electronics

MDPI

Article

Synergism of Fuzzy Leaky Bucket with Virtual Buffer for Large Scale Social Driven Energy Allocation in Emergencies in Smart City Zones

Miltiadis Alamaniotis [1,*] and Michail Alexiou [2]

[1] Department of Electrical and Computer Engineering, University of Texas at San Antonio, San Antonio, TX 78249, USA
[2] Department of Computer Science, Kennesaw State University, Marietta, GA 30060, USA; malexiou@kennesaw.edu
* Correspondence: miltos.alamaniotis@utsa.edu

Abstract: Smart cities can be viewed as expansive systems that optimize operational quality and deliver a range of services, particularly in the realm of energy management. Identifying energy zones within smart cities marks an initial step towards ensuring equitable energy distribution driven by factors beyond energy considerations. This study introduces a socially oriented methodology for energy allocation during emergencies, implemented at the zone level to address justice concerns. The proposed method integrates a fuzzy leaky bucket model with an energy virtual buffer, leveraging extensive data from diverse city zones to allocate energy resources during emergent situations. By employing fuzzy sets and rules, the leaky bucket mechanism distributes buffered energy to zones, aiming to maximize energy utilization while promoting social justice principles. Evaluation of the approach utilizes consumption data from simulated smart city zones during energy-constrained emergencies, comparing it against a uniform allocation method. Results demonstrate the socially equitable allocation facilitated by the proposed methodology.

Keywords: fuzzy logic; leaky bucket; smart city; city zones; energy allocation; emergencies

check for updates

Citation: Alamaniotis, M.; Alexiou, M. Synergism of Fuzzy Leaky Bucket with Virtual Buffer for Large Scale Social Driven Energy Allocation in Emergencies in Smart City Zones. *Electronics* **2024**, *13*, 762. https://doi.org/10.3390/electronics13040762

Academic Editor: Ouri E. Wolfson

Received: 21 November 2023
Revised: 10 February 2024
Accepted: 11 February 2024
Published: 14 February 2024

Copyright: © 2024 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).

1. Introduction

The progress in information and communication technologies has facilitated the rise and conceptualization of smart cities systems. Within smart cities, cyber and physical infrastructures coalesce and engage in mutual interaction, aiming to optimize the utilization of physical resources through data and information [1]. The implementation of a smart city embodies significant complexity due to the intricate interplay among diverse infrastructures, including but not limited to energy, transportation, and lighting [2].

Significantly, the energy infrastructure, particularly the electrical grid, stands as the cornerstone of a smart city, as the entire digital framework relies on electricity consumption [3]. Consequently, it can be argued that the functionality of a smart city hinges on the seamless flow of electricity throughout its premises. The integration of electrical grids with information technologies has birthed the concept of smart grids, which serves as the foundational technology for the development of smart cities. Citizens, who are also consumers, interface with the grid through smart meters equipped with intelligent algorithms designed to act in their best interests [4]. Through digital connectivity facilitated by communication networks, smart meters employ algorithms to make optimal purchasing decisions based on real-time data. Given the scale and population density of cities, coupled with the proliferation of smart meters and digital systems, a vast amount of data is generated within the smart city ecosystem [5]. Consequently, the concept of big data and its subsequent processing become integral components of smart city operations.

Efforts to promote efficient electricity consumption have facilitated the division of urban areas into distinct electricity zones, as noted in [6]. These zones bear resemblance to microgrids, as they may house their own generation sources, such as renewables, alongside their consumer base [7]. Generally, when a zone integrates generation units, it is advisable to prioritize the allocation of generated electricity to local consumers. Consuming electricity locally offers the advantage of optimizing grid usage, as power lines are not tasked with transmitting electrical energy over long distances. This effectively reduces the strain on the grid, lowering the risk of blackouts and overloads [8].

The Texas outage case of 2021 [9] provided us several lessons with regard to the management of energy resources, while also raising concerns about the most efficient strategy for allocating available energy during emergencies. Particularly, utilities are faced with difficult decisions during such crises regarding where and for how long to allocate the limited electrical power to meet citizens' needs to the greatest extent possible. One approach often taken is to implement scheduled power outages in specific city zones for a predetermined period, resulting in certain zones having access to power while others do not. This challenge becomes especially daunting when dealing with large-scale and densely populated cities.

In this context, the fundamental question under scrutiny is how to allocate available electrical power within the various areas (zones) of a city in a manner that is efficient for the grid while also fostering a feeling of justice to the citizens [10]. The management of electricity at the zone level is still in its infancy, although there are ongoing efforts primarily leveraging artificial intelligence. In summary, the existing efforts [11–16] indicate a limited exploration of zone-based allocation in smart cities, particularly concerning emergency scenarios. Furthermore, none of the proposed methods thus far consider social factors as part of their decision-making process, thereby failing to provide a sense of "allocation justice" to the affected citizens.

The present paper addresses this gap by introducing a novel method that leverages artificial intelligence to develop a zone-based, socially driven allocation strategy for emergency electricity supply in smart cities. The proposed approach integrates a synergistic framework encompassing the concept of the leaky bucket [17], employing tools of fuzzy logic [18], and incorporating the concept of energy virtual buffer [19]. By employing fuzzy inference, the proposed method enables the representation of information in the form of fuzzy sets, which in turn facilitates rapid computation at a low cost. The utilization of fuzzy sets accommodates the representation of large data streams using simple functions, while fuzzy rules implicitly support decision-making based on various factors, such as electricity signals and social considerations [20].

The roadmap of this manuscript is as follows: In the next section, the concept and relater work on smart city zones is introduced, while the proposed approach is presented and discussed in Section 3. In Section 4, the fuzzy leaky bucket approach is applied for allocation of electricity in a simulated smart city and the results are discussed, while in Section 5 the main points of the paper are summarized.

2. Related Work on Smart City Zones

The vision of smart cities entails the efficient integration and interplay of data and physical infrastructure in such a way that data are utilized to efficiently operate the physical infrastructure. However, this integration will require the use of thousands of sensors and computing devices that will generate big volumes of data with high velocity. Thus, from a computing point of view smart cities may be characterized as informational and data rich environments.

In such an environment, the services offered within the city take the form of digital services. Furthermore, the integration of digital services with artificial intelligence data analytics and decision-making routines has fully transformed the services into smart services.

Smart energy stands out as a crucial component among the array of smart services in digital cities. It can be succinctly asserted that without efficient energy management,

the provision of other services to citizens may be compromised, considering the reliance of digital services on electricity. In essence, smart energy emerges as a primary pillar in the realization of a smart city environment [21], serving as the foundation for ensuring the continuous availability of digital services to citizens on a 24/7 basis.

Just as physical cities are divided into neighborhoods, a smart city can also be segmented into multiple zones (or partitions) that exhibit common characteristics [22]. Moreover, citizens within these zones can share common objectives and collaborate to optimize the utilization of available services, including energy-related services [23]. Additionally, dividing smart cities into zones enables the provision of specialized services tailored to the specific needs of each zone. The concept of smart city zones was first introduced in [24] as a means to effectively manage electricity consumption in smart cities, as illustrated in Figure 1.

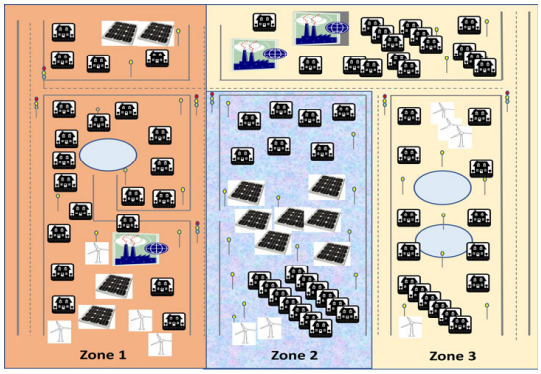


Figure 1. Visualization of Smart City zones (zone has consumers and generators).

It should be noted that that the partitioning of a smart city into zones can be approached in diverse ways, influenced by various factors. Consequently, there is no singular method for determining zones. In [11], a novel method called "morphing to the mean" is introduced, wherein the zone's consumption is optimized using genetic algorithms to maintain a mean value, while [12] utilizes genetic algorithms to optimize consumption within a zone while addressing privacy concerns. Similarly, genetic algorithms, in conjunction with citizen self-elasticities, are employed as presented in [13]. Moving forward, data analytics tools are proposed in [14] to identify zones in smart cities with low carbon emissions. Moreover, [15] discusses a decision support framework focusing on assessing the energy efficiency of buildings in smart cities, while [16] introduces the virtual cost approach for individual energy portfolio citizens. In [25], the partition into zones is based on the concept of microgrids and by utilizing the quantum annealing method. Likewise, a partition of smart grid into islanded areas is proposed in [26], where the partition routine employs graph convolution networks. In a different approach, authors in [27] proposed the development of virtual microgrids as a way to obtain energy partitions directed by renewable energy criteria, while in [28] portioning is driven by optimizing energy storage using genetic algorithms. Partitioning methods based on clustering of distributed generation sources are introduced in [29] and [30] respectively, while a partitioning method based on the synergism of distributed power sources with microgrid forming is presented in [31]. In [32], power grid partitioning into zones by considering as criterion the amount of reactive power. Going further other methods for power and energy driven portioning entail the use of restoration models [33], and the utilization of a shared centralized storage [34].

