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An Emission and Weight-based Road Traffic Congestion Pricing System and Control with Consideration of Investment Worthiness

Obari A. Johnson[1]*, Salawudeen T. Ahmed[2], Idakwo A. Monday[3], Adebiyi H. Busayo[4]
[1,3,4] Department of Computer Engineering, Federal University Lokoja, Lokoja, Nigeria.
[2]Department of Electrical and Electronics Engineering, University of Jos, Jos, Nigeria.

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ABSTRACT

This work presents a knowledge-based approach to traffic congestion pricing system and control. The road traffic congestion has attracted different intelligent contributions which have addressed many real-time traffic scenarios at a toll point unlike the flat toll system that renders parallel toll for every traffic condition. However, existing works on dynamic traffic congestion pricing systems focus entirely on the traffic parameters without taking cognizance of the impacts of the weight of vehicles on the road. More so, despite the numerous health hazards associated with air pollution from vehicle exhaust during traffic peak hour, effects of emission have not been conceived as pivotal input to be circumvented in road toll design. Therefore, a fuzzy logic-based approach to dynamic traffic congestion pricing problems in a 1*2 traffic scenario comprising of a fast lane and a slow lane, is presented. The inputs to the fuzzy inference system are the weights of vehicles, the rate of carbon dioxide emission, and the traffic density on the toll lane; while the output is the congestion price. Simulations results on the MATLAB fuzzy logic toolbox for a case of Lekki Admiralty Toll Gate reveal that a traffic scenario with traffic density of 57.2 V/mile, carbon dioxide emission rate of 339 Kg/m and weight of approaching vehicle of 8860 Kg, the congestion price gives N1130; this value of congestion price for this example scenario indicates an approximate value of 70% return on investment (RoI) when compared to the flat toll.

1. INTRODUCTION

The numerous threats to economic activities in these settlements evidence the impact of traffic congestion in most urban settlements of developing countries. In most developing societies, traffic congestion often results in accidents, pollution-based health hazards, deaths, road users' dissatisfaction, vehicle fuel wastage, vehicular faults, etc. [1]-[3]. Most urban transport networks are always entangled in traffic congestion; however, congestion problems relaxed notably in most cities during the COVID-19 pandemic [4]-[6]. Amidst the traffic congestion scenario, the effects of heavyweight vehicles on the road profile are devastating. Therefore, traffic congestion has received attention in the past to avert the consequences or utilize its impacts for the development of road infrastructures [1][7]. The deployment of technological approaches to address traffic congestion on roads has significantly improved beyond conventional and intelligent traffic lights. Despite the inherent implementation issues, like equity, fairness, awareness, etc., among others, in road traffic congestion pricing, these do not deter many cities from harnessing the problem of traffic congestion into significant economic benefits by utilizing the different congestion pricing systems and control policies. Several studies have justified the superior performance of the area-based congestion pricing system in decreasing emissions. The rate of acceptance and implementation of road traffic congestion pricing policy is increasing across cities [8]-[10]. Congestion pricing evolved to provide better road user satisfaction and reduce travel times [11]. The field of

