Application of System Dynamics to Evaluate the Interaction between Commercial Motorcycle Drivers and Enforcement Agents

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Abstract— **Commercial motorcycle is the use of motorcycles for carrying passengers for a fee. This transport mode serves the mobility needs of many remote areas and offer speed benefits in congested city centres. It is however resistant to regulations and is often in conflict with law enforcement agents. This paper looks at this problem by representing it with a system dynamics (SD) model through the application of systems thinking. A stock-and-flow model is described and operationalized. Execution of the model provides a dynamic response of the various components of the model. It is shown that drivers' errant behaviour and risky violation characteristics can be reduced by improving the modalities for acquiring motorcycles for commercial use.**

Index Terms— **Commercial motorcycle; System Dynamics; Enforcement; Deterrence**

I. INTRODUCTION

Commercial motorcycles are a popular transport mode in various countries of the world including places such as Brazil, Indonesia, Thailand, Cameroon, Sierra Leone, and Nigeria (Aluko, 2014). They are perceived to be fast, reliable, able to provide door to door service, and can serve narrow roads less accessible to other modes (GIZ, 2010; Júnior and Filho, 2002; Konings, 2006). They are therefore an important transport mode in the places where they operate including Nigeria.

Commercial motorcycle is a dominant mode of transportation for urban trips in many Nigerian cities. This was not the case previously. For example, Hathaway (1993) found no single commercial motorcycle in a medium sized city in 1988 in Nigeria. In addition, motorcycles were used in only 12% of non-walking commute trips in his study. However, commercial motorcycles now carry more than 100,000 trips per day in medium sized Nigerian cities (Aluko, 2014). Oyesiku and Odufuwa (2002) find that as much as 80% of commute trips involved the use of commercial motorcycle, a situation which is not likely to have become different today.

Nevertheless, commercial motorcycle operation is characterised with many features which are common with para-transit modes (Cervero, 2007; Sietchiping et al., 2012). This is what Cervero and Golub (2007) described as "collectively damaging behaviour ". They are regarded as being dangerous, usually operating illegally and have been accused as the main cause of traffic disturbance (Kubota and Joewono, 2005). Thus they are usually the target of law enforcement agencies. Various studies however note that despite being the target of law enforcement agencies, their operation has not improved. They are still dangerous as they ignore traffic laws (Aluko, 2014). This study therefore adopts a systems method to look at the operation of this transport mode.

The concept adopted is that of system dynamics. System dynamics approach has its foundation in systems theory. Systems theory provides an improved understanding about the inter-connectivity and interactions between the different components of a system. It presents the behaviour of each component as a response to the interactions between components within the system and the behaviour of the system as a consequence of the combined effect of these interactions. Thus, Conroy and Allen (2010, p.195) note that problems perceived in the outside world are usually the visible part of a much larger and mostly-hidden "iceberg". The system structure that generates the visible patterns apparent about the problem are usually not seen as they lie deep beneath the "iceberg". Systems approach therefore attempts to reveal this hidden iceberg by enabling the problem to be viewed as a reflection of a system and to identify the structure that drives it. This approach seems well suited to understudy the operation of commercial motorcycle with respect to why it has consistently been in conflict with enforcement agencies without any improvement in its regulation.

In the following section, a brief review of the stages involved in data collection and analysis to obtain a causal loop diagram (CLD)) is presented. This is followed by a description of the feedback loop in the CLD and how it is reflected in the subsequent model. Section 4 demonstrates the process of translating CLD into mathematical equations while the fifth section conducts some model responsiveness tests. A brief conclusion is provided at the end of the paper.

II. DATA COLLECTION AND ANALYSIS: THE PROCESS

The data collection method employed is more similar to Turner *(2013*) than the GMB method (Andersen and Richardson, 1997) in system dynamics modelling. Stakeholders were contacted for semi-structured interviews. The semi-structured interviews adopted some general lead-questions; other questions raised during the interview resulted from responses to the lead questions. 25 respondents from seven stakeholder groups participated and granted 13 interview sessions in all. Most of these interviews were audio recorded while others that could not be recorded were documented by hand-written notes. The entire data was transcribed for the ease further analysis. Other written

