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A Time-Delay Smart Grid Communication Optimization Model for Transient Fault Tracing and Load Management

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ABSTRACT:
This paper developed faster communication grid architecture for signaling and information sharing, with robust distributed cloud management architecture that links the processes for both faults and load management. Experiments were carried out on smart grid (SG) layered time-delay optimization model (LTDOM) using schemes such as SG Neural Network Algorithm (proposed technique), SG stackelberg game algorithm (SGSGA), SG chaos-flower pollination algorithm (SGCFPA), SG cuckoo search algorithm (SGCSA), SG differential search algorithm (SGDSA), and SG cournot algorithm (SGCA) were used for validation of the study. Riverbed Modeller software academic version 17.5 was used to setup the experimental design for LTDOM architecture and the various algorithms were developed with C++ to achieve the simulation test-bed. Smart grid metrics such as energy data received, service delays, media access delays and service throughput were used for performance evaluation. For example, the service throughput results showed that the proposed SGNNLA, SGSGA, SGCFPA, SGCSA, SGDSA and SGCA had 24.09%, 21.68%, 16.86%, 15.66%, 12.04% and 9.63% respectively. This implies that as load demands in the peak periods is being shifted to the off-peak periods, the proposed SGNNLA utilized optimum resources while delivering satisfactorily on the grid network when compared to other schemes.

KEYWORDS: Load management, SCADA, Smart grid, Time-delay model, Transient fault tracing.

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1.0 INTRODUCTION:

In modern times, generic grid systems have tried to deal with challenges in maintaining the smooth and uninterrupted supply of grids while carrying out maintenance and switching sources of supply. Kusakana (2016) explained that for any operational grid system either large or small, there has to be proper coordination for optimal operation. Basic power generation, transmission and distribution systems have the common quality of being electrically active weather transmitting or absorbing electricity.

A smart grid (SG) communication system refers to integrated systems that make use of advanced information driven entities in a bi-directional fashion while relying on cyber-computational algorithms to make decisions throughout the complete spectrum of the energy system from generation source to endpoint usage terminal. These same systems being either on or off grid tend to required proper coordination being either grid connected islanded, bidirectional or with an intermittent power flow (IEEE Smart Grid, 2016). It has also been proven that majority of grids tend to be complex and challenging due to their nature and operations. Smart Communication systems constitute a critical aspect of power systems success with seamless communication between the various aspects of the system (Ganesan *et al.*, 2020).

In terms of communication, a number of issues need to be considered. These include: proper selection of communication channels, efficacy of the communication, data security, reliability and redundancy (Rapatwar & Rathkanthiwar, 2015). Tracing and preventing faults have become very significant considering the raising functionality and advancement of distributed power systems.

Failures resulting from faulty distributed power systems appear inevitable but can be addressed (Kondo *et al*., 2010). There are existing algorithms and models previously highlighted for fault management but have yielded very weak results.

In the case of developing countries, due to the poor infrastructural components needed for proper grid communication, the aging infrastructure, communication systems are rather ad hoc and are not tailored to sufficiently communicate in totality for a common system. Ideally, grid communication in the 21st century requires the utilization of duplex networks that have bidirectional flow of information in order to be capable of controlling information and commands where Supervisory control and data acquisition (SCADA) is available (Yan *et al*., 2013). The use of system logs seems to have assisted in tracing faults while preventing failure agents that cause breakdowns (Shatnawi & Ripeanu, 2011).

However, the analysis of the number of total grid failures against the partial grid in Nigeria for 2019 reveals that the inability of the grid to isolate faults before they cause a total collapse is about 10% communication (Kulkarni & AKulkarni, 2016). Furthermore, there is a significant delay in the restoration of full grid function due to the delays in either resetting or rectifying faults and relaying the all clear status to the control center. It was observed that that within the span of six months (from January 2019 to June 2019), a number total grid outages can be attributed to a limited connectivity in the grid network. Effectively, the major difference between a grid partial grid collapse and a full grid collapse is associated with the time in which fault isolation through communication occurs in a timely manner (Kondo *et al*., 2010).

Table 1 shows the frequency and number of faults in the grid in 2019. The difference between a full grid collapse and a partial grid collapse is a result of adequate isolation and protection systems that can identify and isolate a fault condition on the grid before it results in a full grid collapse. Nigam *et al.* (2019) revealed a somewhat duplicated load pattern between the first and second months of the year. This created the motivation to use the first six months of the year as the pilot sample size.

Table 1. Fault collapse scenarios

Month	Event	Occurrence	Full/Partial
Jan 2019	Collapse	4	PPPP
Feb 2019	Collapse	1	F
Mar 2019	Collapse	0	P
Apr 2019	Collapse	2	PF
May 2019	Collapse	1	F
Jun 2019	Collapse	1	P

Where: P = Partial grid collapse and F = Full grid collapse

This phenomenon would imply that the major difference between a full grid collapse and a partial grid collapse is the presence of a communication channel. This would imply that with sufficient empirical data, the probability of a grid collapses can be projected and perhaps predicted. Considering the on and off status of the outages characteristic that can be categorized as a one and a zero for outage and no outage state, it could be possible to adopt a binary connotation to identify and tag the dual states.