*Corresponding Author
Email: johnson.obari@fulokoja.edu.ng

road pricing has experienced emerging trends due to different scholarly exploits of researchers and designers from the conventional flat toll system to the present-day deployment of dynamic, predictive-based, and data-driven approaches. Several studies have revealed the use of cordon-based, traffic density-based, distance-based, surrogate-based approaches, etc., with each approach giving tremendous and varying performance [12]-[16]. Video tolling has been deployed in some world capital cities for the real-time collection of toll charges for congestion pricing and control [17]-[19]. The impacts of income equity of road users on congestion pricing have been studied by the US Department of Transportation [20]. Extensively, the income profiles of commuters may also contribute to the equilibrium and disequilibrium conditions during the peak-hour period [21]. Flat road pricing, though now obsolete, lays the basis for the evolving trends of dynamic and data-driven toll prediction approaches with the deployment of artificial intelligence [22]-[28]. In addressing congestion in [29], travel-time-based prediction was used. The attractiveness of investment in road/toll infrastructures relies on how tariffs on roads are substantiated for economic development [22]. In a fascinating optimal fashion, an electric vehicle charging system has been incorporated into the congestion pricing scheme of an urban transport system and power distribution [30]. In [1], the investment in road and toll infrastructures was considered to develop an optimized congestion pricing system, which helps to make informed decisions on road traffic investment and management. The effects of emissions and travel habits have been comparatively studied in different congestion pricing schemes of an urban transport network [31]. In [32], the effect of congestion price on traffic flow and its impact on carbon emissions were simulated; the result justifies that increased road congestion price resulted in improved relative comfort and reduced emissions. Despite the multifaceted strides and plausibility of the existing literature on congestion pricing, none have included the burdens imposed by these vital principles; the weight of vehicles and the carbon dioxide emission. The adverse effects of heavy-weight vehicles, like trucks, on road profiles are enormous and pose a significant maintenance cost burden. Since air pollution from the exhaust is hazardous to health and the maintenance of a good road profile is highly capital-intensive, there is a need for a design that encompasses the effects of these pivotal components [33][34]. Weight-in-motion and piezoelectric sensors have been designed and deployed to measure vehicles weights [35]-[37]. Some existing sensors are deployable for calculating the carbon dioxide emission rate [38][39]; moreover, traffic density measurement is realizable by utilizing the available infrared-based sensors [40][41].

A knowledge-based strategy is presented to include the effects of vehicles on road profiles and the hazardous emissions from commuters' vehicles in determining the congestion price at a toll point. The theory of fuzzy logic has proven to offer qualitative robustness; it also acts as a panacea for nonlinear problems and renders ease of implementation of systems or designs [42]-[46]. The unique contributions of this work are: the inclusion of air pollution at toll points, intelligent systematization of the weight of vehicles in toll design, and the use of a fuzzy logic-based approach for road congestion pricing systems and management.

The rest of this research is divided into these subsections: Section 2 reveals the adopted methodology, while Section 3 contains the simulation results and discussion. Conclusively, the summary and recommendations for further studies are presented in Section 4.

2. DESIGN METHODOLOGY

The following approaches are used:

2.1. Determination of flat toll

To determine flat toll, the derived annuity-based expression in [1] is used. This is defined and illustrated in Eq.1.

$$p_{flat} = \frac{P(1+r)^n \times r}{t \times k \times q \times \left[(1+r)^n - 1\right]} \tag{1}$$

Where, P= Total principal used in investment of the road and toll facilities, r= Interest rate,
t= Average traffic flow per day of a toll point, q= Number of weeks of operation of toll facilities in a year,
n= Number of years of concession, and,
k= Number of days of operating the tolling system in a week.

For Lekki Admiralty Toll Gate [1], the interest rate is predominantly 18.75%. The principal invested in the road is seventy-five billion Naira - ₦75B, and the concession period is 45 years. Given that the toll facility works for 7 days a week, 52 weeks a year, and that the average number of vehicles/day on the toll lane is 60487 [1]. It is assumed that there are regular maintenance activities on the road to justify the zero effect of depreciation; more so, the impact of inflation is neglected for every financial cushion against inflation in the form of a security or bond.

2.2. Universes of discourse for fuzzy inference systems and partitioning of intervals

The Universe of Discourse for the output variable can be determined by adapting the vital business recommendations on RoI in [47]-[49]. Hence, the following range of the RoI is adopted as expressed in Eq. 2.

$$0.10 \leq RoI \leq 1.0 \tag{2}$$

Correspondingly, this maps out the universe of the discourse for the congestion price P and is thus presented in Eq. 3.

$$1.1p_f \leq P \leq 2p_f \tag{3}$$

Where p_f is the flat toll.

The inputs to the fuzzy inference system are traffic density, weight of approaching vehicles, and carbon dioxide emission rate. Due to the lack of access to sensors for these inputs, some sets of data on vehicular weights, traffic density, and carbon dioxide emission rate of some urban traffic points with similar traffic behavior to Lekki toll gate were obtained from Kaggle repositories. By the granulation technique, the respective mean and standard deviation of each of the three inputs of the collected datasets were used to generate new sets of normally distributed data. By deploying the cumulative probability distribution approach, the universes of discourse for the inputs are [Kmin-σ_k Kmax+σ_k], [Wmin-σ_w Wmax+σ_w], and [Smin-σ_s Smax+σ_s] for the traffic density K, weight of vehicle W, and rate of carbon dioxide emission S, respectively.

