm intelligence after data are received. The 8×8 mobile edge array in Fig. 2 is a two-dimensional view of the fluid sensor network layer in Fig. 1. The position of each mobile edge device is mapped into a geographical coordinate — Latitude and longitude. At the initial stage, the topology of an array is a uniform formation. The perimeter of the array approximately covers the area of interest. When more requests are received, the topology of the array gradually updates itself according to the geographical distribution of EUs and the density of requests. The updating strategy follows steps 1–5 of the SOM algorithm.

The topology of the array reveals important clues for MANETs. 1) The distribution of mobile devices is based on the population of requests. When the density of the population is higher, more mobile devices focus on the area. This implies that more ad hoc nodes provide resources. 2) The communication load of each device is displayed on the hit map of the SOM. Hit maps collect the statistics of selected neurons after requests are input. 3) The edge of the topology shows the original communication path between connected mobile devices. Devices can identify neighbors by checking these edges. 4) The number of connected edges, or node degrees, indicates whether or not a mobile device is a boundary node. Identification of boundary nodes and nonboundary nodes is important when SOMs need expansion.

B. Incremental Self-Organizing Mobile Edge Array

The initial size and the shape of the topology usually follow default settings. When the area is larger than expected or when EU requests increase, the existing array may be incapable of offering sufficient resources. This is the reason why SOMs need expansion and why new mobile devices are required. Furthermore, EUs may relocate, and the perimeter could become boarder than that in the early phase. Although SOMs can update themselves to reflect relocation, a large perimeter lowers efficiency of communications.

Under such a circumstance, Growing Self-Organizing Maps (GSOMs) [13] are suitable for expansion of the mobile edge array. Unlike typical SOMs, the size of GSOMs can be dynamically expanded. This means new mobile devices can join an existing array and share communication loads. When resources are depleted, dispatch centers can send more mobile devices to a target zone of high population density. As long as the number of nodes in the map space increases, the topology of GSOMs can readjust itself. The target zone can be serviced by new mobile devices and their neighbors.

C. Incremental Hierarchical Self-Organizing Mobile Edge Array

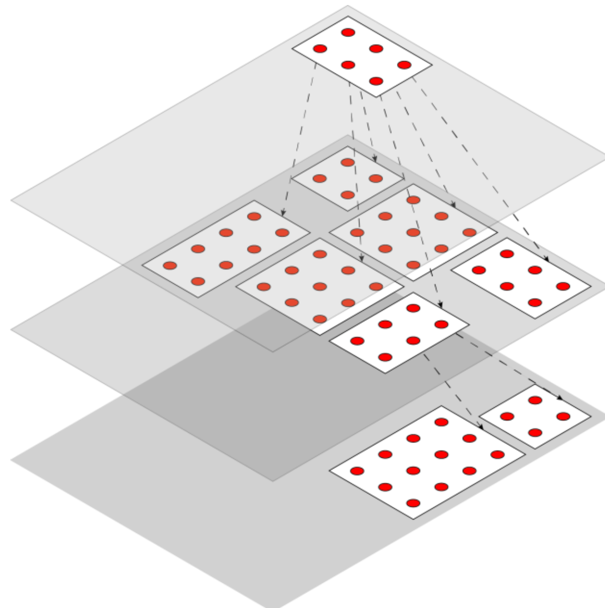

Fig. 3. Sectional drawing of 8×8 neurons based on Fig. 2 when Fig. 2 is presented in a hierarchical structure. White rectangles are GSOMs. Red circles represent neurons. Dashed lines indicate the relation between parent and child GSOMs. For a mobile edge array, the hierarchically structural view represents a logical formation, not a physical one.

In a typical SOM, there is no difference between one neuron and the other ones. Every neuron is equally treated in the same way. This means communications via a mobile edge array has the same priority, and various collected data are processed with the same scheme. Nonetheless, edge sensing could generate data with a variety of rate-distortion characteristics, such as high-definition photographs, acoustic signals, video streams, and environmental readings. This implies multimodal sensing may be blended with complex transmission requirements, e.g., multisources, multidestinations, multirates, and various time sensitivity, which make the system difficult to manage the network.