This paper aims to develop an improved smart grid (SG) architecture that leverages layered time-delay optimization model (LTDOM) for tracing feasible outages. This offers binary array for both load and fault prediction of grid integrity. In context, various algorithms for LTDOM were developed with C++ to achieve the simulation test-bed. Also, this work will present a robust SG architecture that supports Internet protocol and multiprotocol label switch (IP/MPLS) at the gateway broker.

1.1 Review of Related Work

In developing a predictive fault tracing system, as well as, the computation algorithms running on smart grid architecture, a number of methods can be employed. However, for this endeavour, most works prefer binary logistic prediction model, maximum likelihood estimation and time delay estimation (Van-Smeden, 2019; Gazor *et al*., 2010; Lee *et el*., 2008). Zhihai *et al*. (2014) used fault detection signal for distribution power grid fault diagnosis and location. Zhang *et al*. (2019) proposed a new fault location algorithm based on tree topology in smart grid designs. Fan *et al*. (2019) explored large data mining analysis method, including: Spark, Hive, HDFS (Hadoop Distributed File System), MapReduce for smart grid equipment fault prediction and early warning, dynamic operation and maintenance strategy. Lee and Shin (2018) implemented Software-Defined Networking (SDN) concept in Smart Grid for reliable data transmission (fault tolerance). In Aziz *et al*. (2017), an enhanced particle swarm optimization is proposed for optimal network reconfiguration in smart grid based on various branch faults. In Reddy and Chatterjee (2017), superconducting fault current limiters (SFCL) were applied in power system model to address Indian grid system with generation, transmission, and distribution facility. Wu *et al*. (2012) looked at self-diagnosis of Smart Grid using PMU/WAMS to trace the location of disturbance so as to eliminate the source and prevent a recurrence.

In distributed energy management system, Wu *et al*. (2012) modelled an interaction with an interconnection among utility companies, Micro-grids and customers as a two-stage stackelberg game without fault monitoring in distributed energy management algorithm. Ni *et al*. (2019) proposed a bi-level optimal scheduling model based on stackelberg game for the economical fault operation of electric vehicle charging-swapping-storage integrated station. Yang *et al*. (2019) proposed an optimal scheduling scheme for peak load regulation ancillary service market considering stackelberg game. Pandya *et al*. (2018) developed a meta-heuristic optimization algorithm called CHAOS-Flower Pollination Algorithm (CHAOS-FPA) for optimally scheduling distributed energy sources in a smart grid.

Zeng *et al.* (2018) proposed Cuckoos Search (CS) optimization algorithm for maximizing of net profit of distributed PV system based on planning, expansion and reconstruction of distribution system. Cakmak and Altas (2016) focused on Smart grid DSM techniques which increase the efficiency of the grid, and modify consumer's electrical demand via demand response (DR) programs using financial incentives. In their work, shiftable domestic loads scheduled by Cuckoo search algorithm (CSA) was employed to ensure balanced load curve as much as possible while considering the consumers' preferences. Buaklee and Hongesombut (2013) presented an application of the cuckoo search for the optimal sizing and sitting of DG in a smart distribution power system. Soares (2015) explored the application of differential search algorithm (DSA) for solving the day-ahead scheduling in smart grid energy resource scheduling model. Qureshi *et al.* (2018) combined Harmony Search Algorithm (HSA), Enhanced Differential Evolution (EDE) and Wind Driven Optimization (WDO) to achieve DSM in SGs.

Existing works have highlighted optimal scheduling schemes for SG systems without employing time-delay optimization model needed for transient fault tracing. Also, load optimization control in SG systems is yet to be fully evaluated within the context of a robust architecture. These issues are being addressed in the present work.

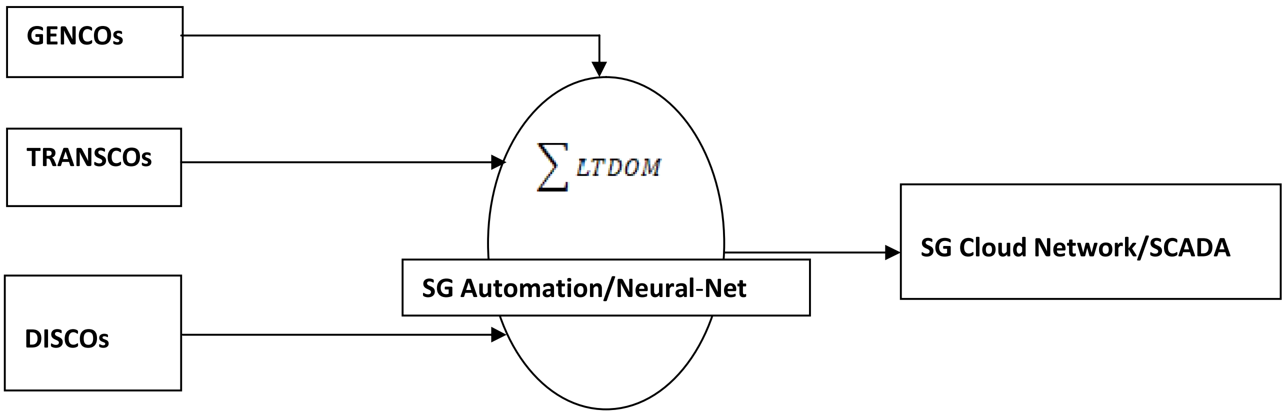
2.0 MATERIALS AND METHODS:

The global system architecture is shown in Fig. 1 depicting fully automated fault monitoring core. Mathematically, the SG model is generally shown where the combinations of several internal and external design factors relating to the power generation, transmission and distribution in a SG ecosystem. The terminal point for overall load control is at the SG cloud network.

Components of the neural driven LTDOM with full fault protection include: Cluster Parent (AMI Tx), AI_base Hub (CIU), Data Aggregator

(AMI_local Concentrator), and the global concentrator (IP backbone). The other components in the grid communication engine include: AMI network construction, data aggregation, encrypted message push from edge to sink, sink AMI node instantiation, local and global concentrator activation, message decryption based on key lengths, Grid OpenFlow firewall full duplex traffic re-orientation, sink closure (accept/discard roles).

For the development, the process node models of LTDOM IP/MPLS, conjugate batch gradient was used instead of stochastic Gradient Descent to build the Smart grid Cluster Parent (AMI Tx). This is because; the later does not require knowledge of a complete training of CIU and AMI node sets.



[GENCOs = Generation Companies, TRANSCOs = Transmission Companies, DISCOs = Distribution Companies, SG = Smart Grid, LTDOM = Layered Time-Delay Optimization Model, SCADA = Supervisory Control and Data Acquisition]

Fig. 1. Grid communication model

This procedure provides a stepwise random projection onto a set of available node set (hyper-node planes) until convergence. The method starts with an arbitrary initial vector CIU node ϑ^0 and at every iteration i, the algorithm randomly selects a CIU row(k) $\in i \in \{1, \dots \dots \dots \dots \dots \dots n\}$ of the layered cluster as the parent nodes. It then uses the sampled data streams to calculate the gradient based on the local loss function i.e $\partial(xi, yi)$ as highlighted in Algorithm I.

The parameter ϑ^k is updated by moving a small step size along the flow gradient as shown in Algorithm II. The CIU and AMI are updated after every sampling provided the buffer limits are not exceeded. In this case, the electrical layer routing communication traffic capacity constitutes the inter-layer capacity constraint.

Algorithm I: CIU input terminals (destination address, source address, queue size, link Information) procedure for user connection from DISCOs.
CIU Data: Source address, destination address, queue size, link Information
CIU Output: DataStream hits local aggregator La_g
Begin ( )
CIU_ Polyadd_CIU & AMI Dest (Input, Output)
Initialize CIU = 0; CIU > 0 ; i ++)
Call Cluster Parent (AMI Tx);
End.

Algorithm II: Cluster Parent (AMI Tx)/ AI_base Hub (CIU) (Conjugate batch Gradient)
#Define CIU as Cluster Parent (AMI Tx)
Initialize: i, iterations T, $\vartheta^k \leftarrow 0$

for (i = 0; i > n ; i++) // convergence or maximum iteration i
Do AMI $\leftarrow 0$ until ($AMIp_o$, AMI_1, $AMIp_2$, $AMIp_3$, $AMIp_4$, $AMIp_5$, $AMIn_{n+1}$) $\overset{\Delta}{\rightarrow}$convergence or maximum iteration i
Int AI_base Hub (CIU);
for i = AMI_0 to $AMIn_{n+1}$
Return Link;
Drawi $\in \{1, \dots \dots \dots \dots \dots \dots n\}$
Map i $\leftarrow$AI_base Hub (CIU)
Upper Limit Buffer $\leftarrow$ Set ETXthersh;
Update$\vartheta^{k+1} = \vartheta^{0k} = \partial(xi, yi)$.
End

Algorithm III shows the data aggregator (AMI_local Concentrator) connection with full fault protection. In this case, the AMI local aggregator models the node process and carries out multiple rounds of Conjugate batch Gradient in parallel on node $i \in \{1, \cdots, n\}$ using the initial parameter ϑ^k obtain from the T-th iteration. The algorithm for the device reduces all the gathered operation that computes ϑ^{k+1} in Algorithm II. This is done via the sample averaging of all the gathered data streams from all the AMI nodes. The AMI local concentrator reduces operation uses synchronization to achieve data aggregation. By applying AMI local concentrator scheme on the edge network, it improves performance with increase in the node size. The data stream queue system occurs in such a manner that stream arrivals reach infinite concentrator queued La_g at time (t). In the algorithm, a read function obtains incoming streams and creates the linked list representing the corresponding input arrivals. All the localized but aggregated data are synchronized further and recycled to the Grid global concentrator for open firewall processing.