Where Kmin, Wmin, and Smin are the respective lowest values of the traffic density, weight of vehicles, and the rate of CO_2 emission in the dataset; Kmax, Wmax, and Smax are the highest values of the traffic density, weight of vehicles, and the rate of CO_2 emission; While σ_k, σ_w, and σ_s are the respective standard deviations of the traffic density, weight of vehicles, and the CO_2 emission.

On the premise of the normality of the dataset, three linguistic variables are defined using the cumulative probability distribution approach. For each input, three intervals are created and partitioned with interval lengths by finding the cumulative probabilities of the lower and the upper bounds. Thereafter, the boundaries are determined using the inverse of the cumulative distribution function.

For n intervals, the lower and upper bound cumulative probabilities are obtained using Eq. 4, Eq. 5, and Eq. 6.

$$P_{LB}^{1} = 0, \tag{4}$$

$$P_{LB}^{i} = \frac{2i-3}{2n}, \tag{5}$$

$$P_{UB}^{i} = \frac{i}{n} \tag{6}$$

Where, P_{LB}^{i} is the lower bound cumulative probathe bility for the i[th] order of interval, P_{UB}^{i} *and* is the upper bound cumulative probability for the i[th] order of the interval.

To obtain the boundaries of each interval, the inverse of the normal cumulative distribution function, which is presented in Eq. 7, is used.

$$P = F(x|c, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} \int_{-\infty}^{x} exp\left\{\frac{-(x-c)^2}{2\sigma^2}\right\} dx \tag{7}$$

Where c and σ are the mean and standard deviation, respectively.

Table 1 and Table 2 show the intervals of the output and the respective intervals for each of the inputs.

Table 1. Partitions and output linguistic values

Linguistic Values of Congestion Price	Lower Bound (LB)(Naira(N))	Upper Bound (UB)(N)(Naira)
Low	$1.1p_f$=702.9	$1.5p_f$=958.5
Medium	$1.35p_f$=862.65	1.7 p_f =1086.3
High	1.6 p_f=1022.4	1.9 p_f=1214.1
Very High	1.8 p_f=1150.2	2 p_f=1278

Table 2. Partitions and linguistic values of the inputs

Linguistic Values	Intervals of K (V/Mile)		Intervals of W (kg)		Intervals of S (kg/m)	
	LB	UB	LB	UB	LB	UB
Low	28.12	51.55	3647.2	8198.9	56.9	225
Medium	47.26	58.45	7393.9	9491.1	193.9	275
High	55	83.07	8845	13905	250	469.7

Interestingly, based on acceptable values of RoI, which births Eq. 3, the universe of discourse of the output for the fuzzy inference system is [$1.1p_f$ $2p_f$]. The result of Eq. 1 is approximately N639, which is the value of the flat toll. Therefore, the universe of discourse of the congestion price is N [702.9 1278]. The intervals of the four sub-universes of the congestion price with their corresponding linguistic variables are formed by the designer's specification as depicted in Table 1.

2.3. Fuzzification and rule evaluation

The triangular membership function is used for the fuzzification of both the inputs and outputs of the fuzzy inference system. The choice of the triangular membership function is based on its ubiquity and wide suitability for all data or systems, as justified in [50]-[51]. More so, it is one of the vital matching components to a cumulative probability distribution function-based generation of fuzzy numbers [52]-[54].

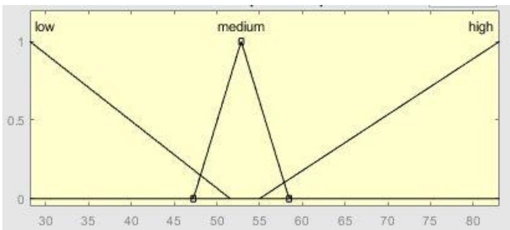
Mamdani's fuzzy inference system is used to develop the congestion pricing system. The simplicity of the Mamdani's inference system accounts for its wide deployment in many decision systems. The following are some of the 27 rules that are generated for the Mamdani-type fuzzy inference system based on expert knowledge:

If traffic density is *high*, the rate of carbon dioxide emission is *high,* and the weight of the vehicle is *low*, then the price is *very high*

If traffic density is *low*, the rate of carbon dioxide emission is *medium,* and the vehicle's weight is *high*, then the price is *high.*

If traffic density is *low*, the rate of carbon dioxide emission is *low,* and the weight of the vehicle is *high*, then the price is *medium*

Figure of the membership functions of the inputs to the fuzzy inference system are shown in Figure 1, while the membership functions of the output are depicted in Figure 2. The membership functions of the inputs reveal the evidence of the normally distributed dataset of the inputs, while the outputs' membership functions behave responsively to the expert's intuition.



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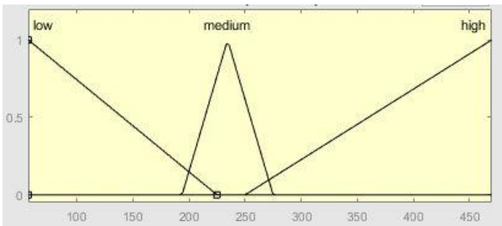

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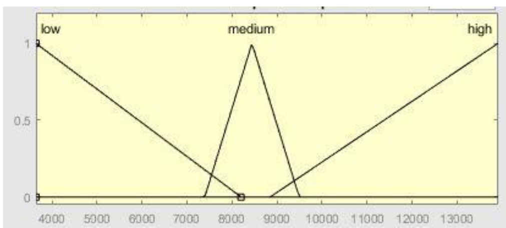

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Figure 1. Membership functions of the inputs to the FIS: (a) Traffic density (b) CO_2 emission (c) Weight of Vehicles

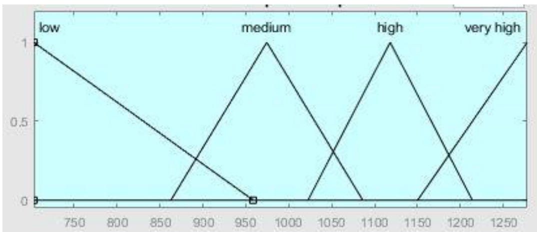

Figure 2. Membership functions for the output (congestion price)

2.4. Defuzzification

After the rule evaluation and aggregation, the centroid method obtains the crisp output value, the congestion price. Although the centroid method is a high computational burden, it has excellent technical and accurate plausibility [44]. Hence, among other defuzzification methods like bisection, weighted-average, mean-max, etc., the centroid method or its variants have gained massive recognition in many real-world applications. The summary of the adopted methodology is depicted in Figure 3.

The simulation and results are discussed in the next section.

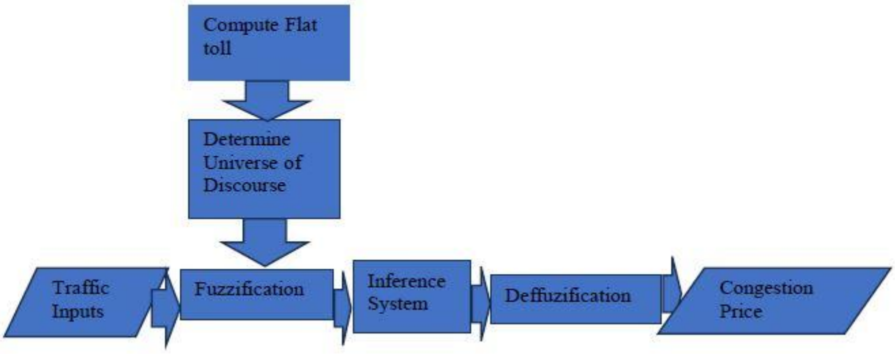

Figure 3. Adopted methodology for congestion pricing scheme

3. RESULTS AND DISCUSSION

The simulation was done on the fuzzy logic toolbox of MATLAB 2020b on a DELL Latitude 3340 PC. Proceeding with the values of the traffic parameters and the profile of concession of the toll gate as stated in the methodology, the computed value of the flat toll is N639. This indicates that to arrive at investment worthiness on the Lekki toll gate, the congestion price at any traffic condition can never be less than this value of the flat toll. The tables for the linguistic variables of the inputs and outputs have been presented in Table 1 and Table 2, respectively. In addition, their membership functions are illustrated accordingly in Figures 1 and 2.