For such a problem, the Growing Hierarchical Self-Organizing Map (GHSOM) [13] is a feasible solution to heterogeneous sensing networks among MANETs. GHSOMs are variants of GSOMs, where the topology can be vertically and horizontally expanded. Fig. 3 shows that a typical edge array can own a hierarchical topology when different groups of edge devices need to be isolated. Fig. 2 is the top view, whereas Fig. 3 is a side view. The sizes of the both arrays are 8×8. In Fig. 3, each SOM (marked as a white rectangle) has the capability of growing nodes (denoted as red dots) automatically. Namely, each SOM is a GSOM. Besides, layers are automatically and gradually formed based on EU requests. The top layer is the initial layer. The lower layers are derived from the higher ones. Directed edges are used to indicate the relation between parent and child layers. The head, or the terminal vertex, with an arrow points at child layers, whereas the tail, or the initial vertex, represents source nodes from parent layers. Whether or not a node in the parent layer grows a child layer relies on the learning/adaptation phase. This means not every node in the parent layer points at a GSOM in a child layer. Furthermore, it is worth noting that an arrow points at a GSOM instead of a node. A layer without any child layer is a leaf layer.

Both the topology of each layer and each SOM can be dynamically expanded, depending on the learning/adaptation phase. In fact, GHSOMs can be viewed as nested GSOMs. The node of an outer GSOM can accommodate an inner GSOM. When a node in an outer GSOM has an inner GSOM inside, this node becomes a bridge. Communications across GSOMs or layers must go through bridges. With the hieratical structure of GHSOMs, MANETs can be divided into subnets to meet diverse purposes. When all the mobile devices in the same GSOM are responsible for the same type of data sensing or communications, they are homogeneous. If two separate GSOMs are homogeneous and derived from the same parent GSOM, the parent GSOM may become heterogeneous. In highly diverse heterogeneous MANETs, where homogeneous and heterogeneous GSOMs coexist, bridges are important. They can isolate heterogeneous subnets and control flows (e.g., prioritizing data streams). Based on this concept, the communication functionality of mobile edge arrays at least has two modes — Terminals and bridges. Terminals are for data harvesting. Bridges coordinate subnets and prioritize transmissions. Besides, bridges can also work as sink nodes for data pooling before collected data are transmitted to cloud centers.

In MANETs, security and privacy [14] are important topics, especially on terminal sides, where harvested data are exposed to entire networks. Protection can be done inside the hardware of individual devices by using obfuscation or encryption mechanisms. Sensitive data, e.g., user locations, can therefore be protected in hardware. This prevents information leakage in the software level before data are pooled in sink nodes and transmitted to clouds. Another challenge is self-organization since it requires intensive cloud computing to decide locations of deployment. Future advancement could rely on decentralized computing to accelerate calculation.

III. City Resiliency Management by Prediction and Planning

In the previous section, SOMs are used to determine the best location for deploying each edge device of a fluid array based on current crowds. However, crowds may appear in other regions in the future, and those regions, e.g., peripheral suburban/rural areas on the outskirt, may still contain insufficient information on crowds currently. This causes uncertainty. To resolve such a problem in advance, one of incomplete data analyses “Collaborative Filtering (CF)” is introduced herein to forecast crowds. Subsequently, predicted crowds can be fed back into SOMs in consideration of future deployment. A brief diagram of CF planning is presented in the top of Fig. 4. The detail is described as follows.

CF is a technique for missing-value imputation. Imputation means to fill in entries that contain missing values with approximate values. At present, CF has developed many approaches, such as item-based methods and matrix factorization. This article particularly concentrates on the category of matrix factorization, where nonnegative matrix factorization is examined, because it fits urban monitoring applications. When nonnegative matrix factorization works on matrices, it decomposes a matrix into two matrix factors, where elements are nonnegative. With criteria like Frobenius norm, nonnegative matrix factorization is capable of handling matrices with missing values. In urban planning, the layout of a city can be converted to a planar map. Based on this map, the entire city including suburban/rural regions can be divided into rectangular subregions. Each subregion may contain various partial statistics from urban sensing. Typically, one representative value is selected for a subregion. For crowd prediction, the process is the same as imputation. Given a grid view of a city map $\mathbf{X}$, nonnegative matrix factorization can decompose $\mathbf{X}$ into two factors $\mathbf{W}$ and $\mathbf{H}$, such that $\mathbf{X} \approx \mathbf{WH}$. At the initial stage, zeros are placed in those entries with missing values to enable arithmetic computation. Meanwhile, $\mathbf{W}$ and $\mathbf{H}$ are initialized with random nonnegative numbers. The imputation is based on minimizing Frobenius norm of errors, or equivalently the distance between $\mathbf{X}$ and $\mathbf{WH}$. To minimize errors, the decomposition employs an iterative process, consisting of two phases. One is element-wise computation of Frobenius errors, and the other is the element-wise gradient update of the two factors. Both phases disregard the entries with missing values and focus on complete ones. When the iteration converges, those missing values can be imputed by simply taking the product of $\mathbf{W}$ and $\mathbf{H}$.