In the current study, the delineation of city zones is predicated on electricity-related criteria, as outlined in [35]. Significantly, the process of determining zones in smart cities facilitates the introduction of specialized and customized services tailored to specific zones [6,35].

3. Socially Driven Energy Allocation Approach

This section outlines the proposed approach for allocating electrical energy during emergencies within the zones of a smart city. The approach entails making decisions regarding the quantity of energy to be supplied to each specific zone.

3.1. Problem Statement

Emergency scenarios such as heavy snowfall or extensive rainfall can pose significant challenges to electrical systems and, consequently, to the overall energy supply of a city. Among the most common issues encountered in such situations is the grid's inability to meet the full demand of consumers. This shortfall may arise from either an exceptionally high demand exceeding the capacity of generated electricity or technical difficulties impairing the grid's delivery capacity. These challenges are particularly prevalent in densely populated areas, such as large metropolitan cities.

Up to this point, utilities typically address the aforementioned challenge by implementing selective shutdowns of electricity supply to various areas within the city, which entails providing a uniform supply of energy per area. These shutdowns remain in effect for a predetermined duration, after which electricity flow is restored. However, simultaneously, shutdowns occur in zones located in other areas of the city. It's important to note that critical facilities such as hospitals and universities are exempt from these shutdowns unless there is a complete grid failure. However, the strategy of employing uniform shutdowns described above often leads to a sense of injustice among citizens, particularly those from lower social strata who lack access to modern generation technologies. This sense of injustice is heightened within the context of smart cities.

3.2. Leaky Bucket

The leaky bucket is an algorithm that has been successfully applied to several engineering domains aiming at controlling a process. Its main concept comes from the everyday life and more specifically from leaking water filled buckets. The algorithm is driven by the simple idea that the bucket may overflow when the leakage rate is lower than the incoming water rate. The algorithmic leaky bucket aims at limiting the actions associated with occurred events (in most cases discrete ones). Well-known applications of the leaky bucket entail controlling of the data packet transmission in communication networks [36], and the flow in service networks [37].

Figure 2 presents a graphical representation of the leaky bucket algorithm. We observe that the bucket takes one of the two states: (i) *overflown* state when the incoming flow rate (F) is higher than the leakage (L), i.e., $F > L$, and (ii) *non-flown* state when the leakage (L) is higher than the incoming flow, i.e., $F < L$.

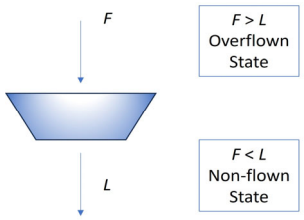


Figure 2. Visualization of a leaky bucket and its states, s, where F and L denote the incoming and outcoming flow respectively.

An alternative rendition of the leaky bucket is the token-driven leaky bucket, primarily employed to regulate the rate of leakage from the bucket. The block diagram of this version is depicted in Figure 3. The fundamental concept revolves around two buffers: the data buffer and the token buffer. The data buffer receives input data packets, while the token buffer receives tokens. A data packet is released from the buffer only if the number of buffered tokens surpasses a predefined threshold. Importantly, the threshold is determined by the modeler based on the requirements of the specific application in question.

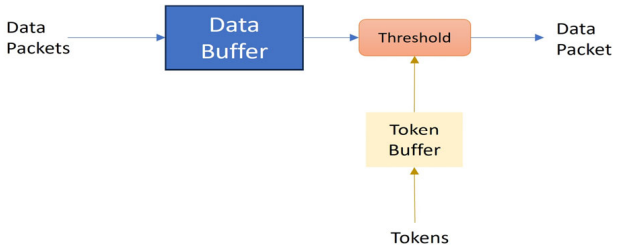


Figure 3. Token Driven Leaky Bucket approach.

The token driven algorithm allows the control of data release from the buffer. The higher the threshold (T), the higher the number of tokens that need to arrive before a data packet is released.

3.3. Fuzzy Leaky Bucket and Energy Virtual Buffer

In this section, we introduce the proposed fuzzy leaky bucket algorithm designed to allocate the available energy—significantly reduced compared to normal conditions—during emergencies. The primary objective of the algorithm is to ensure a fair distribution of the limited energy supply during emergencies, wherein the capacity of the electricity grid is constrained by non-normal conditions. The algorithm aims to determine the amount of energy allocated to each city zone. To achieve this, we propose a token-driven fuzzy leaky bucket algorithm that incorporates social factors into the token definition process. By doing so, the algorithm promotes a sense of justice in the allocation of energy during emergencies.

The block diagram illustrating the fuzzy leaky bucket algorithm for energy allocation is provided in Figure 4. It's important to note that this method involves the utilization of a fuzzy logic inference system to determine the number of tokens in the leaky bucket, consequently influencing the release of energy from the buffer. Another innovative aspect is the introduction of energy packets, which integrate with the concept of the virtual buffer [38]. The term "energy virtual buffer" refers to the data structure that "virtually stores" energy amounts. This data structure is crucial since energy is a commodity that must be consumed in real time and cannot be stored on a large scale [39,40].

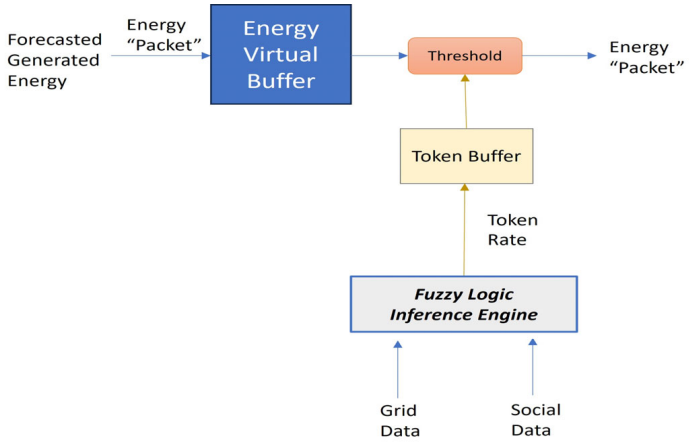


Figure 4. Synergistic approach of the fuzzy leaky bucket with energy virtual buffer for energy allocation.

Central to executing the energy allocation process is the availability of knowledge, typically obtained through forecasting, regarding the generated energy, and its structuring into "packets" [41,42]. It's important to highlight that in practical terms, energy cannot be physically divided into packets. However, since this division is forecasted data—representing energy that has not yet been generated but is scheduled—artificially splitting it into packets

becomes feasible [43,44]. The objective of the fuzzy leaky bucket algorithm is to allocate an appropriate number of energy packets stored in the virtual buffer to the respective zones. This proves invaluable during emergencies, where the unique conditions necessitate special handling of energy allocation.

The cornerstone of the proposed bucket type lies in the creation of a fuzzy inference engine. The architecture of the engine, including all input and output variables, is depicted in Figure 5. Notably, the fuzzy inference system comprises four socially related variables and two energy variables. The input variables associated with the zone are as follows:

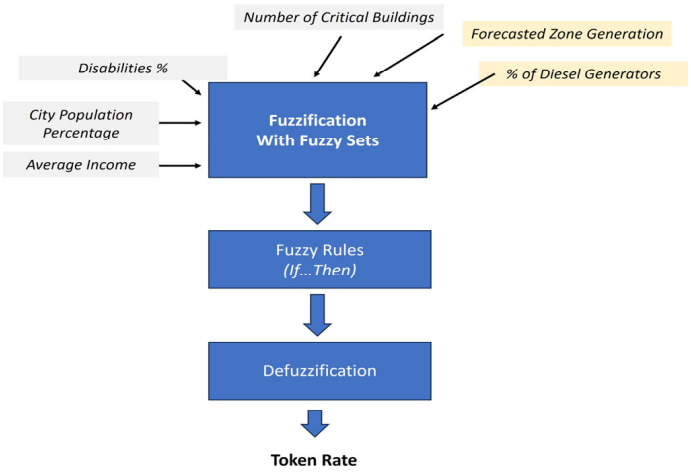


Figure 5. Fuzzy Inference System for token rate determination.

1. Average Income (Social): This social variable reflects the average wealth of the zone's citizens. It helps gauge the economic status of a zone, with "non-wealthy" zones potentially requiring more energy compared to affluent zones, which may rely on individual generators like diesel generators.
2. City Population Percentage (Social): This variable indicates the percentage population density of the zone as the ratio of zone's population residing within the geographical area of the zone.
3. Disability Percentage (Social): This variable represents the percentage of the zone's population officially registered as disabled. It supports zones with citizens with declared disabilities, considering their vulnerability and potential need for energy to operate essential equipment and instruments.
4. Number of Critical Buildings (Social): This variable denotes the count of critical buildings within the zone. Critical buildings may include hospitals, airports, and schools, among others.
5. Zone Forecasted Generation (Energy): This variable signifies the forecasted generation within the zone from its resources, such as renewables.
6. Percentage of Diesel Generators (Energy): This variable indicates the percentage of zone residents who possess secondary electricity generation using diesel generators. Diesel generators can serve as auxiliary suppliers, operating independently of the main power grid or microgrid.
7. Token Number (Output Variable): This variable represents the token number determined by the fuzzy system.