Figure 1 illustrates a normal distribution of the input variables with their respective linguistic components. The simplicity, wide usability, and suitability of the triangular membership function for any dataset account for the designer's choice. Other membership functions, like trapezoidal, Gaussian membership functions, etc., can be used; however, it depends on the nature of the dataset. The cumulative probability distribution approach (CPDA) as a granulating technique relies on the normality of the dataset; hence, the normality of the dataset must be ascertained before using the CPDA for the partitioning of intervals. By the granulating technique, normality can be achieved by generating a new set of data based on the estimates of the mean and standard deviation of the raw data. Similarly, the triangular membership functions are used to define the linguistic variables of the output (congestion price).

In Figure 4, the fuzzy inference system depicts a particular traffic scenario at the toll point where the traffic density is 57.2 V/mile, the carbon dioxide emission rate is 339kg/m, and the weight of the approaching vehicle is 8860kg. This gives a congestion price of N1130, which is high. A high value of emitted CO_2 indicates a potential health hazard. Hence, a commuter may consider an alternate lane to avoid possible consequences on their health.

For a high traffic density value, relatively moderate vehicular weight, and rate of CO_2 emission, the congestion price is high, as revealed in Figure 5. In this scenario, the traffic density is 74.8V/mile, the rate of CO_2 emission is 243kg/m, and the weight of the vehicle is 7910kg; this gives a congestion price of N1120. Here, the heavy traffic congestion on the toll lane accounts for the corresponding increase in congestion price. This is anticipated to control the traffic flow on the fast lane.

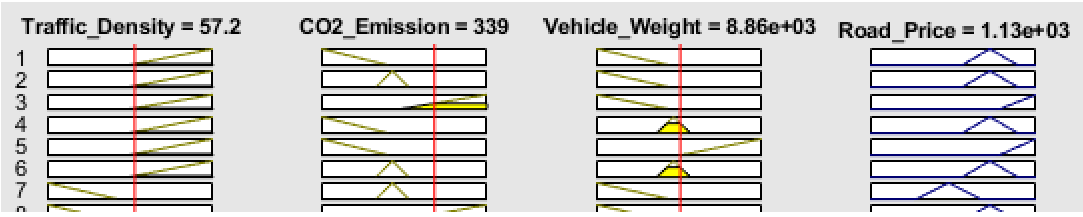

Figure 4. The Congestion price for a high CO_2 emission.

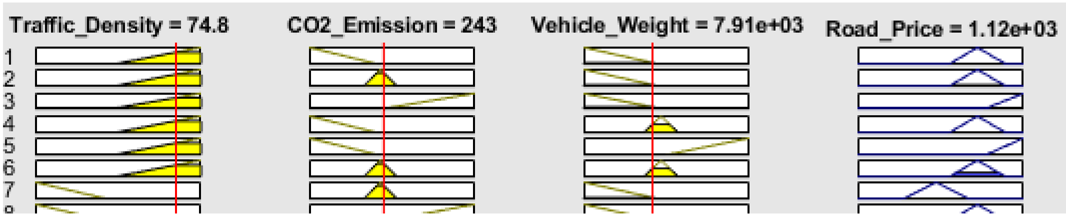

Figure 5. The congestion price for a high traffic density

In another traffic scenario, as depicted in Figure 6, where the vehicle's weight is significantly high (12500kg), the congestion price is high (N1050). The burden imposed by the heavy weight of cars on the road profile is enormous, and hence, it is correspondingly penalized by the expert system.

