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RESEARCH ARTICLE

Micro Software Defined Control (μSDC): Empowering Smart Grids With Enhanced Control and Optimization

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ABSTRACT It has become a fundamental component of the electrical networking system, both in residential and industrial settings, to adopt advanced power meter architecture. With traditional smart meters, a bi-channel communication network is established between homes and utility companies, providing consumers with information regarding their daily power consumption. Manual meter reading, however, may result in inaccurate meter logging and incorrect billing criteria, which will lead to an increase in overhead costs associated with deploying meter readers and billing power consumption for each site within metropolitan and large urban areas. Moreover, the current smart metering system does not enable consumers to predict their future energy consumption, only providing insights into their current power consumption and accumulative costs. In order to address these issues, we propose a novel intelligent Software-Defined Control (SDC) super cluster with a comprehensive architecture based on SDN routing capabilities, which differs from conventional commercial smart meters. The developed micro cluster is enhanced to run full availability and high performance compared to traditional metering system. Moreover it deploys intelligent capabilities to predict the consumption of power per home, we implemented a polynomial model experimentally. Furthermore, we propose an intelligent Software-Defined Controller Gateway (SDN-GW) to serve as a traffic predictor between distributed metering nodes and the cloud data warehouse, eliminating congestion caused by the large volumes of traffic data generated periodically by the metering nodes. Based on the experimental results, the software-defined control system was estimated to have 97.75% percent accuracy in power prediction, and the traffic flow predictor demonstrated 98.79% percent accuracy in network traffic prediction. Furthermore, the proposed SDN-GW achieved 29.37% power consumption rate compared to standard routing engine.

INDEX TERMS Software-defined control, neural networks, congestion control, power consumption, smart meters.

I. INTRODUCTION

Smart power meters have been playing a vital role in revolutionizing the electrical grid with advanced monitoring in the past decade. The deployment of distributed smart meters allow fine-grained power consumption and fault management [1], [2]. However, in this paper, we are discussing a case study for traditional electrical grid that encounter big challenges such as insufficient grid infrastructure, non-sufficient generation and non-developed grid components such as home power meters. Currently, there is a big demand to transit from existing grid to new grid generation grid to

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allow supervised control and monitoring of power consumption and to notify consumers of their power consumption in real-time which will make the power grid more efficient and reliable and reduce power demands overhead [3], [4], [5]. The limitation of traditional networking architecture cause high levels of failures that are becoming a normal event in the grid data center environment. Additionally, a high overhead cost that is related to processing each device separately in terms of upgrades and configuration. To solve this dilemma, Software-Defined Controllers (SDN) is introduced as an emerging networking paradigm. First, it breaks the vertical dependency by the separation of the control plane from the data plane. The separation will provide centralized management overall under layer nodes [6]. The SDN requires a special protocol to work with that is OpenFlow (OF) protocol. OpenFlow allows the forwarding engine to communicate with the SDN controller via the southbound interface for configuration policy updates such as installing new forwarding rules or updating the forwarding table entry. Each OF rule matches a subset of packets and implements specific actions such as (dropping, forwarding, redirecting, etc.) on the incoming traffic [7]. Fig 1 shows an SDN paradigm that is separated into three major planes: control plane, data plane and application plane connected through programmable interfaces.

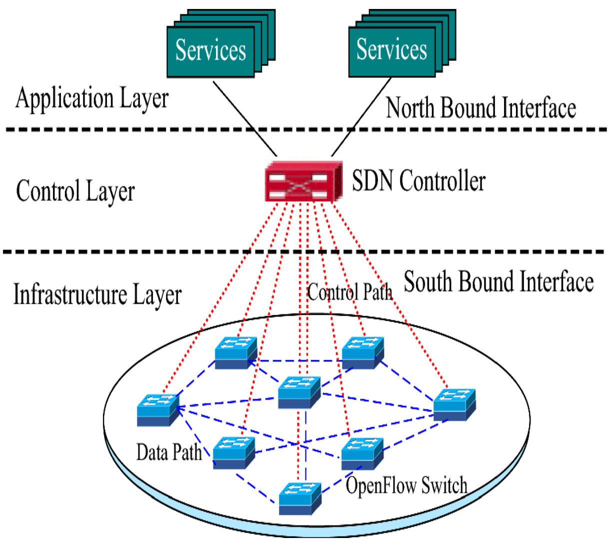

FIGURE 1. SDN control plane schematics [8].