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documents such as newspaper reports and literature on commercial motorcycle safety provided information that influenced the researcher's frame during data analysis.
The data collection phase was followed by data coding using Miles et al. (*2014*) *causation coding* and Burnard's (1991) steps for coding interview data. The codes obtained were first sorted into small clusters as a starting point for generating meanings in the analysis. Both Miles et al. (*2014*) and Saldana (2013) suggest the use of graphical representations called *causal networks* for the outcome of a coding process to support "sense-making". Causal networks are graphical illustrations of cause and effect as they are deduced from the data. They are drawn with the use of arrows and codes. Arrows link codes to one another and indicate how one thing leads to (or is affected by) the other. In all, five networks were obtained. The causal networks obtained were combine to form a single network. There were redundancies in the form of repetitions that were removed in preparation for the next step in the data analysis process.

The next step was the generation a worded description of all the links present in the causal network. This description helps to provide a story-like account of how and, often, why one cause leads/ relates to its effect. This description is called a "narrative" (Miles et al., *2014*). A narrative provides a complete description of a system's causality relationship as found in the data without including illustrations, examples, and other less important information that make the original data bulky. There are no rules about the starting and end points of the narrative. It is however important that all the links and codes in the causal network are included in the description.

From this narrative, the processes/cycles/dynamics in the system were extracted as summary points. These summary points are what make dynamic hypothesis required for building a (CLD). This summary is different from the narrative in that while the narrative is a story-like description of all the links identified in the data, the summary is a list of bullet points/ statements of the content of the story. The summary identifies processes/ events in the story and why they happen the way they do. More specifically, for the purpose of the development of a CLD, these summary statements describe processes and their feedback loops in a manner that they form a dynamic hypothesis for the problem structure in the system being analysed.
While the process describe thus far is a typical qualitative analysis method found in (Miles et al., *2014*), the possibility at this stage to obtain summaries that can form dynamic hypothesis makes the method suitable for adoption in developing conceptual models such as a CLD. One of the dynamic hypotheses generated from this process is labelled *Deterrence* and is presented below:

Enforcement operation should deter drivers from engaging in violations and build the culture of safe driving behaviour but this process is weak.

III. THE FEEDBACK LOOP IN THE CLD

Based on the dynamic hypothesis presented above, a balancing feedback loop (Rehak, et al., 2006) was identified and is shown below. This is deterrence feedback loop. The names in the figure is first explained.

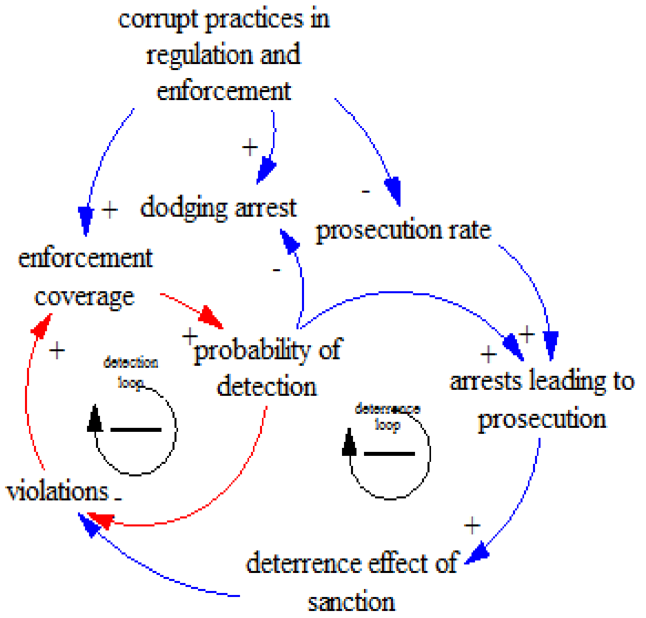


Figure 1: Deterrence CLD (Aluko, 2014)