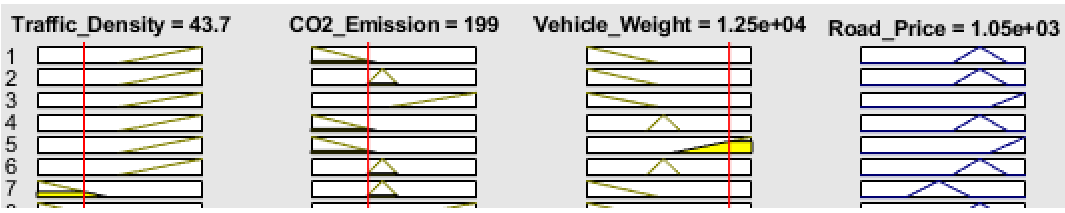

Figure 6. The congestion price for a heavy-weight vehicle

In reality, the interaction of these physical variables in determining the road traffic congestion price, as developed in this work, is valid. Figure 7 shows how the different combinations of two input variables affect the congestion pricing. In Figure 7(a), the 3D-surface representation reveals the combined effects of carbon dioxide emission and traffic density on the road traffic congestion price irrespective of the weight of the vehicle. It is observed that the congestion price is high if any of the variables has a high value, and the effect of externality (weight of vehicle) is revealed in the hill-climbing nature of the surface, even at very low traffic density and low CO_2 emission. Hence, congestion prices may retain high values in terms of low carbon dioxide emission and traffic density values. Similarly, in Figure 7(b), the congestion price is high if the traffic density or weight of the approaching vehicle is high. However, the congestion price navigates a steep gradient at low traffic density and vehicle weight values, irrespective of the externality value (carbon dioxide emission), unlike in Figure 7(a). In addition, the gradient becomes easier as the values of the two inputs span within their medium intervals. Finally, the effects of vehicular weight and carbon dioxide emission are depicted in Figure 7(c). Here, although the congestion price is huge for a high value of any of the traffic input parameters, it is easier to navigate the hill upwards by adjusting vehicular weight than by manipulating carbon dioxide emissions for the case of the Lekki toll gate.

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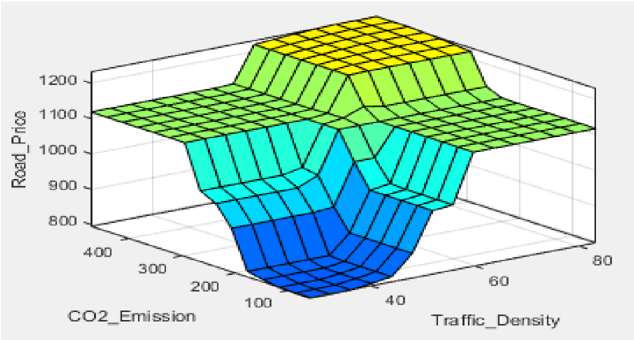

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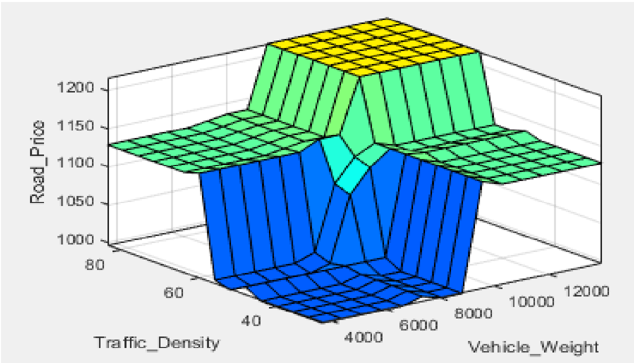

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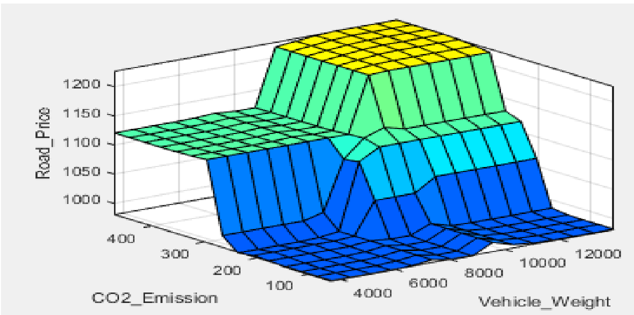

(c)

Figure 7. Interactive effects of the inputs on the congestion price: (a) CO_2 emission and traffic density, (b) Vehicular weight and traffic density, (c) Vehicular weight and CO_2 emission

Conclusively, apart from the ability to handle the nonlinear nature of the congestion pricing problem, one superior advantage of this approach over existing dynamic traffic congestion pricing systems lies in its ability to give a discrete and real-time value of the congestion price for any traffic scenario with little computational burden and simplicity. More so, commuters are penalized for using the fast lane when the rate of emissions is high; this may subject commuters to arrive at a compromise between seeking the safety of health and having easy commuting. Since the computation of the flat toll is based on the annuity concept, another superior advantage of this approach to traffic management and investment system is a total guarantee of improved return on investment (RoI) within the concession period. Hence, investment in road-toll design by using this approach guarantees improved cost efficiency over existing methods.