Algorithm III: AMI local concentrator/ local aggregator
Input: local ID, destination ID, queue size, link Information
Output: Gather up streams and dispatch the infinite queues to Global sink
Draw AMI_local Connection ( ); AMI_Global Connection *j* ( )
Initialize: *i*, iterations T, $\vartheta^k \leftarrow 0$; $\vartheta^k(CIU\ \&\ AMI)$
Map AMI data (individual nodes)
While all data (i) not converged (Buffer) do
For all i (AMI) $\in \{0, \dots \dots \dots \dots \dots \dots n-1\}$
do read (i);
For i:=0 to N-1 **do** read (φ[i]);
For i:=0 to N-1 **do** read (∂[i]);
For i:=0 to N-1 **do** read (n_{k+1}[i]);
For j:=0 to N-1 **do** read ϑr[i]: = φ([i]);+ ∂([i]);+………(n_{k+1}[i]);
For i:=0 to N-1 **do** write (j[i]);

$$\vartheta^{k+1}(CIU\ \&\ AMI) = \frac{1}{N}\sum_{i=1}^{N} \vartheta^k$$

End

3.0 RESULTS AND DISCUSSION

3.1 Dynamic Simulation of Smart Grid LTDOM

For smart fault tracing, the AMI component use to address real time feedback routine. For load management via the cloud, a layered time-delay optimization model (LTDOM) for smart grid backbone Communication Network (SBCN) was implemented. The proposed Neural Network LTDOM algorithm (NNLA) was implemented to satisfy the Quality-of-Service (QoS) requirements needed for fault tracing and load management at all times.

3.2 LTDOM Test Bed Validations

Riverbed Modeller software Academic Version 17.5 was used to setup the experimental design for LTDOM architecture shown in Fig. 2. In the distribution automation, Cisco 7705 SAR-Hc and 7705 SAR-W are used in the field area network to provide connectivity to sensors and field devices (such as reclosers, voltage controllers, and capacitors) for remote control and monitoring of faults, as well as aggregation for smart grid AMI. It depicts the Smart grid LTDOM dispatching mode with energy users. Besides, Figure 2 shows a smart grid communication network conceptual model. This equally uses IP/MPLS communication network and offers trust from a circuit-based network to an IP network while enabling network convergence, virtualization and resiliency. DISCO energy users access the LTDOM servers using the Algorithms I to III.

In addition, Nigam *et al.* (2019) highlighted that a good methodology is expected to utilize key measurable components such as careful scoping, focal/reference point concept review, etc., necessary for validation. As can be seen in this work, the LTDOM and (QoS) parameters were chosen and scoped adequately with the intent to be measured and referenced adequately.

Table 1: Simulation Design parameters for LTDOM

Design Parameters/ Specifications	Descriptions
Smart grid link Connection	40GB Ethernet
Grid Servers	7705 SAR-18
Cloud Virtualization Type	EXSi Scale
Local concentrator	7750 SR
Load balancer Address	Auto Configured
Broker Gateway	Fog layer (cyber_ethernet4_slip8_gateway_adv);
Number of Clients	50 AMI nodes
IP Core	IP/MPLS Enabled OpenFlow
Profile Configuration	Http
Client Address	DHCP Assigned
Attack Vector	DDoS (450 GB)
Transmission substation	2

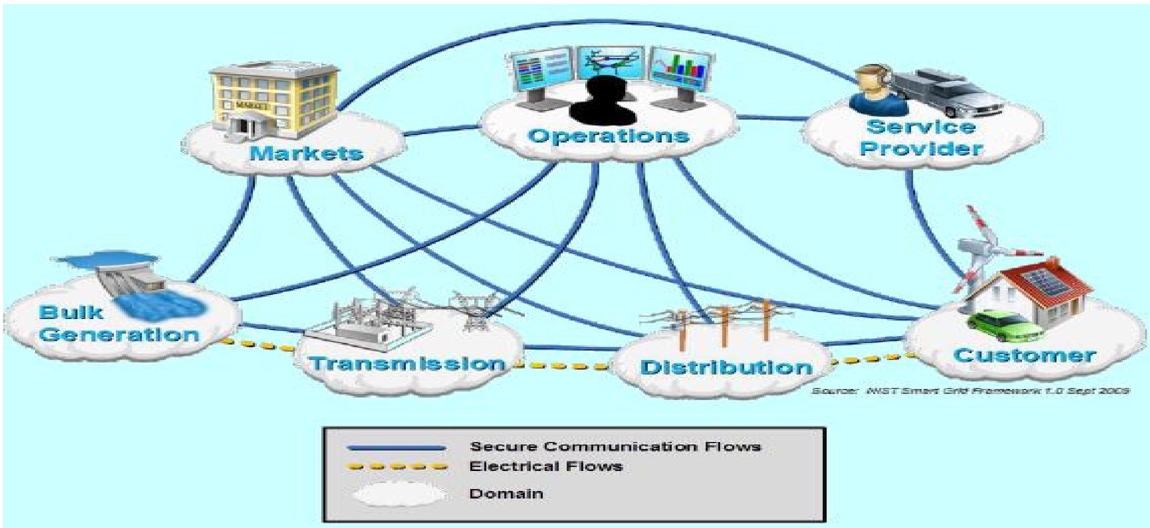


Fig. 2. Smart grid communication network conceptual model (Source: Ipakchi & Albuyeh, 2009)