As illustrated in Figure 5, the aforementioned variables are transformed into fuzzy variables through fuzzification, with each variable depicted in Figure 6 as fuzzy sets. It's important to note that fuzzy sets enable the expression and large-scale representation of multiple values within the variables using simple linguistic terms [45–48]. Furthermore, fuzzy logic facilitates the fusion of fuzzy variables into a single output, which takes the form of token numbers in this manuscript. Selection of the type of the fuzzy sets, which take

the form of triangles, is based on past experience of the modelers; furthermore, triangular fuzzy sets is a common choice in fuzzy inference systems.

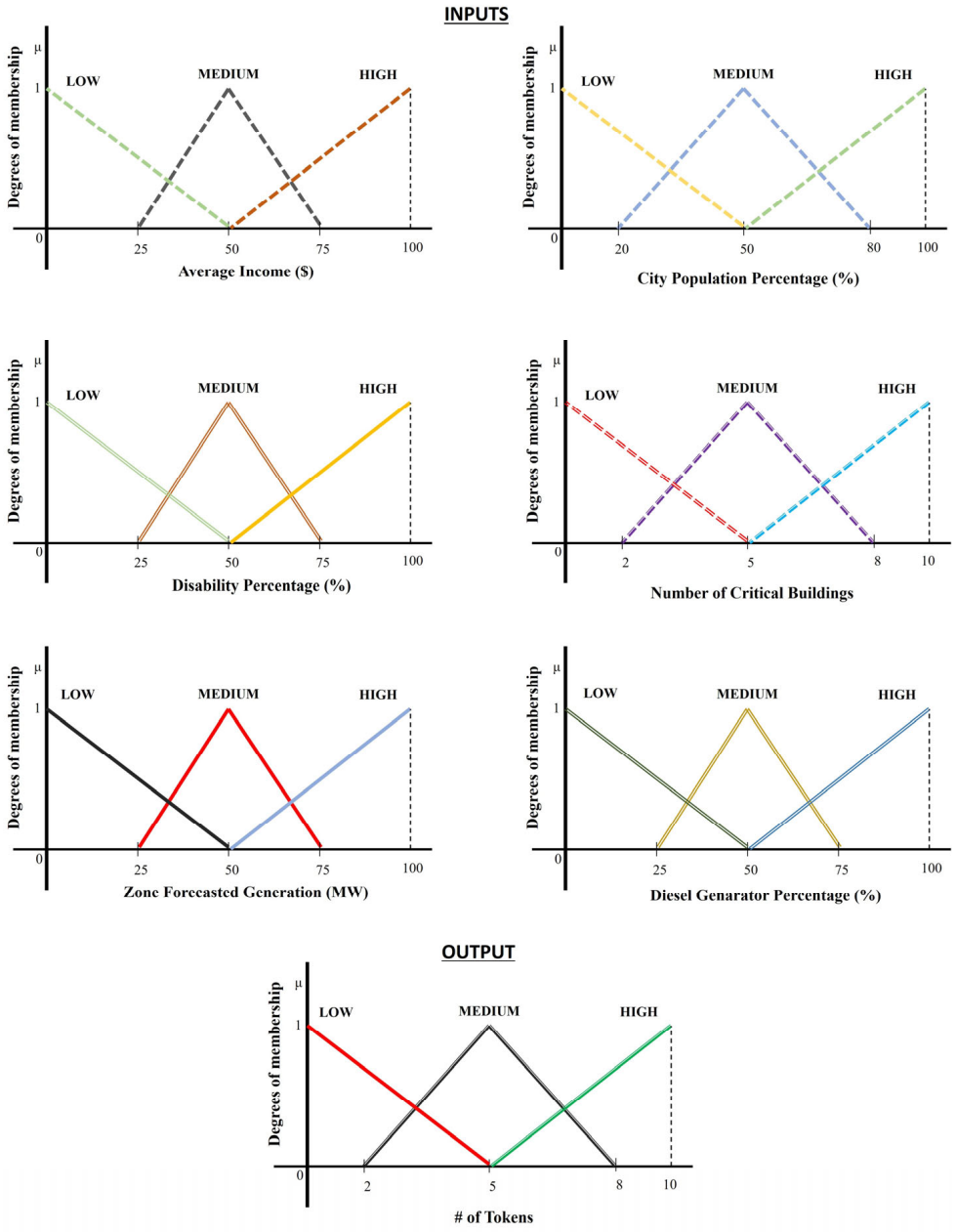


Figure 6. Fuzzy Sets for fuzzification of input and output variables.

In our study, information fusion is achieved through a set of 62 fuzzy rules that correlate social and energy inputs to the number of tokens. The fuzzy rules, presented in Table 1, encapsulate the variables 1-7, succinctly denoted as (in Table 1):

- "Income," refers to Average Income (Social)
- "Population," refers to City Population Percentage (Social)
- "Disability," refers to Disability Percentage (Social)
- "Building," refers to Number of Critical Buildings (Social)
- "Forecast," refers to Zone Forecasted Generation (Energy)
- "Diesel," refers to Percentage of Diesel Generators (Energy)
- "Tokens" refers to Token Number (Output Variable)

Table 1. Fuzzy Inference Rules for determining the number of tokens.

1.	'IF Income is LOW AND Population is LOW AND Disability is LOW AND Building is LOW AND Forecast is LOW AND Diesel is LOW THEN Tokens is LOW'
2.	'IF Income is LOW AND Population is MEDIUM AND Disability is MEDIUM AND Building is LOW AND Forecast is LOW AND Diesel is LOW THEN Tokens is MEDIUM'
3.	'IF Income is LOW AND Population is MEDIUM AND Disability is MEDIUM AND Building is MEDIUM AND Forecast is LOW AND Diesel is LOW THEN Tokens is MEDIUM'
4.	'IF Income is LOW AND Population is MEDIUM AND Disability is MEDIUM AND Building is MEDIUM AND Forecast is MEDIUM AND Diesel is LOW THEN Tokens is MEDIUM'
5.	'IF Income is LOW AND Population is MEDIUM AND Disability is MEDIUM AND Building is MEDIUM AND Forecast is HIGH AND Diesel is LOW THEN Tokens is HIGH'
6.	'IF Income is LOW AND Population is MEDIUM AND Disability is MEDIUM AND Building is MEDIUM AND Forecast is MEDIUM AND Diesel is MEDIUM THEN Tokens is MEDIUM'
7.	'IF Income is LOW AND Population is MEDIUM AND Disability is MEDIUM AND Building is MEDIUM AND Forecast is HIGH AND Diesel is MEDIUM THEN Tokens is MEDIUM'
8.	'IF Income is LOW AND Population is MEDIUM AND Disability is MEDIUM AND Building is MEDIUM AND Forecast is HIGH AND Diesel is MEDIUM THEN Tokens is LOW'
9.	'IF Income is LOW AND Population is MEDIUM AND Disability is MEDIUM AND Building is MEDIUM AND Forecast is HIGH AND Diesel is LOW THEN Tokens is HIGH'
10.	'IF Income is LOW AND Population is MEDIUM AND Disability is MEDIUM AND Building is HIGH AND Forecast is HIGH AND Diesel is LOW THEN Tokens is HIGH'
11.	'IF Income is LOW AND Population is MEDIUM AND Disability is MEDIUM AND Building is HIGH AND Forecast is HIGH AND Diesel is MEDIUM THEN Tokens is HIGH'
12.	'IF Income is LOW AND Population is MEDIUM AND Disability is MEDIUM AND Building is HIGH AND Forecast is HIGH AND Diesel is HIGH THEN Tokens is MEDIUM'
13.	'IF Income is LOW AND Population is HIGH AND Disability is LOW AND Building is MEDIUM AND Forecast is LOW AND Diesel is LOW THEN Tokens is MEDIUM'
14.	'IF Income is LOW AND Population is HIGH AND Disability is LOW AND Building is MEDIUM AND Forecast is MEDIUM AND Diesel is LOW THEN Tokens is MEDIUM'
15.	'IF Income is LOW AND Population is HIGH AND Disability is LOW AND Building is MEDIUM AND Forecast is HIGH AND Diesel is LOW THEN Tokens is HIGH'
16.	'IF Income is LOW AND Population is HIGH AND Disability is LOW AND Building is MEDIUM AND Forecast is HIGH AND Diesel is MEDIUM THEN Tokens is MEDIUM'
17.	'IF Income is LOW AND Population is HIGH AND Disability is LOW AND Building is MEDIUM AND Forecast is HIGH AND Diesel is HIGH THEN Tokens is LOW'
18.	'IF Income is LOW AND Population is HIGH AND Disability is LOW AND Building is HIGH AND Forecast is HIGH AND Diesel is HIGH THEN Tokens is MEDIUM'
19.	'IF Income is LOW AND Population is HIGH AND Disability is LOW AND Building is HIGH AND Forecast is HIGH AND Diesel is MEDIUM THEN Tokens is HIGH'
20.	'IF Income is LOW AND Population is HIGH AND Disability is LOW AND Building is HIGH AND Forecast is HIGH AND Diesel is LOW THEN Tokens is HIGH'
21.	'IF Income is MEDIUM AND Population is LOW AND Disability is LOW AND Building is LOW AND Forecast is LOW AND Diesel is LOW THEN Tokens is LOW'
22.	'IF Income is MEDIUM AND Population is LOW AND Disability is LOW AND Building is MEDIUM AND Forecast is LOW AND Diesel is LOW THEN Tokens is LOW'
23.	'IF Income is MEDIUM AND Population is LOW AND Disability is LOW AND Building is MEDIUM AND Forecast is MEDIUM AND Diesel is LOW THEN Tokens is MEDIUM'
24.	'IF Income is MEDIUM AND Population is LOW AND Disability is LOW AND Building is MEDIUM AND Forecast is MEDIUM AND Diesel is MEDIUM THEN Tokens is LOW'
25.	'IF Income is MEDIUM AND Population is LOW AND Disability is LOW AND Building is MEDIUM AND Forecast is MEDIUM AND Diesel is HIGH THEN Tokens is LOW'
26.	'IF Income is MEDIUM AND Population is LOW AND Disability is LOW AND Building is MEDIUM AND Forecast is HIGH AND Diesel is HIGH THEN Tokens is MEDIUM'