With CF, city planners can evaluate and predict the statistics of new regions. Such data help city planners, for instance, determine whether or not a new base station should be built in a new region. To illustrate such a concept, this work uses Fig. 4 to show CF. For convenience, EU requests are employed as an example of crowd activities. Assume green and pale blue dots represent existing and predicted EU requests, respectively. CF aims for predicting pale blue dots by using green ones. Existing EU requests, or green dots, are collected from existing city blocks, surrounded by a red rectangle, i.e., $\mathbf{X}$. When a city expands, existing data $\mathbf{X}$ are used to predict new EU requests on the outskirts, encompassed by a larger purple border, i.e., $\mathbf{X}'$. For better visualization, an abstraction layer is placed at the top part of Fig. 4. The data within red/purple rectangles of the layer reflect the same data at the bottom of Fig. 4. In brief, city planners can estimate $\mathbf{X}'$ with the use of $\mathbf{X}$ when CF is applied. The predicted data are fed back into SOMs for autonomous topological formation.

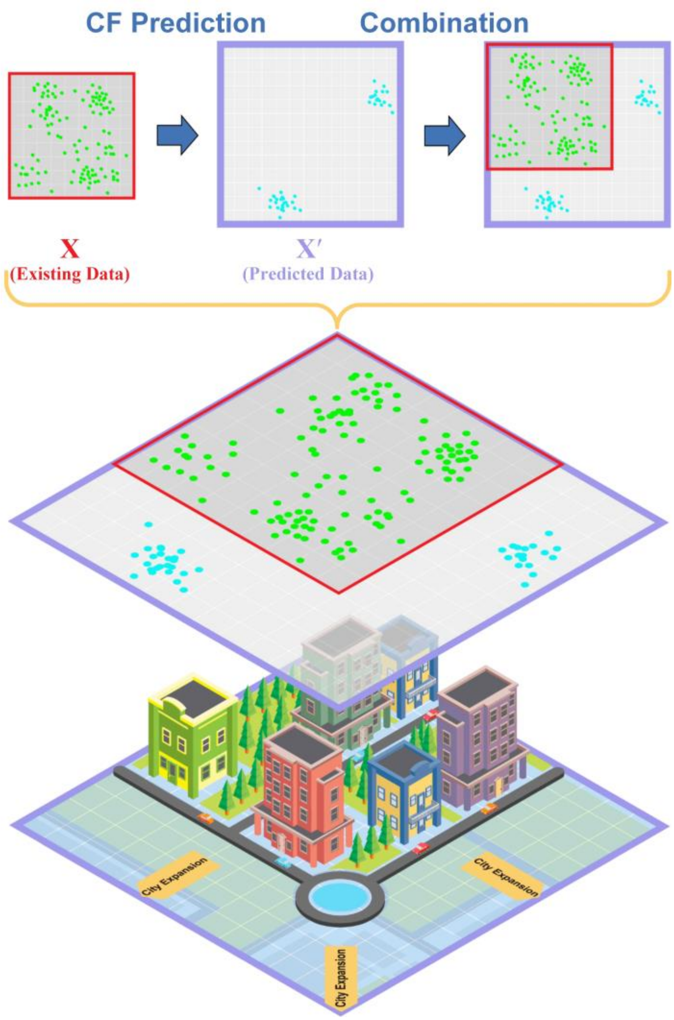

Fig. 4. Crowd prediction based on CF. Green and pale blue dots represent existing and predicted EU requests, respectively. CF uses green dots **X**, surrounded by a red rectangle, to predict pale blue ones **X′**, marked with purple.

After the prediction/analysis by CF, city planners can make arrangements in advance by subsequently examining SOM simulation results. For instance, assume CF predicts that more EU requests appear in the new region, marked with pale blue in Fig. 5. SOM simulations on such a new distribution can reveal the movement of existing mobile edge devices after the new EU requests are input. Fig. 5 shows that the lower cluster of the edge array slightly moves towards the new region to maintain an equilibrium. City planners can determine whether or not the new coverage satisfies the growing EU requests and make arrangements for resource allocation in advance.

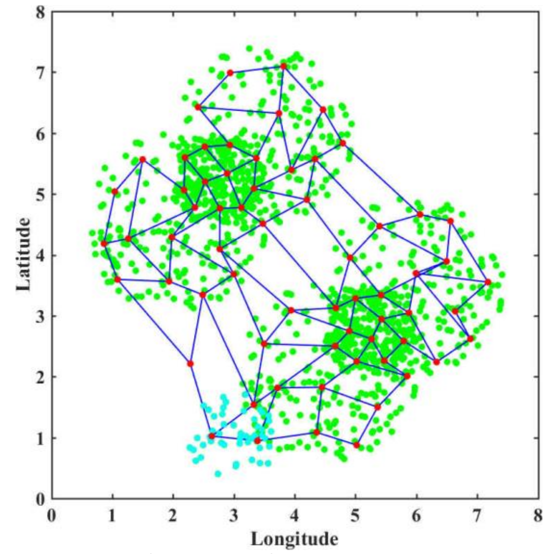

Fig. 5. Incremental self-adaptation of the proposed array to newly added EU requests (marked with pale blue) based on Fig. 2. These new data are predicted by CF. Fig. 5 uses the status of Fig. 2 as the initial topology for the same 8×8 array. When new data arrive, the topology in the vicinity of new data changes. Edge devices move towards the new zone where new EU requests are generated.