3.3 Performance Evaluation

We compared six distinct scheduling algorithms for fault tracing and load management in the SG system including viz: SG Neural Network Algorithm (Proposed SGNNLA), SG Stackelberg Game Algorithm (SGSGA), SG CHAOS-Flower Pollination Algorithm (SGCFPA), SG Cuckoo Search Algorithm (SGCSA), SG Differential Search Algorithm (SGDSA) and SG Cournot Algorithm (SGCA). SG Metrics such as Service delays, throughput payload, energy data received, cryptographic overhead, and Service traffic availability were carefully selected and investigated in order to understudy the impact of load scheduling on SG ecosystems. Neural network application algorithm was used to determine the system performance accuracy and error margin. During scheduling, SG energy data were received. SG service delay, SG media access delay, SG service throughput payload, and SG availability with IP Gateway, VLAN and Cloud-OpenFLow (proposed).

Fig. 3 shows the SG LTDOM received energy data from the DISCO AMIs considering fault sensing. For both peak and non-peak load demands, energy data is constantly moved into the cloud for analytics (load management, billing, auditing, etc.). The reliability of energy data received in the cloud assume that there are no packets lost in the transmission between AMI nodes, the local concentrators and the cloud OpenFlow gateway as a result of full duplex synchronization and beacon collision avoidance mechanisms. Hence reliability in terms of energy data received from the low-level AMI nodes into the cloud is 100% (i.e., the total reliability of the AMI data delivery into the Cloud). During load scheduling on the SG network, it was observed from the riverbed statistics engine that the SGSGA, Proposed SGNNLA, SGCFPA, SGCSA, SGDSA and SGCA had 20.54%, 27.39%, 26.71%, 6.84%, 17.12% and 1.42% respectively. This implies that as load demands in the peak periods is been shifted to the off-peak periods, the proposed SGNNLA gives better reliable data reception at the cloud when compared to other schemes. This will make the objective of reducing the utility bills and peak loads feasible

Fig. 4 shows SG LTDOM packetization service delays of electrical data signals used for fault sensing. This delay depicts the overall time needed to transverse all the transmitted data from the AMI to the Cloud. Hence data-rate delays affect SG communication for fault tracing. During load scheduling on the SG network, it was observed from the riverbed statistics engine that the SGSSGA, Proposed SGNNLA, SGCFPA, SGCSA, SGDSA and SGCA had 18.78%, 12.28%, 18.64%, 20.23%, 18.49% and 11.56% respectively. This implies that as load demands in the peak periods is been shifted to the off-peak periods, the proposed SGNNLA gives relative packetization service delays on the grid network when compared to other schemes. This will make the objective of reducing the utility bills and peak loads feasible under load management.

Fig. 5 shows the SG LTDOM media access delays on Ethernet switching interfaces. It denotes the timeframe between two or more consecutive allocation of resources to similar users during load management on the grid. During load scheduling on the SG network, it was observed from the riverbed statistics engine that the SGSGA, Proposed SGNNLA, SGCFPA, SGCSA, SGDSA and SGCA had 32.25%, 15.32%, 28.22%, 25.40%, 20.16% and 4.03% respectively. This implies that as load demands in the peak periods is been shifted to the off-peak periods, the proposed SGNNLA utilized optimum resources on the grid network when compared to other schemes. This will make the

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objective of reducing the utility bills and peak loads feasible.

Fig. 6 gives the SG LTDOM service throughput need for fault tracing and load management. Owing to the structure of the SG network, service throughput describes the aggregate sum rate of successful load management data traffic delivery over the entire network link logically. Despite SG LTDOM service constraints such as physical medium, attacks, processing power, traffic protocols, the maximum achievable throughput is always preferred. During load scheduling on the SG network, it was observed from the riverbed statistics engine that the proposed SGNNLA, SGSGA, SGCFPA, SGCSA, SGDSA and SGCA had 24.09%, 21.68%, 16.86%, 15.66%, 12.04% and 9.63% respectively. This implies that as load demands in the peak periods is been shifted to the off-peak periods, the proposed SGNNLA utilized optimum resources while delivering satisfactorily on the grid network when compared to other schemes. This will make the objective of reducing the utility bills and peak loads feasible.