Table 1. *Cont.*

27.	'IF Income is MEDIUM AND Population is LOW AND Disability is LOW AND Building is HIGH AND Forecast is HIGH AND Diesel is HIGH THEN Tokens is MEDIUM'
28.	'IF Income is MEDIUM AND Population is LOW AND Disability is MEDIUM AND Building is HIGH AND Forecast is HIGH AND Diesel is HIGH THEN Tokens is MEDIUM'
29.	'IF Income is MEDIUM AND Population is LOW AND Disability is HIGH AND Building is HIGH AND Forecast is HIGH AND Diesel is HIGH THEN Tokens is HIGH'
30.	'IF Income is MEDIUM AND Population is MEDIUM AND Disability is HIGH AND Building is HIGH AND Forecast is HIGH AND Diesel is HIGH THEN Tokens is HIGH'
31.	'IF Income is MEDIUM AND Population is HIGH AND Disability is HIGH AND Building is HIGH AND Forecast is HIGH AND Diesel is HIGH THEN Tokens is MEDIUM'
32.	'IF Income is HIGH AND Population is LOW AND Disability is LOW AND Building is LOW AND Forecast is LOW AND Diesel is HIGH THEN Tokens is LOW'
33.	'IF Income is HIGH AND Population is LOW AND Disability is LOW AND Building is MEDIUM AND Forecast is LOW AND Diesel is HIGH THEN Tokens is LOW'
34.	'IF Income is HIGH AND Population is LOW AND Disability is LOW AND Building is LOW AND Forecast is MEDIUM AND Diesel is HIGH THEN Tokens is LOW'
35.	'IF Income is HIGH AND Population is LOW AND Disability is LOW AND Building is HIGH AND Forecast is MEDIUM AND Diesel is HIGH THEN Tokens is LOW'
36.	'IF Income is HIGH AND Population is LOW AND Disability is LOW AND Building is HIGH AND Forecast is MEDIUM AND Diesel is MEDIUM THEN Tokens is LOW'
37.	'IF Income is HIGH AND Population is LOW AND Disability is LOW AND Building is HIGH AND Forecast is MEDIUM AND Diesel is LOW THEN Tokens is LOW'
38.	'IF Income is HIGH AND Population is LOW AND Disability is LOW AND Building is MEDIUM AND Forecast is MEDIUM AND Diesel is LOW THEN Tokens is LOW'
39.	'IF Income is HIGH AND Population is LOW AND Disability is LOW AND Building is MEDIUM AND Forecast is HIGH AND Diesel is LOW THEN Tokens is MEDIUM'
40.	'IF Income is HIGH AND Population is LOW AND Disability is MEDIUM AND Building is MEDIUM AND Forecast is HIGH AND Diesel is LOW THEN Tokens is MEDIUM'
41.	'IF Income is HIGH AND Population is LOW AND Disability is HIGH AND Building is MEDIUM AND Forecast is HIGH AND Diesel is LOW THEN Tokens is MEDIUM'
42.	'IF Income is HIGH AND Population is MEDIUM AND Disability is HIGH AND Building is MEDIUM AND Forecast is HIGH AND Diesel is LOW THEN Tokens is MEDIUM'
43.	'IF Income is HIGH AND Population is MEDIUM AND Disability is HIGH AND Building is MEDIUM AND Forecast is MEDIUM AND Diesel is LOW THEN Tokens is LOW'
44.	'IF Income is HIGH AND Population is MEDIUM AND Disability is HIGH AND Building is MEDIUM AND Forecast is LOW AND Diesel is LOW THEN Tokens is LOW'
45.	'IF Income is HIGH AND Population is HIGH AND Disability is LOW AND Building is MEDIUM AND Forecast is LOW AND Diesel is LOW THEN Tokens is LOW'
46.	'IF Income is HIGH AND Population is HIGH AND Disability is MEDIUM AND Building is MEDIUM AND Forecast is LOW AND Diesel is LOW THEN Tokens is LOW'
47.	'IF Income is HIGH AND Population is HIGH AND Disability is HIGH AND Building is MEDIUM AND Forecast is LOW AND Diesel is LOW THEN Tokens is LOW'
48.	'IF Income is HIGH AND Population is HIGH AND Disability is MEDIUM AND Building is LOW AND Forecast is LOW AND Diesel is LOW THEN Tokens is LOW'
49.	'IF Income is HIGH AND Population is HIGH AND Disability is MEDIUM AND Building is HIGH AND Forecast is LOW AND Diesel is LOW THEN Tokens is MEDIUM'
50.	'IF Income is HIGH AND Population is HIGH AND Disability is MEDIUM AND Building is HIGH AND Forecast is MEDIUM AND Diesel is LOW THEN Tokens is MEDIUM'
51.	'IF Income is HIGH AND Population is HIGH AND Disability is MEDIUM AND Building is HIGH AND Forecast is HIGH AND Diesel is LOW THEN Tokens is MEDIUM'
52.	'IF Income is HIGH AND Population is HIGH AND Disability is MEDIUM AND Building is HIGH AND Forecast is HIGH AND Diesel is MEDIUM THEN Tokens is MEDIUM'

Table 1. *Cont.*

53.	'IF Income is HIGH AND Population is HIGH AND Disability is MEDIUM AND Building is HIGH AND Forecast is HIGH AND Diesel is HIGH THEN Tokens is LOW'
54.	'IF Income is HIGH AND Population is HIGH AND Disability is MEDIUM AND Building is MEDIUM AND Forecast is HIGH AND Diesel is HIGH THEN Tokens is LOW'
55.	'IF Income is HIGH AND Population is HIGH AND Disability is HIGH AND Building is HIGH AND Forecast is HIGH AND Diesel is HIGH THEN Tokens is LOW'
56.	'IF Income is HIGH AND Population is HIGH AND Disability is HIGH AND Building is MEDIUM AND Forecast is HIGH AND Diesel is HIGH THEN Tokens is LOW'
57.	'IF Income is HIGH AND Population is HIGH AND Disability is HIGH AND Building is LOW AND Forecast is HIGH AND Diesel is HIGH THEN Tokens is LOW'
58.	'IF Income is HIGH AND Population is MEDIUM AND Disability is HIGH AND Building is LOW AND Forecast is HIGH AND Diesel is HIGH THEN Tokens is LOW'
59.	'IF Income is HIGH AND Population is MEDIUM AND Disability is HIGH AND Building is LOW AND Forecast is LOW AND Diesel is HIGH THEN Tokens is LOW'
60.	'IF Income is HIGH AND Population is MEDIUM AND Disability is HIGH AND Building is LOW AND Forecast is MEDIUM AND Diesel is HIGH THEN Tokens is LOW'
61.	'IF Income is LOW AND Population is HIGH THEN Tokens is HIGH'
62.	'IF Income is LOW AND Population is HIGH AND Disability is HIGH AND Building is HIGH THEN Tokens is HIGH'

To enhance clarity in the decision-making process, we have outlined the steps for obtaining the final token number in Figure 7.

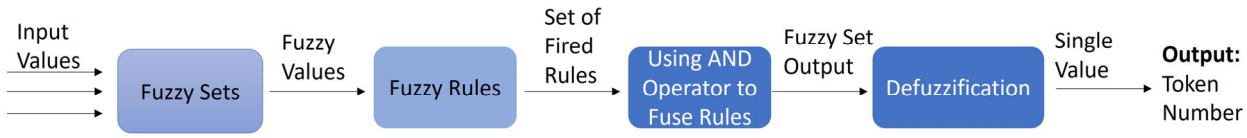


Figure 7. Block diagram of the token evaluation process.

The fuzzy leaky bucket is employed synergistically with a First-in-First-out (FiFo) queue [49] to allocate energy packets to the zones. The zones are placed in the queue and await the fuzzy leaky bucket to provide the number of tokens for a specific cycle. Subsequently, the number of generated tokens is compared with the bucket's threshold T. If the number of tokens exceeds the threshold, the energy packet is released [50]. This mechanism ensures an orderly and efficient allocation of energy packets based on the fuzzy logic-driven token determination process.