In the figure above, eight names are used. These are *enforcement coverage, probability of detection* and *violations*. Others are *deterrent effect of sanctions, arrests leading to prosecution, prosecution rate, dodging arrest,* and *corrupt practices in regulation and enforcement*. **Enforcement coverage** is used to describe the number of police posts mounted on the highway to monitor traffic. **Probability of detection** means the likelihood of a violation committed being detected by the police. **Violations** are the traffic offences usually committed and for which arrests can be made. **Arrests leading to prosecution** means the number of arrested violators who face prosecution. **Dodging arrest** is when drivers flee officers to avoid being arrested. **Corrupt practices in regulation and enforcement** represents corruption in regulation and enforcement processes (Anbarci et al., 2006). **Deterrent effect of sanctions** is the behavioural pattern that the application of sanctions is able to cultivate particularly with respect to the tendency to refrain from committing a violation. **Prosecution rate** is the percentage of arrested violators that are prosecuted.
From figure 1 above, it shown that increase in **enforcement coverage** leads to increase in the **probability of detection**. Thus the number of police posts on highways often relates to the level of violation of/ adherence to traffic rules. As the **probability of detection** increases, there is a fall in the number of **violations** committed by drivers and this can ultimately result in less **enforcement coverage**. Moreover, increase in probability of detection leads to increase in the number of **arrests leading to prosecution**. As the **arrests leading to prosecution** increases, the **deterrence effect of sanction** improves. Improvement in the **deterrence effect of sanction** leads to a fall in the number of **violations** committed by drivers. However, **corrupt practices in regulation and enforcement** reduces **prosecution rate**. A fall in **prosecution rate** reduces the number of **arrests leading to prosecution** so that the **deterrence effect of sanction** does not improve as it should be.
The deterrence dynamic hypothesis can now be translated into stock and flow diagrams (SFDs). The term stock and flow diagram is used in the system dynamics model to mathematically represent CLD. While CLD is a qualitative

description, SFD contains mathematical description of the relationships indicated in the CLD. The process of formalisation follows from here.

IV. MODEL FORMALISATION OF THE DETECTION MODULE

In this section, an illustration of how the model is formalised is presented.

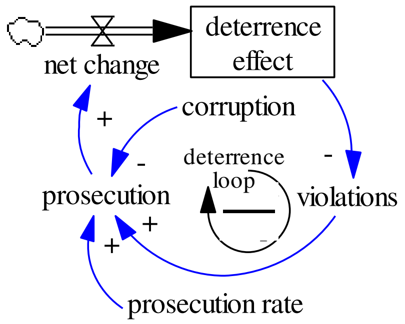


Figure 2: Deterrence SFD

The deterrence module represents the effect of sanction on the behaviour of drivers. This representation follows the theory of deterrence[1]. A simple formalisation for the deterrence effect is shown in figure 2 above. The figure shows that **deterrence effect** changes in response to **net change** while **net change** varies in response to **prosecution**. **Prosecution** is the consequence of **violations** but depends on **corruption** and **prosecution rate**. Thus, whether **prosecution** will improve **deterrence effect** and reduce **violation** depends on **prosecution rate** and **corruption**. These factors are treated under the following two units: **deterrence effect**, and **prosecution and associated factors**. These are therefore represented in the sub-models as *deterrence effect* and *prosecution*:

4.1 Deterrence effect

The deterrence effect of sanction is an attitude (or behaviour) factor. It builds up over time and so can be represented by a stock. This stock is now called **tendency to violate** in figure 3 (no longer *deterrence effect* as in figure 2) below.

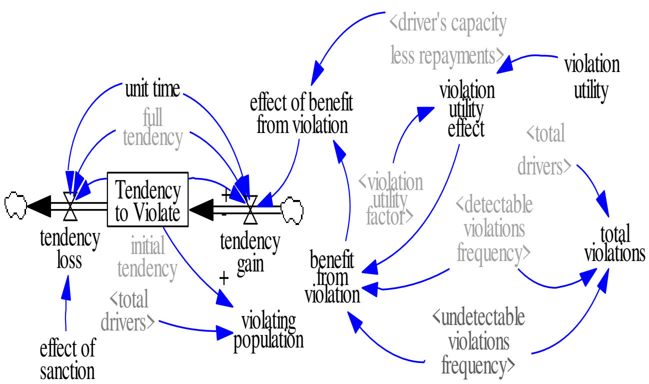


Figure 3: SFD for deterrence effect

Tendency to violate: this is a measure of drivers' attitude to violation, i.e., a measure of the likelihood of a violation action for a representative driver faced with the option of committing a violation. Driver behaviour is widely acclaimed in safety studies to be mainly responsible for safety problems drivers have (Cheng et al., 2011; Stanojevic et al., 2011). In this model, it is depicted as a behavioural predisposition and by that assumption it develops over time and is therefore represented as a stock. Mehmood (2010) supports this variable as a stock by showing that past behaviour directly influences future behaviour. It is given an initial value of 0.45 in this model to indicate that tendency to violate was in place prior to the emergence of commercial motorcycle[2]. This parameter is given by