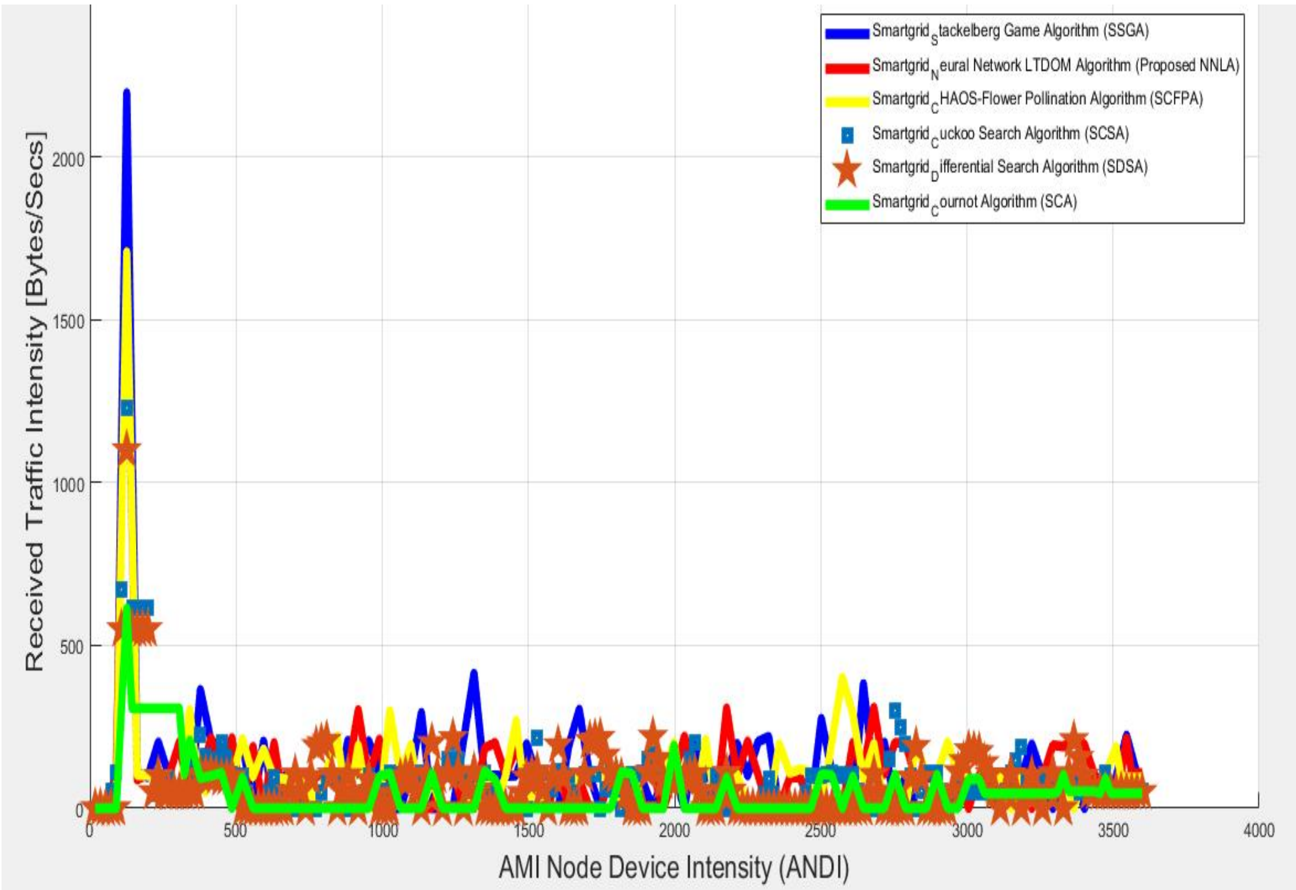

Fig. 3. SG LTDOM received energy data

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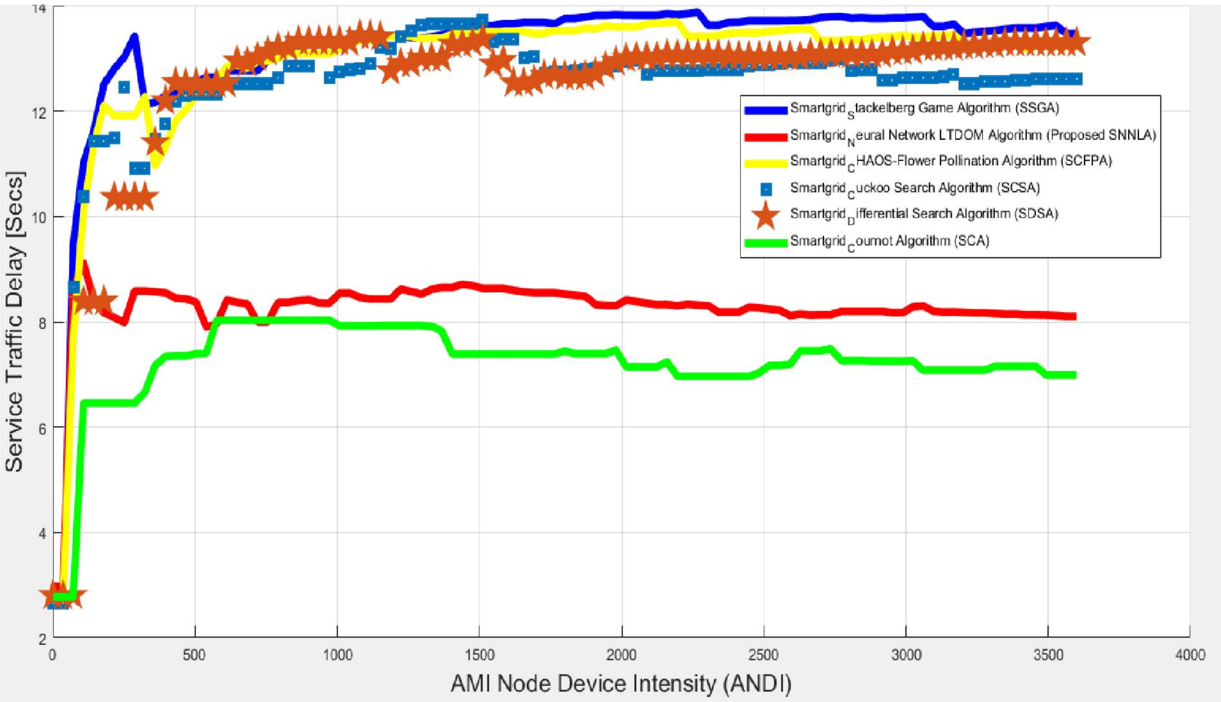