At this point, it's essential to emphasize that the virtual buffer holds the entire available energy for the upcoming hour. However, it's crucial to understand that the buffered energy is constrained due to emergency conditions, significantly less compared to what would be available under normal circumstances (where socially fair allocation is not necessary) [51–54]. In summary, the allocation process unfolds through the following steps:

1. The available energy for the next hour is placed in the virtual buffer.
2. Zones are organized in a first-in-first-out (FIFO) structure, with the sequence of zones selected randomly.
3. The available buffered energy is divided into a set of energy packets, with the number of packets determined by the system operator.
4. The fuzzy leaky bucket is invoked, and the number of tokens is obtained for the first zone in the FIFO.
5. The number of tokens is compared with a predetermined threshold T.
6. If the number of tokens is below the threshold, no energy packet is released.
7. If the number of tokens is above the threshold, one energy packet is released.
8. If the number of tokens is above 2*T, then 2 energy packets are released.
9. If the number of tokens is above N*T, then N energy packets are released.

10. The zone is then removed from the list, and the next zone is selected.
11. The process returns to step 4.
12. Steps 4-11 are repeated for all zones until no energy packets remain or all zones have been allocated energy packets.
13. If there are residual energy packets—i.e., all zones have been processed but there is still available energy—then the remaining packets are distributed uniformly among all zones.

It's important to emphasize that the process outlined in steps 1-13 occurs every hour to allocate the available energy on an hourly basis. In order to ensure fairness across all zones, the order in which the zones are placed in the FIFO structure is determined randomly. This means that the sequence of zones is randomized each hour, for instance, using a randomizer, to prevent any bias or favoritism in the allocation process.

4. Test Results

4.1. Simulation Setup

This section presents the test results obtained from an emergency scenario in a smart city comprising 1000 residents distributed across various social and energy variable combinations [55,56]. Our simulations involved the use of a randomizer to generate diverse scenarios based on the social and energy values of our city, allowing us to explore different conditions [57–59]. Moreover, the buffered energy was also randomized, providing values in the range of 0-100 MW. The available energy was divided into 100 virtual energy packets to be allocated among zones, with the city partitioned into 10 zones. For benchmarking purposes, we implemented a simple uniform round-robin method where each zone received an equal amount of energy. Additionally, the threshold for the Fuzzy Leaky Bucket to release an energy packet was set to 10 tokens, meaning that 84 tokens would release 8 packets. These parameters and methods enabled us to conduct comprehensive tests and analyze the effectiveness of the proposed allocation approach in emergency situations within smart cities.

4.2. Results

The simulated results have been meticulously recorded and are presented to showcase the social justice aspect of the proposed approach. We simulated 10 different scenarios, the values of which are detailed in Table 2. The allocated energy for each scenario is depicted as a function of the social variables outlined in the preceding section. The results obtained are illustrated in Figure 8, where the energy allocation using the Fuzzy Leaky Bucket is compared to that obtained with the uniform round-robin method in terms of the percentage of available energy allocated to each zone. These comparisons provide valuable insights into the effectiveness and fairness of the proposed approach, offering a clear evaluation of how energy is distributed across different zones under varying social and energy conditions within the smart city.

Table 2 illustrates a wide array of simulated scenarios, each reflecting distinct social differences within the city zones. For instance, in scenario 10, we observe a significant disparity between zones, with one zone having an average income of approximately $83,000 and another zone with an average income of around $19,000. Income is a primary social criterion that profoundly influences everyday life, and our simulated scenarios vividly showcase the diverse social levels present within the city. This disparity becomes even more apparent as one examines the detailed social values presented in Table 2, emphasizing the significant variations across different zones within the smart city environment.

The obtained results shed light on the allocation of limited available energy, constrained by emergency conditions, across the smart city zones. While the uniform allocation of energy packets to all zones may appear fair at first glance, it fails to account for the individual characteristics of each zone. This limitation becomes evident in Figure 8, where the available energy is consistently distributed equally to all zones, resulting in a constant 10% allocation rate per zone. Essentially, the uniform distribution method provides a flat

allocation rate, disregarding any zone-specific features. Although this approach may be quick and computationally inexpensive, it lacks a sense of social fairness.

Table 2. Smart city scenarios and values per simulated zone.

Zone #	Average Income	City Population Percentage	Disability Percentage	Number of Critical Buildings	Zone Forecasted Generation	Percentage of Diesel Generators
Scenario 1 [available Energy: 117.4632 MW]						
Zone 1	39.8896	26.8124	83.2513	9.9537	64.9751	70.3953
Zone 2	93.2303	68.7653	56.8354	3.8085	63.4579	36.3229
Zone 3	40.7619	36.87	46.8399	5.0341	91.0536	20.6431
Zone 4	33.8604	57.4126	48.6932	2.6222	57.9593	87.8328
Zone 5	6.095	44.0876	8.4258	5.6324	53.9311	76.8058
Zone 6	23.309	58.7362	45.8974	8.6098	66.0836	35.3879
Zone 7	34.7186	25.3718	95.2528	2.982	15.8406	36.1297
Zone 8	74.1629	70.59	70.0892	0.0623	37.4346	90.1496
Zone 9	31.8345	59.7083	29.7795	1.2501	38.8356	81.7688
Zone 10	98.1176	86.199	8.3821	3.3771	23.6129	31.7805
Scenario 2 [available Energy: 482.1283 MW]						
Zone 1	67.1151	29.9175	53.1127	0.0146	88.3789	40.4384
Zone 2	30.1206	95.0582	46.0648	2.8765	8.4627	58.2181
Zone 3	15.3069	7.3094	58.0565	2.8701	36.192	72.4825
Zone 4	85.8312	34.7916	96.1746	9.5357	20.6037	76.8245
Zone 5	61.5532	91.8922	60.2537	7.0214	74.3675	38.5102
Zone 6	25.1504	3.676	47.2123	6.4507	27.897	51.7861
Zone 7	24.5667	29.7508	65.0474	8.9139	86.1106	20.9915
Zone 8	39.9094	88.7883	25.6528	9.668	61.9157	16.5346
Zone 9	82.6199	65.5693	54.6453	2.5133	4.0156	23.3375
Zone 10	36.1113	63.3455	98.6098	2.0716	75.7084	88.6328
Scenario 3 [available Energy: 236.1149 MW]						
Zone 1	15.8914	81.0921	47.6508	1.1629	87.5721	63.5186
Zone 2	9.7281	90.8439	3.5016	0.3975	98.8568	68.6182
Zone 3	37.6689	50.4324	76.3496	0.4887	72.5928	70.1328
Zone 4	45.8891	58.2295	33.909	1.7063	39.9193	91.9777
Zone 5	22.6045	36.1007	32.4562	0.8358	51.2666	83.2865
Zone 6	90.4613	72.3596	38.2996	2.9802	69.1712	88.0457
Zone 7	92.4548	8.1253	48.2673	1.2827	25.2911	88.3962
Zone 8	19.6277	12.1354	54.3695	3.1462	38.2041	79.1539
Zone 9	83.9179	68.0236	41.6922	6.4289	21.4081	61.7271
Zone 10	67.5191	60.1023	34.631	3.644	17.1481	79.5362
Scenario 4 [available Energy: 246.3335 MW]						
Zone 1	35.4623	77.5061	23.6805	8.4483	81.6527	84.6228
Zone 2	37.0187	38.323	86.1335	4.6391	57.0548	69.5307
Zone 3	96.0917	54.6313	63.6577	5.7089	92.7112	86.3766

Table 2. *Cont.*

Zone #	Average Income	City Population Percentage	Disability Percentage	Number of Critical Buildings	Zone Forecasted Generation	Percentage of Diesel Generators
Zone 4	16.9839	17.8699	24.3504	7.5178	19.9134	98.2941
Zone 5	70.9639	17.5436	85.8297	9.0941	96.1663	57.06
Zone 6	56.2879	17.6661	51.3679	5.4847	16.5277	49.3893
Zone 7	53.5117	19.8807	62.3169	0.2632	31.8791	53.3
Zone 8	32.6774	60.219	36.1933	1.3492	91.3814	64.0559
Zone 9	65.8774	67.533	74.4558	8.4218	51.6657	15.1869
Zone 10	38.0664	82.1019	17.1364	3.2998	96.6472	80.6293
Scenario 5 [available Energy: 426.6855MW]						
Zone 1	39.8118	11.5494	8.0281	3.6047	82.8906	21.461
Zone 2	79.104	65.4688	2.6146	7.8578	92.2563	49.2313
Zone 3	83.4012	13.1354	75.9783	9.2574	83.2708	25.9401
Zone 4	21.3022	52.2315	39.7357	4.7911	99.3904	60.4478
Zone 5	94.4909	49.0442	43.7947	7.7266	74.4067	44.2904
Zone 6	5.3	8.7822	79.7986	6.5558	3.2336	55.7067
Zone 7	71.9802	11.0408	21.6647	8.1102	13.8662	88.1899
Zone 8	92.3556	1.2756	37.7159	1.6781	54.0223	10.1662
Zone 9	3.9268	93.3229	97.1592	3.6093	64.4205	6.7947
Zone 10	20.7912	3.9604	46.9359	1.501	99.1307	42.7062
Scenario 6 [available Energy: 330.8675MW]						
Zone 1	60.2773	47.3818	35.6256	4.7558	67.1022	95.9645
Zone 2	8.9084	79.7742	59.0776	9.122	10.1129	29.3295
Zone 3	5.1588	50.4128	76.8376	2.8299	22.536	33.129
Zone 4	45.3251	73.7385	50.9886	3.8251	90.5483	96.5258
Zone 5	62.8267	13.2031	61.8302	3.8302	99.1194	28.6827
Zone 6	70.6191	53.5206	19.3211	6.8944	5.0455	18.4434
Zone 7	4.5658	88.5042	83.9794	1.1816	41.0415	12.0229
Zone 8	57.2093	94.939	25.6385	9.8987	34.9808	20.8522
Zone 9	66.5827	97.3345	62.27	0.6354	37.351	16.6252
Zone 10	23.1278	5.2209	90.1756	7.9329	37.3014	83.2055
Scenario 7 [available Energy: 171.4019 MW]						
Zone 1	61.8806	45.3021	1.0163	5.9908	60.1568	64.9417
Zone 2	34.2721	49.3299	70.1774	8.8780	5.5058	9.8362
Zone 3	64.9783	76.4071	98.7959	1.2532	36.4477	67.6230
Zone 4	37.5758	86.3458	29.1977	1.3347	67.2651	20.2585
Zone 5	86.8515	75.1157	41.9380	0.0023	14.9464	27.3834
Zone 6	87.2425	60.1251	32.1188	2.8429	43.5316	90.3759
Zone 7	92.5106	50.5292	62.7582	7.1926	2.3913	57.4933
Zone 8	4.6534	42.2531	46.7734	0.2263	6.5074	92.3956
Zone 9	53.4143	36.6796	36.3946	1.5137	14.9609	35.0802
Zone 10	33.5966	78.4028	48.6739	4.6480	13.1253	88.6391