$$TTV_t = TTV_{t(t-1)} + \sum(TG_t - TL_t)\ ;\ TTV_{t(0)} = 0.45 \qquad (1)$$

where TTV is the **tendency to violate** by a representative driver. It is given the unit **dimensionless**. $(TG_t - TL_t)$ is the summation of changes in the tendency at any time. TG and TL are **tendency gain** and **tendency loss** respectively and are described below:

Tendency gain and **tendency loss**: **Tendency gain** is a parameter that increases the level of **tendency to violate**. It is caused by the **effect of benefit from violation** on driver behaviour. **Tendency loss**, on the other hand, is caused by the **effect of sanction**. Since **tendency to violate** is presented as a behavioural tendency, it is treated as an index between 0 and 1. Its state at any time depends on its state at the previous time period. This is captured by assuming that the growth pattern follows a logistic function. This is represented in the equations for **tendency gain** and **tendency loss** given as

$$TG_t = \frac{EBF_t}{UT} * TTV_{t(t-1)} * \left(1 - \frac{TTV_{t(t-1)}}{FT}\right) \qquad (2)$$

where $TG$is the **tendency gain**, EBF is the **effect of benefit from violation**, FT is **full tendency** to violate, meaning 100% violation tendency, and TTV is **tendency to violate**,, UT is **unit time**. The unit of measurement is per time period, i.e.,**1/week**.

In the case of **tendency loss**, the equation is similar as shown below

$$TL_t = \frac{EOSC_t}{UT} * TTV_{t(t-1)} * \left(\frac{TTV_{t(t-1)}}{FT}\right) \qquad (3)$$

where TL is **tendency loss**, UT is **unit time**, and $EOSC$ is **effect of sanction**. The unit of measurement is**1/week**.

Effect of sanction: this parameter measures how the cost of violation (i.e., money paid by drivers in form of fine and bribes) affects driver behaviour. It estimates this impact by taking the ratio of violation cost to drivers' income capacity. It is assumed that the more the value of this ratio, the higher the **effect of sanctions** and vice versa. The equation is given as

$$EOSC_t = \max_0 \left(\min_1 \frac{APPD_t}{DCLR_t}\right) \qquad (4)$$

where $EOSC$ is **effect of sanction** on a representative driver, $APPD$ is **average payment per day**, and $DCLR$ is **driver's capacity less repayments**. **Effect of sanction** is an index that takes values between zero and one. Its unit is **dimensionless**. **Driver's capacity less repayments** is parameter is used to show the difference between driver's income when and when not having repayments by bringing in the cost of repayment.

[1] This theory rests on the proposition that human behaviour is, to some degree, rational and that individual's actions can be modified when the potential punishment is weighed against the potential benefits. (more information can be found in Garoupa, 1997; Chang et al., 2000)

[2] The literature indicates that the disregard for safety rule is one of the reasons for high accident rate in many developing countries. It is not peculiar to commercial motorcycles.

Effect of benefit from violation: this parameter measures how benefit from violation (i.e., monetised value of violations to drivers) affects driver behaviour. It estimates this impact by comparing the monetised benefit as a ratio to drivers' income capacity. It is assumed that the more the value of this ratio, the higher the effect of this benefit and vice versa. The equation is given as

$$EBF_t = \max_0 \left(\min_1 \frac{BFV_t}{DCLR_t}\right) \qquad (5)$$

where EBF is **effect of benefit from violation** of a representative driver, BFV is **benefit from violation**, and $DCLR$ is **driver's capacity less repayments**. It takes values between zero and one too and its unit is **dimensionless**.

Benefit from violation: This is the estimated total monetary benefit a driver derives from committing violation in a day. It is given by

$$BFV_t = VF_t * VUE \qquad (6)$$

where BFV is **benefit from violation**, VF is **violation frequency**, and VUE is **violation utility effect**. Its unit is **NGN/(Week*day*driver)**.