Fig. 4. SG LTDOM service delays

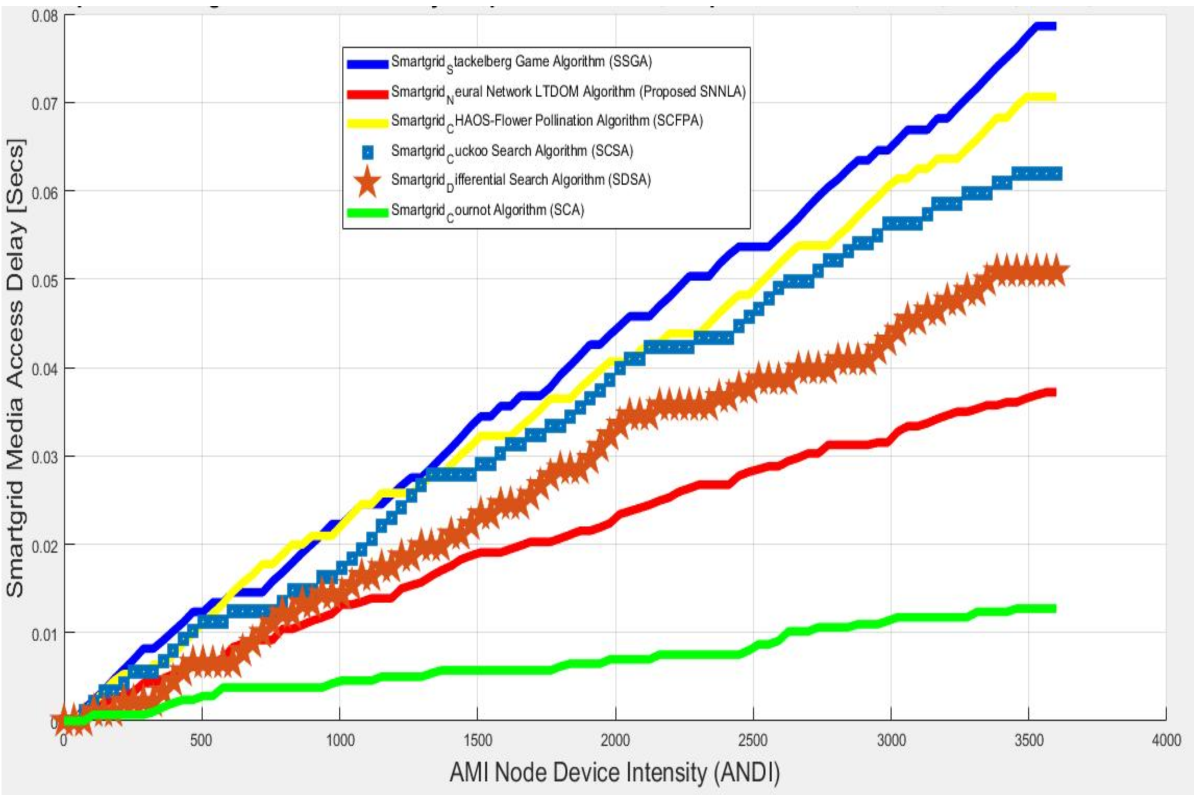

Fig. 5. SG LTDOM media access delays

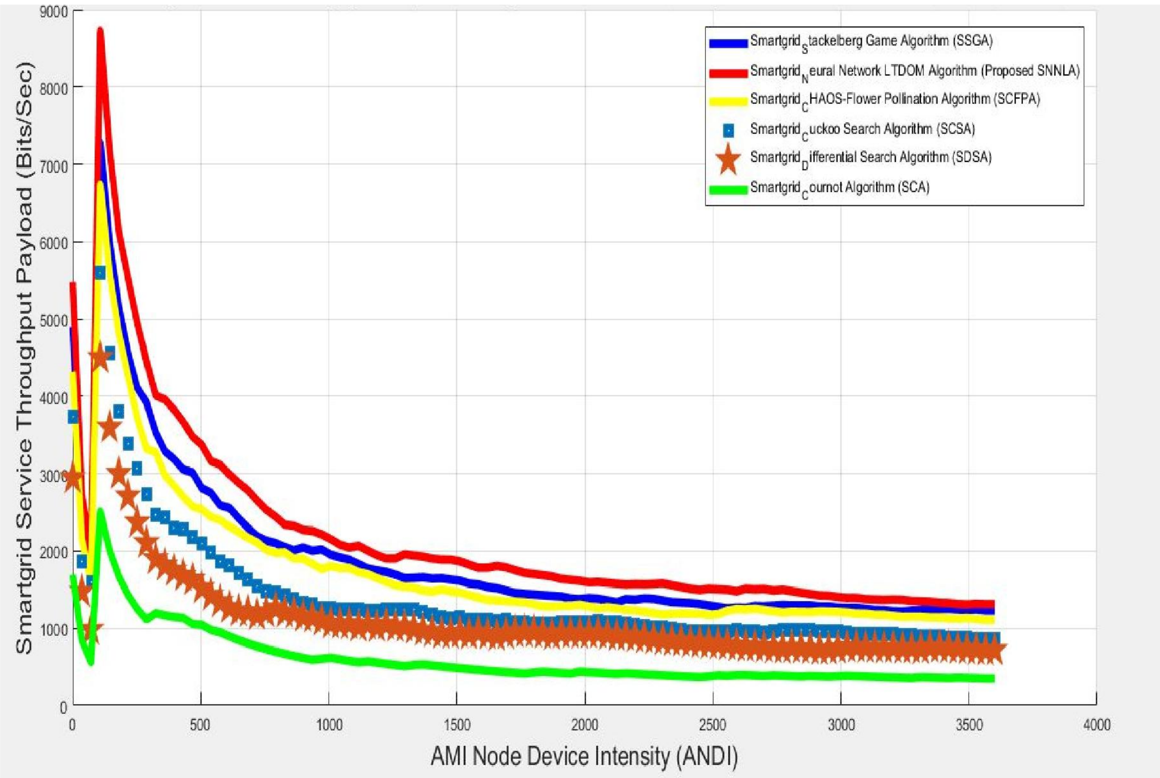

Fig. 6. SG LTDOM service throughput

The proposed technique in this work is quite streamlined and effective, as it shows the behavioral characteristics of the different aspects of the Nigeria grid system from more than one perspective. Baimel *et al.* (2019) offered a more simplistic approach to the behavioral qualities of a system where legacy systems (off-the shelf components) are purchased and fitted into the system in what can be seen as a form of adoption. This would limit the flexibility of such a network, as the network would only operate within prior working limits. Consequently, the study does not proffer a potential solution to system improvement and is rather unbeneficial.

Martins *et al.* (2019) highlighted the merits if time domain studies, that 2-way communication within a system is the bane of smart networks. They opined that demand response monitoring is a good way to control power consumption. In addition, and highlighted a potent tool, which is the study of power quality index using fuzzy-wavelet packet transform-based approach as one of the suitable tools for the monitoring of power quality. The present work is quite apt and serves as a validation of the need for studies on time response and performance for Quality of Service.

4.0 CONCLUSION:

Load management schemes for smart grid (SG) deployment, tracing and preventing faults and rapid fault monitoring. This paper developed SG Communication using Time-Delay Optimization Model for Transient Fault Tracing and Load Management. The technique was used achieve SG automation system that is suitable for Nigerian power grid. AMI hardware, SG Hardware Neural Network and SG scheduling/load management were covered. First, computation models were introduced while exploring neural network based layered time-delay optimization model (LTDOM) in the SG system. This was implemented to satisfy load management as well as Quality-of-Service (QoS) requirements for fault sensing and load management in the SG architecture. The system offers a reliable method for managing load demand using a combined symmetry of exponential and extreme hyperbolic gamma distributions for GENCOs (power generation).

Various integration algorithms were developed and implemented from the edge to cloud (LTDOM IP/MPLS core) while monitoring the network. In the SG network validation, six schemes were used for validation on a simulated SG DCell layered architecture. In all instances of load shifting for demand side management (DSM) strategy, the neural network algorithm was used to minimize the peak load demand. SG Stackelberg Game Algorithm (SGSGA), SG CHAOS-Flower Pollination Algorithm (SGCFPA), SG Cuckoo Search Algorithm (SGCSA), SG Differential Search Algorithm (SGDSA) and SG Cournot Algorithm (CA) where compared with the proposed scheduling scheme - SG Neural Network Algorithm (SGNNLA).

SG metrics such as energy data received, service delays, media access delays and service throughput were carefully selected and investigated in order to understudy the impact of load scheduling on SG ecosystems. The results showed that the proposed SG algorithm offered significant improvements.

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