Table 2. *Cont.*

Zone #	Average Income	City Population Percentage	Disability Percentage	Number of Critical Buildings	Zone Forecasted Generation	Percentage of Diesel Generators
Scenario 8 [available Energy: 203.2368 MW]						
Zone 1	95.1807	91.1985	95.1414	3.4600	29.0244	88.6701
Zone 2	21.0031	13.0877	52.0516	9.0546	40.2530	21.5761
Zone 3	7.8739	93.3060	60.2872	3.7749	66.4931	79.2190
Zone 4	33.3492	69.2659	20.3816	9.5871	71.1832	16.6907
Zone 5	44.2777	63.2994	92.9967	5.2933	62.6474	68.0819
Zone 6	92.3198	15.2834	40.5721	3.1248	69.3899	89.0688
Zone 7	49.0671	80.5824	32.6439	5.4988	38.8784	89.6829
Zone 8	67.6120	82.8397	11.0089	2.7923	76.7636	21.6057
Zone 9	3.4062	43.6552	93.6864	2.6209	56.9745	35.9553
Zone 10	2.6839	50.0419	82.7015	2.5898	4.5885	24.6472
Scenario 9 [available Energy: 31.0735 MW]						
Zone 1	70.1843	8.6482	61.6787	1.7377	65.1401	49.8696
Zone 2	28.4511	83.056	81.836	9.3817	0.0326	64.0389
Zone 3	0.7356	10.6421	10.6794	3.6711	23.9608	34.614
Zone 4	24.962	38.7064	42.1038	6.4008	78.7553	26.9994
Zone 5	84.3982	74.0468	82.6102	1.8219	6.5436	61.035
Zone 6	70.1553	11.1618	9.5824	5.9783	81.2233	81.4578
Zone 7	8.9437	73.1279	90.3857	4.5223	7.0688	24.1278
Zone 8	73.1865	4.0492	42.4523	5.4022	95.3828	20.8906
Zone 9	11.6332	64.622	10.8411	9.835	24.8344	60.6356
Zone 10	81.6695	83.0054	48.9039	7.6073	91.5108	90.0975
Scenario 10 [available Energy: 107.1188 MW]						
Zone 1	54.7061	78.4709	19.4441	7.4689	47.5558	58.3259
Zone 2	26.0548	8.4822	29.8133	9.1713	47.0518	26.9468
Zone 3	76.297	77.2172	2.13	8.7999	79.817	32.4165
Zone 4	66.9044	29.6294	92.9952	2.8196	16.888	74.5167
Zone 5	47.7134	65.3445	96.6576	3.1303	7.6439	79.1415
Zone 6	36.5384	58.5099	18.3337	0.7692	15.3663	82.6876
Zone 7	30.0957	38.3884	65.0749	8.1737	76.6266	37.4176
Zone 8	18.9862	64.6502	0.3605	2.8289	63.8601	59.2075
Zone 9	32.5289	98.8951	12.3236	7.3588	15.6617	43.4647
Zone 10	83.2243	35.991	7.6238	5.5693	27.393	13.2055



Figure 8. Results obtained with fuzzy leaky bucket in the form of the percent of available energy allocated to each of the city's zones and compared with the uniform distribution.

In contrast, the proposed fuzzy leaky bucket approach, in synergy with the virtual buffer, allocates energy packets differently by considering the social features of each zone. As depicted in Figure 8, the fuzzy leaky bucket does not provide a uniform allocation in any of the tested scenarios, indicating its distinct behavior compared to the uniform approach. Moreover, by accounting for the social characteristics of the zones, the allocation varies while ensuring that all zones are satisfactorily supplied with energy. Importantly, no zone receives zero energy allocation, underscoring the fuzzy leaky bucket's consideration of individual zone characteristics.

A closer examination of the decisions in Figure 8 reveals that zones with lower values in their social characteristics receive higher energy allocations. This validates the design of our algorithm, which leverages social variables and developed fuzzy rules to support zones with lower social variables. Scenario 8 serves as a notable example of this strategy: zones 1 and 7, with lower average incomes, receive higher energy allocations compared to zone 6, which has a higher income rate and self-generation capacity. This trend is consistent across all scenarios, emphasizing the algorithm's commitment to justice for all city citizens through equitable energy allocation.

Finally, the distribution of each variable in scenario 1 is illustrated in Figure 9. Additionally, the distribution allocation derived from the fuzzy leaky approach is presented in the same graph. It's evident from this graph that the final allocation does not perfectly resemble any of the other distributions. Consequently, we conclude that all variables contribute to the final allocation, indicating that the proposed approach can be deemed fair to all zones.

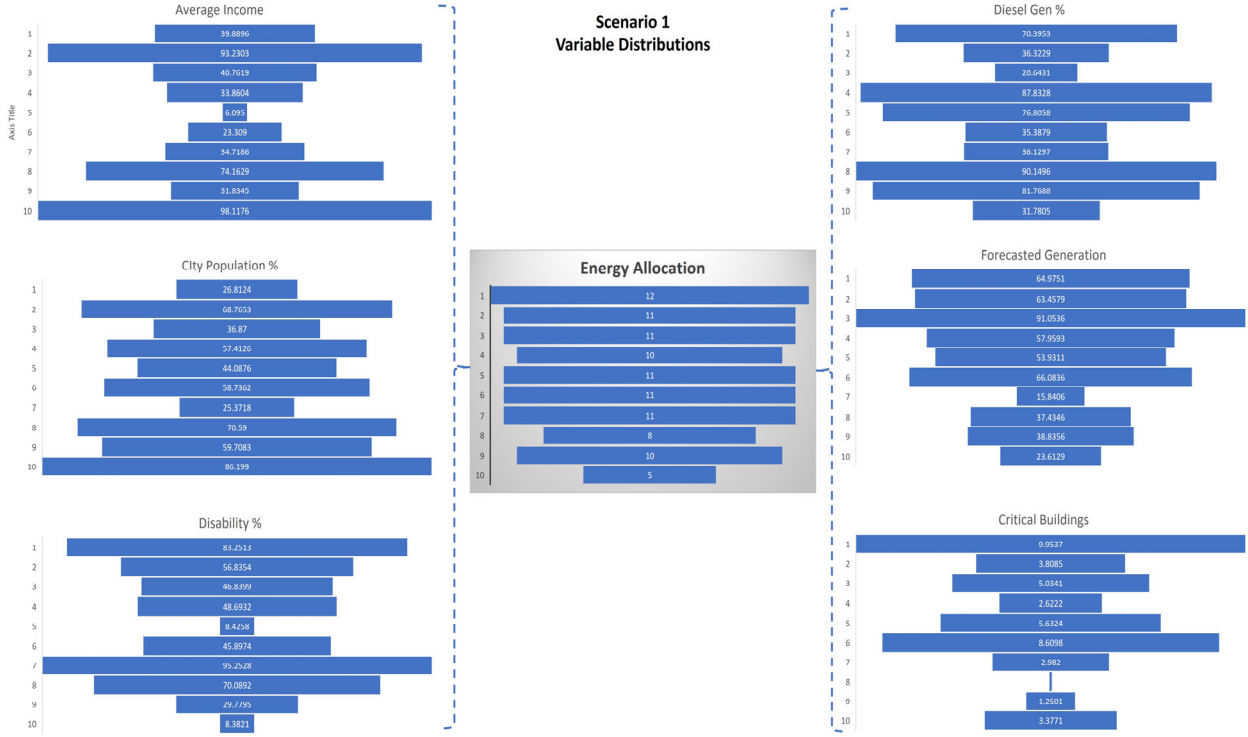


Figure 9. Graph representing the distribution per variable for scenario 1. We observe that the energy allocation has a non-uniform distribution that does not resemble any of the rest implying that all variables have their effect on allocation distribution.