Although CF helps crowd prediction, the major challenge is that it needs sufficient observed data in an area when the system uses the area as the baseline evidence to predict new areas. This indicates if most of subregions in this area have no data, prediction errors increase. Another problem is that different types of statistics are separately predicted in CF. However, indicators could be interconnected and influenced by each other. Individual CF on independent variables does not reflect such a relation by describing weights. Future work could focus on coplanning by CF to model covariates [15].

IV. Experimental Result

Experiments for swarm intelligence-enabled fluid arrays and CF planning were conducted on open "Call Data Records (CDRs)" (dandelion.eu). For testing fluid arrays, 1000 records were extracted from the dataset, and their coordinates were used for modelling an array. The sizes of arrays included 2×2, 3×3,…, and 20×20. Statistics about service ranges and the number of serviced users for an edge device were computed. Fig. 6 displays the SOM results, where the vertical axes respectively represent "the average distance between a user and an edge device," "the average number of serviced users," and "adaptation time." The horizontal axis denotes "the size of the array." Standard deviation is denoted as "I" shapes, whereas circles represent means. As shown in Fig. 6, when array sizes became larger, each device was closer to users and serviced a balanced number of users.

For CF, the same CDRs were used, but their coordinates were normalized. The entire geographic area covering all the CDRs was divided into 10×10–20×20 subregions. Thus, each subregion contained partial CDRs. This was the ground truth. To test CF, the experiment randomly selected 10%–30% of the subregions. During selection, the CDRs inside the selected subregions were removed and became zero. The system then employed CF to predict CDRs in those empty subregions and compared predicted values with the ground truth. Experimental results indicated when the number of CDRs was fixed, more subregions enhanced prediction accuracy. Root-mean-squared errors of prediction were decreased from 2.814 to 0.782 when the number of subregions was increased from 10^2 to 20^2 with 30% of the subregions containing removed CDRs.

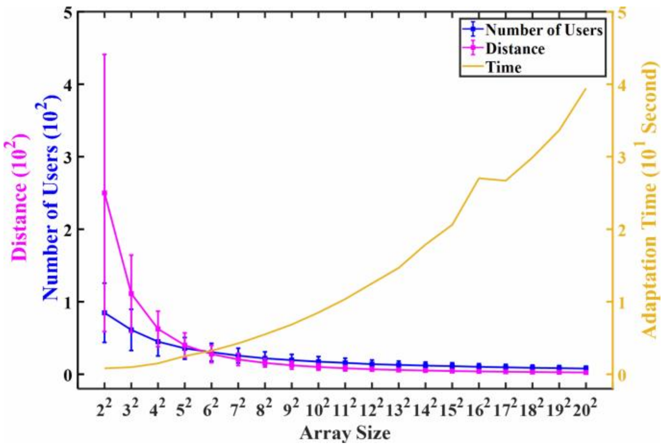

Fig. 6. Performance the swarm intelligence-enabled fluid array.

V. Conclusion

This article presents an urban self-reasoning model — How knowledge of city dynamics can be adaptively collected and used for planning. The former relies on swarm intelligence, where a fluid mobile edge array is adopted for self-organizing sensing. The latter utilizes collected data and context-aware CF for resource/crowd prediction during city expansion. The prediction can be fed back to the swarm intelligence model for validating the future influence on resource balance after resource allocation is made. Two methods resonate and iterate to discover solutions. Such an urban self-reasoning model can benefit both city planners and business operators in strategic making.

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B.-W. Chen (M'14–SM'17) is with the Department of Electrical Engineering, National Sun Yat-Sen University, Taiwan. His research interests include data analytics, machine learning, and sensor networks.

M. Imran is with the College of Applied Computer Science, King Saud University, Saudi Arabia. His research interest includes mobile wireless networks, the Internet of Things, and software-defined networking.

N. Nasser is with the College of Engineering, Alfaisal University, Saudi Arabia.

M. Shoaib is with the College of Computer and Information Sciences, King Saud University, Saudi Arabia.