4. CONCLUSION

In this research, a fuzzy logic-based dynamic traffic congestion pricing system has been presented with a unique inclusion of the weight of vehicles and the rate of carbon dioxide emission. The design improves return on investment (RoI) on road and toll design. Emphatically, the sustainability of the toll design is justified by the well-posedness of the annuity-based concept that was used to obtain the flat toll from existing literature; this is premised upon these assumptions: regular maintenance of toll and road facilities, zero inflation through financial security measures, uniform average traffic flow per day, etc., among others. This approach can be deployed on any urban road traffic network where there is an excess traffic demand on a fast lane. By detecting the vehicle's plate number through image/video processing, commuters can be charged appropriately to access a fast lane in any traffic scenario. In future works, the cross-sectional effects of the other lane (slow lane) can be explored. It is also recommended that users' behaviours, such as their average income profile, should be considered in the design of the tolling system, mainly when the operator's specifics optimally encompass minimal congestion. This can be formulated as a multi-objective optimization problem where the designer can compromise between achieving free traffic flow and having a high return on investment. The dataset used for this research is accessible through the link https://shorturl.at/OLE5H.

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BIOGRAPHIES OF AUTHORS

Obari Johnson A. is a lecturer at the Department of Computer Engineering of the Federal University Lokoja, Nigeria. He obtained a BEng. in Electrical Engineering and MSc. in Control Engineering from Ahmadu Bello University, Zaria, Nigeria. He is presently pursuing his PhD degree in Computer Engineering at the Federal University of Technology, Minna, Nigeria. His main research interests are computational intelligence, control engineering, power system control & management, and artificial intelligence. He can be contacted by email through this address: johnson.obari@fulokoja.edu.ng

Salawudeen Tijani A. is a lecturer at the Department of Electrical and Electronic Engineering in the University of Jos, Nigeria. He obtained a BEng. in Electrical Engineering, an MSc. in Control Engineering, and a PhD in Control Engineering from Ahmadu Bello University, Zaria, Nigeria. He had his postdoctoral fellowship at the Institute for Automation of Complex Power Systems at RWTH Aachen University, Germany, between 2022 and 2024 through the Alexander von Humboldt postdoctoral fellowship. His main research interests are control systems, microgrid systems, renewable energy systems, and optimization techniques for power system operation and planning. He can be reached through this email address- atsalawudeen@unijos.edu.ng.

Idakwo Monday A. is a lecturer at the Department of Computer Engineering of the Federal University Lokoja, Nigeria. He obtained a BEng. in Computer Engineering at the Caritas University, Enugu, Nigeria, an MSc. and a PhD in Computer Engineering from the Ahmadu Bello University, Zaria, Nigeria. He is presently the research lead personnel of the Department of Computer Engineering, Federal University, Lokoja and he holds key positions in some central committees of the university. His main research interests are wireless sensor networks, big data, machine learning, and digital image processing. He can be contacted by email through this email address- monday.idakwo@fulokoja.edu.ng.

Adebiyi Busayo H. is a lecturer at the Department of Computer Engineering of the Federal University Lokoja, Nigeria. He holds two bachelor's degrees: one in Physics and the other in Electrical and Electronics Engineering. He obtained an MSc. in Control Engineering from Ahmadu Bello University, Zaria, Nigeria, where he is pursuing his PhD. He is a member of IEEE; he is a member of the Nigerian Society of Engineers (NSE) and he is a licensed engineer. His main research interests are control and autonomous systems, deep learning, reinforcement learning, and optimization techniques. He can be contacted by email through this email address-busayo.adebiyi@fulokoja.edu.ng.