It is noteworthy that zone 1 has received the minimum allocation of energy, whereas Zone 10 has received the maximum amount. Consequently, the energy disparity between these two zones is the most significant among all pairs within the simulated city. This variance in energy allocation is primarily driven by the social factors considered by the fuzzy inference system. Zones 1 and 10 exhibit the highest disparity across the variables 'Income,' 'Population,' 'Disability,' and 'Building,' whereas this disparity is not as pronounced in the two energy-related variables. This observation underscores the impact of social variables on the final energy allocation. Thus, we can confidently assert that the proposed method ensures social justice of energy allocation in emergencies.

5. Conclusions

This work introduces a novel approach to allocating available energy during emergencies within the framework of smart cities. At its core, the approach leverages digital

connectivity capabilities and advanced data processing techniques to facilitate more efficient and equitable decision-making processes. To achieve this goal, the proposed approach integrates a fuzzy leaky bucket mechanism in conjunction with an energy virtual buffer to regulate the allocation of energy during emergency situations.

The limitation in energy distribution during emergent situations often leads to perceptions of unfair treatment among residents, fostering feelings of marginalization and social injustice. This paper addresses this gap by introducing an approach that allocates energy while considering the social characteristics of smart city residents. By dividing the city into consumption zones and assigning virtual energy packets to each zone, the approach aims to mitigate disparities in energy distribution.

Central to this approach is the use of fuzzy logic-based leaky bucket, which enables the processing of large volumes of data and subsequent decision-making through fuzzy sets and rules. These fuzzy tools facilitate the transformation of diverse residential data into an efficient and socially equitable decision-making framework. Additionally, the strength of fuzzy logic lies in its ability to represent large datasets using linguistic terms, thereby enabling the integration of both energy and social variables into the decision-making process.

The presented approach has undergone testing using a set of 10 large-scale scenarios within a smart city, incorporating diverse values for social and energy variables. Results from these tests are compared with the uniform distribution of energy and highlight three main observations: (i) Our approach consistently deviates from uniform allocation across all test scenarios. (ii) It ensures that no zone receives zero energy allocation. (iii) It prioritizes support for lower social strata consumers while ensuring adequate energy provision to all zones.

In summary, the variation in allocation patterns achieved by the fuzzy leaky bucket, in contrast to the uniform pattern, demonstrates an acceptable social allocation that fosters a sense of "social justice" among residents.

Author Contributions: Conceptualization, M.A. (Miltiadis Alamaniotis); methodology, M.A. (Miltiadis Alamaniotis) and M.A. (Michail Alexiou); software, M.A. (Miltiadis Alamaniotis); validation, M.A. (Miltiadis Alamaniotis) and M.A. (Michail Alexiou); formal analysis, M.A. (Miltiadis Alamaniotis); data curation, M.A. (Michail Alexiou); writing—original draft preparation, M.A. (Miltiadis Alamaniotis); writing—review and editing, M.A. (Michail Alexiou); All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The data are available upon request to the corresponding author.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Taha, W.M.; Taha, A.E.M.; Thunberg, J. *Cyber-Physical Systems: A Model-Based Approach*; Springer Nature: Berlin/Heidelberg, Germany, 2021; p. 187.
2. Silva, B.N.; Khan, M.; Han, K. Towards sustainable smart cities: A review of trends, architectures, components, and open challenges in smart cities. *Sustain. Cities Soc.* **2018**, *38*, 697–713. [CrossRef]
3. Alamaniotis, M. Challenges and AI-Based Solutions for Smart Energy Consumption in Smart Cities. In *Advances in Artificial Intelligence-Based Technologies: Selected Papers in Honour of Professor Nikolaos G. Bourbakis*; Tsihrintzis, G., Virvou, M., Tsoukalas, L., Esposito, A., Jain, L., Eds.; Springer: Berlin/Heidelberg, Germany, 2022; Volume 1, pp. 111–124.
4. Hussain, S.S.; Nadeem, F.; Aftab, M.A.; Ali, I.; Ustun, T.S. The emerging energy internet: Architecture, benefits, challenges, and future prospects. *Electronics* **2019**, *8*, 1037. [CrossRef]
5. Nasiakou, A. Next Generation Energy Markets and Applications. Ph.D. Thesis, University of Thessaly, Volos, Greece, 2020.
6. Nasiakou, A.; Alamaniotis, M.; Tsoukalas, L.H.; Karagiannis, G. A three-stage scheme for consumers' partitioning using hierarchical clustering algorithm. In Proceedings of the 8th International Conference on Information, Intelligence, Systems & Applications (IISA), Larnaca, Cyprus,, 27–30 August 2017.
7. Farmanbar, M.; Parham, K.; Arild, Ø.; Rong, C. A widespread review of smart grids towards smart cities. *Energies* **2019**, *12*, 4484. [CrossRef]

8. Doss-Gollin, J.; Farnham, D.J.; Lall, U.; Modi, V. How unprecedented was the February 2021 Texas cold snap? *Environ. Res. Lett.* **2021**, *16*, 064056. [CrossRef]
9. Kazerani, M.; Tehrani, K. Grid of Hybrid AC/DC Microgrids: A New Paradigm for Smart City of Tomorrow. In Proceedings of the IEEE 15th International Conference of System of Systems Engineering (SoSE), Budapest, Hungary, 2–4 June 2020.
10. Casalicchio, V.; Manzolini, G.; Prina, M.G.; Moser, D. Optimal Allocation Method for a Fair Distribution of the Benefits in an Energy Community. *Sol. RRL* **2022**, *6*, 2100473. [CrossRef]
11. Alamaniotis, M. Morphing to the mean approach of anticipated electricity demand in smart city partitions using citizen elasticities. In Proceedings of the 2018 IEEE International Smart Cities Conference (ISC2), Kansas City, MO, USA, 16–19 September 2018.
12. Alamaniotis, M.; Gatsis, N. Evolutionary multi-objective cost and privacy driven load morphing in smart electricity grid partition. *Energies* **2019**, *12*, 2470. [CrossRef]
13. Alamaniotis, M.; Bourbakis, N.; Tsoukalas, L.H. Enhancing privacy of electricity consumption in smart cities through morphing of anticipated demand pattern utilizing self-elasticity and genetic algorithms. *Sustain. Cities Soc.* **2019**, *46*, 101426. [CrossRef]
14. Deakin, M.; Reid, A. Smart cities: Under-gridding the sustainability of city-districts as energy efficient-low carbon zones. *J. Clean. Prod.* **2018**, *173*, 39–48. [CrossRef]
15. Papastamatiou, I.; Marinakis, V.; Doukas, H.; Psarras, J. A decision support framework for smart cities energy assessment and optimization. *Energy Procedia* **2017**, *111*, 800–809. [CrossRef]
16. Alamaniotis, M.; Tsoukalas, L.H.; Bourbakis, N. Virtual cost approach: Electricity consumption scheduling for smart grids/cities in price-directed electricity markets. In Proceedings of the 5th International Conference on Information, Intelligence, Systems and Applications, Chania, Greece, 7–9 July 2014.
17. Velinov, E.; Petrenko, Y.; Vechkinzova, E.; Denisov, I.; Ochoa Siguencia, L.; Gródek-Szostak, Z. "Leaky Bucket" of Kazakhstan's Power Grid: Losses and Inefficient Distribution of Electric Power. *Energies* **2020**, *13*, 2947. [CrossRef]
18. Gerla, G. *Fuzzy Logic: Mathematical Tools for Approximate Reasoning*; Springer Science & Business Media: Berlin/Heidelberg, Germany, 2013; Volume 11.
19. Gao, R.; Tsoukalas, L.H. Implementing virtual buffer for electric power grids. In *Computational Science–ICCS 2007: 7th International Conference, Beijing, China, 27–30 May 2007, Proceedings, Part I 7*; Springer: Berlin/Heidelberg, Germany, 2007; pp. 1083–1089.
20. Chen, X.; Leung, K.C.; Lam, A.Y. Leaky bucket-inspired power output smoothing with load-adaptive algorithm. In Proceedings of the 2017 IEEE International Conference on Communications (ICC), Paris, France, 21–25 May 2017; pp. 1–6.
21. O'dwyer, E.; Pan, I.; Acha, S.; Shah, N. Smart energy systems for sustainable smart cities: Current developments, trends and future directions. *Appl. Energy* **2019**, *237*, 581–597. [CrossRef]
22. Zhao, C.; Zhao, J.; Wu, C.; Wang, X.; Xue, F.; Lu, S. Power grid partitioning based on functional community structure. *IEEE Access* **2019**, *7*, 152624–152634. [CrossRef]
23. Nasiakou, A.; Alamaniotis, M.; Tsoukalas, L.H. Power Distribution Network Partitioning in Big Data Environment Using K-Means and Fuzzy Logic. In Proceedings of the 10th Mediterranean Conference on Power Generation, Transmission, Distribution and Energy Conversion (Med Power 2016), Belgrade, Serbia, 6–9 November 2016.
24. Bertsekas, D.; Gallager, R. *Data Networks*; Athena Scientific: Nashua, NH, USA, 2021.
25. Wang, D.; Zheng, K.; Chen, Q.; Li, Z.; Liu, S. Quantum annealing computing for grid partition in large-scale power systems. In Proceedings of the 2022 IEEE 5th International Electrical and Energy Conference (CIEEC), Nangjing, China, 27–29 May 2022; pp. 2004–2009.
26. Li, Q.; Dai, S.; Li, X.; Li, W.; Sun, W. Graph Convolution Networks-Based Island Partition for Energy and Information Coupled Active Distribution Systems. In Proceedings of the 2021 IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids (SmartGridComm), Aachen, Germany, 25–28 October 2021; pp. 315–320.
27. Wu, Q.; Xue, F.; Wang, X.; Lu, S.; Han, B.; Piao, L. Planning of Virtual Microgrids by Integrated Partition and DER Allocation. In Proceedings of the 2021 IEEE 5th Conference on Energy Internet and Energy System Integration (EI2), Taiyuan, China, 22–24 October 2021; pp. 66–71.
28. Chen, J.; Sun, B.; Zeng, Y.; Jing, R.; Liang, G.; Huang, B. An Island Partition Method with Energy Storage Based on Genetic Algorithm. In Proceedings of the 2022 IEEE 6th Conference on Energy Internet and Energy System Integration (EI2), Chengdu, China, 11–13 November 2022; pp. 976–980.
29. Zhao, J.; Zhu, J.; Jia, R.; Liu, S.; Ye, C. Method for Cluster Partition of Distributed Generation Considering Flexible Supply and Demand Balance and Response Speed. In Proceedings of the 2021 3rd International Conference on Smart Power & Internet Energy Systems (SPIES), Shanghai, China, 25–28 September 2021; pp. 35–38.
30. Chen, J.; Sun, B.; Li, Y.; Jing, R.; Zeng, Y.; Li, M. An evaluation method of distributed generation credible capacity based on island partition. *Energy Rep.* **2022**, *8*, 11271–11287. [CrossRef]
31. Wu, F.; Li, H.; Ma, X. An Island Partition Method for New Distribution Network. In Proceedings of the 2023 IEEE/IAS Industrial and Commercial Power System Asia (I&CPS Asia), Chongqing, China, 7–9 July 2023; pp. 877–882.
32. Jay, D.; Shanti Swarup, K. Reactive Power and Network Partitioning. In *Market Operation for Reactive Power Ancillary Service: Design and Analysis with GAMS Code*; Springer Nature: Singapore, 2024; pp. 47–61.
33. Wang, Z.; Ding, T.; Mu, C.; Huang, Y.; Yang, M.; Yang, Y.; Chen, Z.; Lin, Y.; Li, M. An ADMM-based power system partitioned black-start and parallel restoration method considering high-penetrated renewable energy. *Int. J. Electr. Power Energy Syst.* **2024**, *155*, 109532. [CrossRef]