The value of **violation utility** used in the model is very high: it is the equivalence of one hour of work of a commercial motorcycle driver. As Garoupa (2003) notes, violators are limited in rationality more so as "people seem to exaggerate a small or zero probability and have difficulty in processing probabilistic losses" and that "individual prefer more to less income"(Garoupa, 2003, p.8). Based on this, it is possible to explain why violation is prized so high. Notwithstanding, it is important to note that not all violations offer monetary reward. They are, however, monetised for convenience of computation.

4.2 Prosecution effect

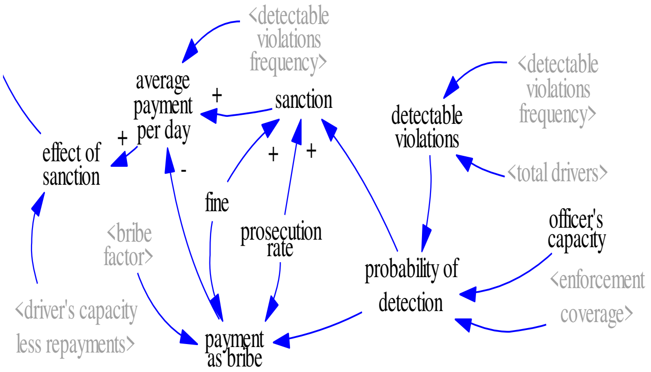


Figure 4: SFD for prosecution and its associated parameters

This part of the model shows how the parameter: **effect of sanction** shown in figure 3 is generated. It shows that it is a function of **probability of detection**, **prosecution rate,** and **fine**, amidst other things. The SFD representing this part is shown in figure 4 above.

Probability of detection: is a measure of the likelihood of a violation committed by a driver being caught by an officer. Polinsky and Shavell (1999, p.6) note that "fine and the probability of apprehension" are usually chosen to maximise benefit to the society. In this model, the value of the probability of detection has been chosen to range from 0 to 1 depending on the level of violations and **enforcement coverage**. Equation for **probability of detection** is given as

$$POD_t = \begin{cases} POD_{LKP} : \frac{DV_t}{EC_t * OC}, & EC_t * OC \geq DV_t \\ POD_{LKP} : \frac{EC_t * OC}{DV_t}, & EC_t * OC < DV_t \end{cases} \qquad (7)$$

where POD is the **probability of detection**, EC is the **enforcement coverage** of officers, OC is **officer's capacity**, meant to estimate the number of violations an officer can deal with in a typical day, and DV is the number of **detectable violations**. The number of violations an officer can deal with is not known. An heuristic relationship is used to make up for this. OC is however included for dimensional consistency.POD_{LKP} is a heuristic relation used to retain the values between zero and one. It follows from the findings of Elliot and Broughton (2004) (see also (de Waard and Rooijers, 1994). Similar relationship is used in Mehmood (2010). This function is shown below. The unit of measurement of **probability of detection** is **dimensionless**.

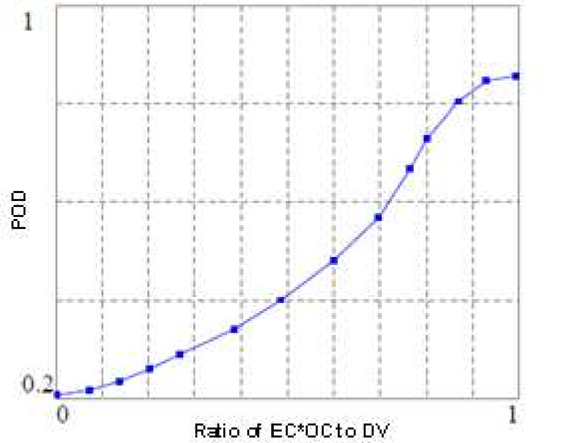


Figure 5: Heuristic function for probability of detection (POD, EC, OC, and DV are define above)

Detectable violations: a distinction is made between **detectable violations** and **undetectable violations**. **Detectable violations** can be easily enforced but **undetectable violations** are difficult to enforce as there are no ready or clear evidence about them due to, for example, unavailability of automatic traffic monitors such as speed cameras. It is shown here that what enforcement operation can focus, enforce and prosecute are **detectable violations**. **Detectable violation** is given as the product of the frequency of violation and total number of drivers, i.e.

$$DV_t = \max_1 DVF_t * TD_t \qquad (8)$$

where DV is **detectable violations**. Its unit of measurement is **violation/(week*day)**. DVF is the **detectable violation frequency**, the frequency of committing violations by a representative driver. TD is **total drivers**. Its unit of measurement is **driver**.