34. Li, J.; Fang, Z.; Wang, Q.; Zhang, M.; Li, Y.; Zhang, W. Optimal Operation with Dynamic Partitioning Strategy for Centralized Shared Energy Storage Station with Integration of Large-Scale Renewable Energy. *J. Mod. Power Syst. Clean Energy* **2024**, 1–13.
35. Parekh, A.K.; Gallager, R.G. A generalized processor sharing approach to flow control in integrated services networks: The multiple node case. *IEEE/ACM Trans. Netw.* **1994**, *2*, 137–150. [CrossRef]
36. Cao, J.; Yang, M. Energy internet–Towards smart grid 2.0. In Proceedings of the 2013 Fourth International Conference on Networking and Distributed Computing, Los Angeles, CA, USA, 21–24 December 2013; pp. 105–110.
37. Bergan, P.G.; Greiner, C.J. A new type of large scale thermal energy storage. *Energy Procedia* **2014**, *58*, 152–159. [CrossRef]
38. Hameer, S.; van Niekerk, J.L. A review of large-scale electrical energy storage. *Int. J. Energy Res.* **2015**, *39*, 1179–1195. [CrossRef]
39. Wade, N.S.; Taylor, P.C.; Lang, P.D.; Jones, P.R. Evaluating the benefits of an electrical energy storage system in a future smart grid. *Energy Policy* **2010**, *38*, 7180–7188. [CrossRef]
40. Gelenbe, E.; Ceran, E.T. Energy packet networks with energy harvesting. *IEEE Access* **2016**, *4*, 1321–1331. [CrossRef]
41. Gelenbe, E.; Zhang, Y. Performance optimization with energy packets. *IEEE Syst. J.* **2019**, *13*, 3770–3780. [CrossRef]
42. Corzine, K.A. Energy packets enabling the energy internet. In Proceedings of the 2014 Clemson University Power Systems Conference, Clemson, SC, USA, 11–14 March 2014; pp. 1–5.
43. Ray, P.P. Energy packet networks: An annotated bibliography. *SN Comput. Sci.* **2020**, *1*, 6. [CrossRef]
44. Liu, P.; Zhang, X. A new hesitant fuzzy linguistic approach for multiple attribute decision making based on Dempster–Shafer evidence theory. *Appl. Soft Comput.* **2020**, *86*, 105897. [CrossRef]
45. Adeel, A.; Akram, M.; Koam, A.N. Group decision-making based on m-polar fuzzy linguistic TOPSIS method. *Symmetry* **2019**, *11*, 735. [CrossRef]
46. Seiti, H.; Hafezalkotob, A.; Herrera-Viedma, E. A novel linguistic approach for multi-granular information fusion and decision-making using risk-based linguistic D numbers. *Inf. Sci.* **2020**, *530*, 43–65. [CrossRef]
47. Vashishtha, S.; Gupta, V.; Mittal, M. Sentiment analysis using fuzzy logic: A comprehensive literature review. *Wiley Interdiscip. Rev. Data Min. Knowl. Discov.* **2023**, *13*, e1509. [CrossRef]
48. Alyasiry, A.M.; Forbes, M.; Bulmer, M. An exact algorithm for the pickup and delivery problem with time windows and last-in-first-out loading. *Transp. Sci.* **2019**, *53*, 1695–1705. [CrossRef]
49. Anitha, P.; Vimala, H.S.; Shreyas, J. PQTBA: Priority Queue based Token Bucket Algorithm for congestion control in IoT network. In Proceedings of the 2023 IEEE 8th International Conference for Convergence in Technology (I2CT), Lonavla, India, 7–9 April 2023; pp. 1–7.
50. Zhao, K.; Zhang, X.; Wang, H.; Gai, Y.; Wang, H. Allocation of Resources for Emergency Response to Coal-to-Oil Hazardous Chemical Accidents under Railway Transportation Mode. *Sustainability* **2022**, *14*, 16777. [CrossRef]
51. Cvetković, D.; Nešović, A.; Terzić, I. Impact of people's behavior on the energy sustainability of the residential sector in emergency situations caused by COVID-19. *Energy Build.* **2021**, *230*, 110532. [CrossRef]
52. Nygard, K.E.; Ghosn, S.B.; Chowdhury, M.M.; Loegering, D.; McCulloch, R.; Ranganathan, P. Optimization models for energy reallocation in a smart grid. In Proceedings of the 2011 IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS), Shanghai, China, 10–15 April 2011; pp. 186–190.
53. Poudel, S.; Dubey, A. Critical load restoration using distributed energy resources for resilient power distribution system. *IEEE Trans. Power Syst.* **2018**, *34*, 52–63. [CrossRef]
54. Saroj, A.; Roy, S.; Guin, A.; Hunter, M.; Fujimoto, R. Smart city real-time data-driven transportation simulation. In Proceedings of the 2018 Winter Simulation Conference (WSC), Gothenburg, Sweden, 9–12 December 2018; pp. 857–868.
55. Adil, S.H.; Abd Aziz, A.; Akber, T.; Ebrahim, M.; Ali, S.S.A.; Raza, K. 3D smart city simulator. In Proceedings of the 2017 IEEE 3rd International Symposium in Robotics and Manufacturing Automation (ROMA), Kuala Lumpur, Malaysia, 19–21 September 2017; pp. 1–5.
56. Del Esposte, A.D.M.; Santana, E.F.; Kanashiro, L.; Costa, F.M.; Braghetto, K.R.; Lago, N.; Kon, F. Design and evaluation of a scalable smart city software platform with large-scale simulations. *Future Gener. Comput. Syst.* **2019**, *93*, 427–441. [CrossRef]
57. Dong, S.; Ma, M.; Feng, L. A smart city simulation platform with uncertainty. In Proceedings of the ACM/IEEE 12th International Conference on Cyber-Physical Systems, Nashville, TN, USA, 19–21 May 2021; pp. 229–230.
58. Yamagata, Y.; Seya, H. Simulating a future smart city: An integrated land use-energy model. *Appl. Energy* **2013**, *112*, 1466–1474. [CrossRef]
59. Vázquez-Canteli, J.R.; Ulyanin, S.; Kämpf, J.; Nagy, Z. Fusing TensorFlow with building energy simulation for intelligent energy management in smart cities. *Sustain. Cities Soc.* **2019**, *45*, 243–257. [CrossRef]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.