Prosecution rate: is the ratio of violations prosecuted to the total number of detected violations. The index of corruption (CPI)[3] provided by Transparency International available online provides a guide for the value chosen. The value of 0.275 is used in this model. The unit is **dimensionless**.

Average payment per day: assuming a frequency for the violating drivers, the hypothetical cost of violation to each violating driver is what is described by average payment per day. It is given by

$$APPD_t = DVF_t * (S_t + PAB_t) \qquad (9)$$

where $APPD$ is **average payment per day**, DVF is **detectable violation frequency**, PAB is **payment as bribe**,

[3] CPI – corruption perception index. The website http://www.transparency.org/cpi2012/results shows Nigeria's CPI to range between 0.22 and 0.31 for the year 2012 (the year for data collection)

and S is **sanction**. The unit of measurement is **NGN/(day*Week*driver)**[4].

Sanction: this is the hypothetical average amount of money a violator pays by law for committing a violation. It depends on the probability of detection in the system (Polinsky and Shavel, 2001) and is given as

$$S_t = \max_0 PR * F * POD_t \qquad (10)$$

where S is **sanction** , F is fine, $POD_.$ is **probability of detection**, and $PR_.$ is **prosecution rate**. The unit of measurement is **NGN/violation**.

Payment as bribe: is the hypothetical average amount of money a typical violating driver pays out to officers as bribe for being caught for a violation. Its equation is formed to take account of possible changes in the prosecution rate. It is given as

$$PAB_t = \begin{cases} \max_0 BF * (1 - PR_t) * F_t * POD_t, & PR_t < 1 \\ 0, & PR_t \geq 1 \end{cases} \qquad (11)$$

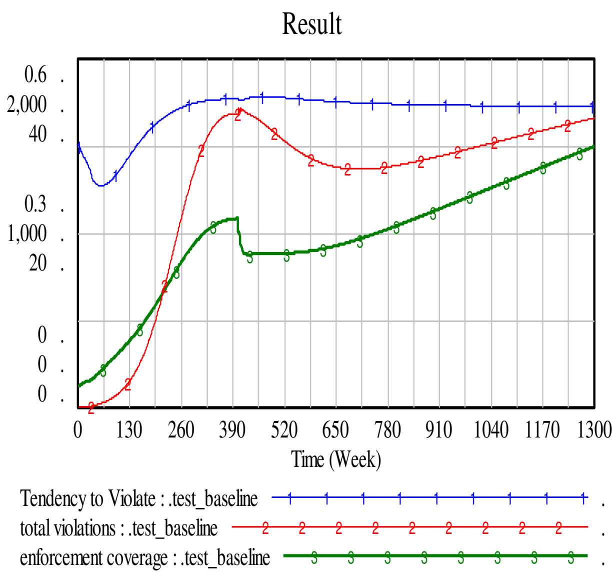
where PAB denotes **payment as bribe** for a violation, BF is the **bribe factor**, also called "bargaining power of the enforcer" by Polinsky and Shavell (2001, p.4), PR is the **prosecution rate**, F is the average legal **fine** being charged when caught for a violation, and POD is the **probability of detection** of a violation. The unit for **payment as bribe** is **NGN/violation**.

V. MODEL RESPONSIVENESS TESTING

A way to demonstrate the usefulness of the model developed is to undertake tests that check the responsiveness of its outputs to interventions. Three different parameter values are changed at the end of the simulation period (15 years) and their impact on the system, run over a period of additional 10 years (to make 25 years) is discussed. These tests include:

1. Change The Assumption About Expensive Ownership Options
2. Remove The Effect Of Competition

First, the base line scenario is presented below in figure 6 below



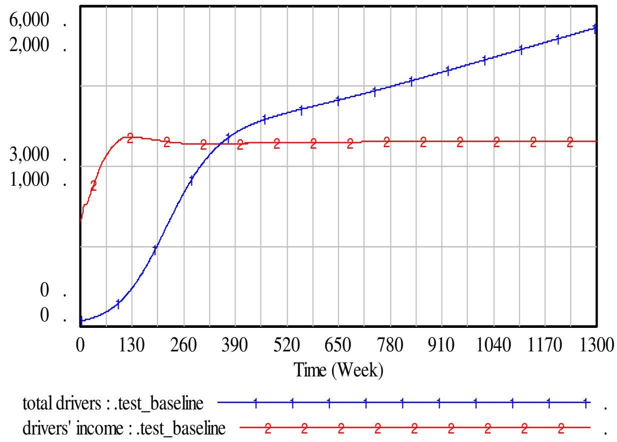
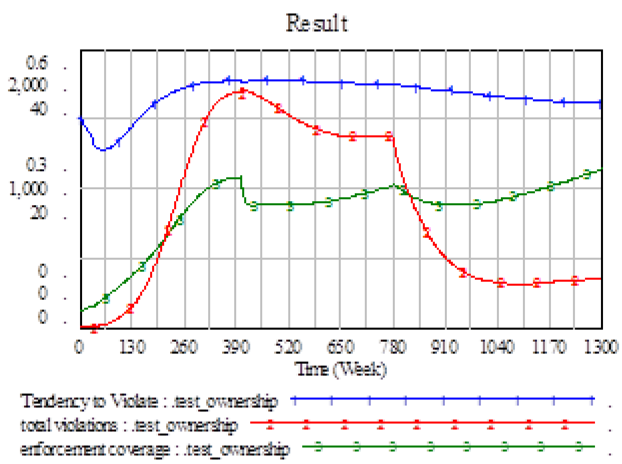


Figure 6 Baseline scenario for some model parameters (Aluko, 2014).

Figure 6 shows the base line scenario as obtained from the model. In the first of the two diagrams, the blue line labelled "1" represents **tendency to violate**, the red line labelled "2" represents the **total violations** while the green line (labelled "3") in the figure represents **enforcement coverage**. This simulation period covers 25 years: 15years into the past (between 1997 and 2011) and 10years into the future, taking the year 2011 as the reference point. The graph shows that drivers' **tendency to violate** remains high past the first 15 ending at 0.52 unit. Similarly, the **total violations** committed in the system continue to rise after a dip that followed aggressive enforcement. **Total violations** ended at 1674 violations/week-day while **enforcement coverage** ended at 30.24 officers. The number of drivers grew to about 5598 drivers while their income ended at about NGN1158 per day.

5.1 Change The Assumption About Expensive Ownership Options

This is a test to check the soundness of model behaviour 10 years into the future. It assumes that an attempt is made to stop new drivers from acquiring motorcycles by means that require expensive repayment cost when joining the trade. To test this change, some equations were modified/ added. The effect of this test as found by the model is shown below in figure 7.



[4] NGN means Nigerian Naira

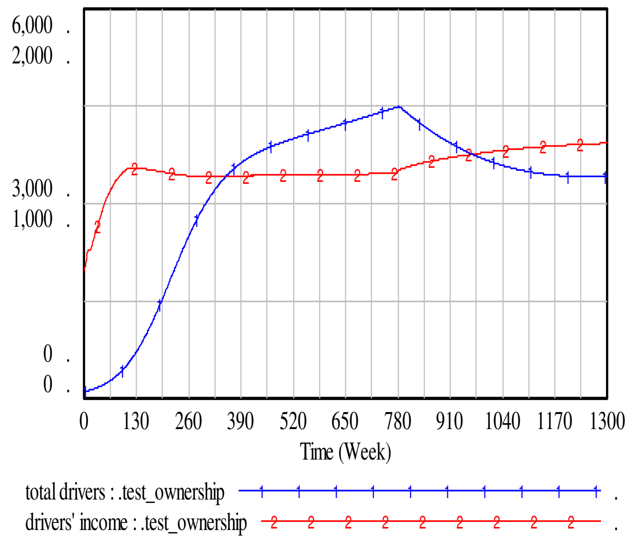


Figure 7 Model behaviour under a test on expensive ownership options(Aluko, 2014).

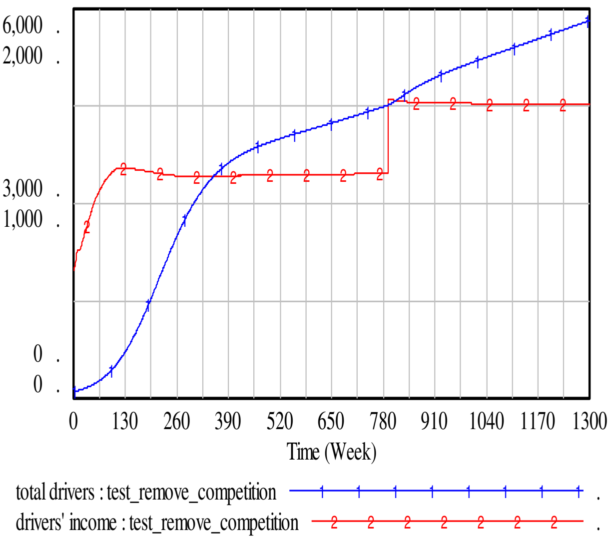
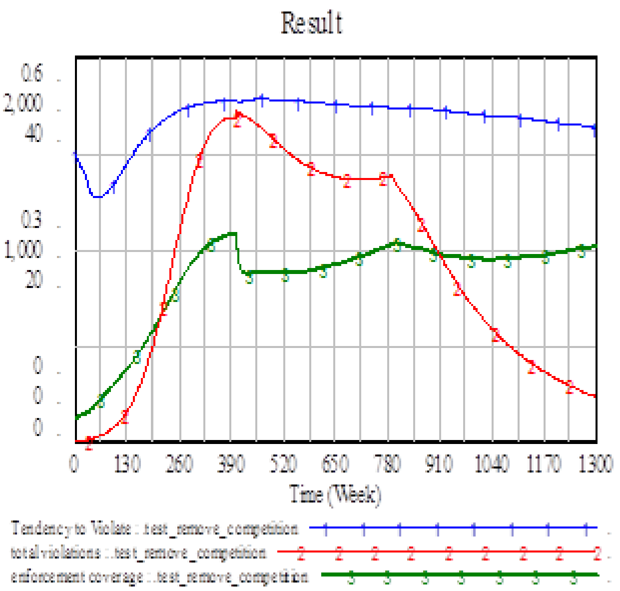


Figure 8 Model behaviour under a test to remove competition effect (Aluko, 2014).

As shown in figure 7 above, **tendency to violate** fell slightly to about 0.48 in this test from 0.52 unit. The **total violations** fell significantly from its previous value of 1674 to about 352.5 violations/week-day. It however shows that **enforcement coverage** requirement later rose – with a smooth rise from about 18 to 22.69officers. Compared with the baseline, the **enforcement coverage** is 22.69 officers (30.24 for baseline). The number of drivers under this condition fell to about 3418 drivers (5598 for baseline) while their income rose slightly from NGN1158 in the baseline condition to NGN1309.This result shows the importance of ownership characteristics in risky violations.

5.2 Remove The Effect Of Competition

This is a policy that implies that drivers' income is guaranteed and so removes all pressure that competition normally brings. To run this test, some equations are modified/ added. First, the variable, **new driver** in the model is multiplied by a test factor, **test to secure income.**



The simulation output for this test is shown in figure 8.The figure shows that removing the effect of this parameter(ECI) would reduce the number of violations committed significantly to 236.5 from 1674 violations/week-day in the baseline case. It is also shown in this test that less **enforcement coverage** of 20.57 officers would be required compared to the baseline case of 30.2. Similarly, drivers' **tendency to violate** will come down to about 0.49 unit from 0.52. The total number of drivers under this test is higher than the baseline case of 5598 at 5820 drivers while drivers' income is NGN1507 up from NGN1158 baseline case. This result emphasise the contribution of competition to unsafe driver behaviour.

VI. CONCLUSION

This paper points out that the interaction between the enforcement agencies and the drivers of commercial motorcycles has not improved the operation of this mode. Presenting system dynamics approach, the paper notes that the approach treats the characteristics of a system as the outcome of the interactions within its elements. It shows that an improved understanding about commercial motorcycle operation can be obtained by treating it as a system and understudying the system's characteristics.

Following the above, the paper looks at commercial motorcycle characteristics and interactions using systems approach. Generating a causal loop diagram and a stock and flow model, a scenario analysis was conducted to see how changing some characteristics can impact the system characteristics. The analysis shows that the uncontrolled manner by which new drivers join the trade and the type of funding adopted to own their motorcycles affect their behaviours and makes it difficult to be safety conscious.

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