Recently, researchers have been using statistical modeling in forecasting of power generation. One of the most main techniques in this approach is using the Artificial Neural Network (ANN) [9] which is mathematical modeling for information processing that is based on the human brain neural function. Typically, neural networks consists of multiple layers that are the input layer, hidden layer, and output layer. The hidden layer consists of multiple layers which are called "deep layers". Currently, ANN is considered as an alternative approach to classical predication methods [10]. The efficiency of ANN over traditional statistical methods is that it does not require any assumptions, and it uses historical data sets to predict by optimizing the non-linearity of the model. The process of prediction is implemented by feeding the data into the input layer and each neuron train the next neuron with regards to weight and activation values [11]. Moreover, smart grid [12] enables new forms of power management by modernizing the electric grid with communication technology to actively monitor and manage the power grid. An intelligent grid increase the reliability and real-time control of grid equipment by identifying the efficient replacement of equipment and identifying the power distribution faults [13] that may occur in the power lines. The implementation of smart grid will revolutionize the traditional electrical grid by allowing homes and businesses to interact with electricity network and wider energy system. With all that being said, smart meters functionality are still limited and not expanded to higher levels [14]. Nonetheless, we can summarize the potential benefits of the implementation of smart meters as: a) collection energy consumption statistic per house hold as this will help grid supplier on having a total overview of power consumption per zone, b) provide consumers with real-time power consumption, c) analysis of power consumption statistics. d) Efficient forecast of power production. Current traditional smart metering system uses a bi-channel communication with the cloud to provide it with real-time power consumption. Moreover, data collected by smart meters requires a huge computational volume of power and space in data processing center and requires high-end servers for data to be processed for thousands of sites per zone. According to the output of the intelligent meter that we need to predict the power consumption based on previous historical data. The overall system architecture of our proposed intelligent meter system integrated with the SDN-GW can be expressed in Fig 2. In our proposed work, we have developed an SDN control meter that is self-optimized with AI model to predict power consumption without relying on the core network cloud. This approach will reduce load traffic on the core network and eliminate traditional meter readings by adding intelligent and evolved IoT approach. The proposed meter is different from the known smart meter as it is fully intelligent and does not rely on the grid network for configuration management changes and data warehousing (only minimal).

The main contributions of this paper can be expressed as follows:

- We propose an intelligent distributed SDC power meter system that operates autonomously, consisting of a network of power meters deployed across different locations within the grid infrastructure.A testbed of RPIs nodes model to predict the total consumed power. The decentralization of the intelligent platform in the meter will provide on-site power prediction and will reduce the congestion in the grid cloud network by decentralizing the intelligent agent from the main cloud into each meter. This process will provide direct power optimization to the consumer even with cloud link failure. Moreover, the distribution of the artificial computing agent will reduce overhead on the cloud in terms of power consumption

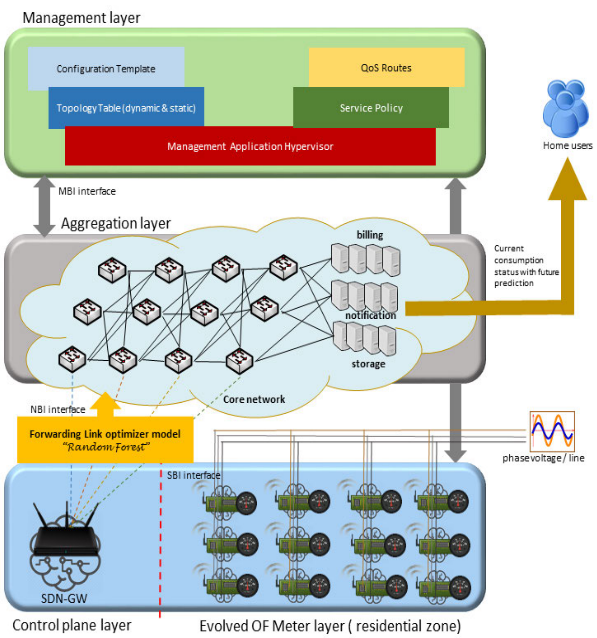

FIGURE 2. Proposed intelligent network architecture schematics.

and traffic congestion. The system is built using RPI4 clusters with LAN and WLAN network capabilities. Moreover, a management orchestrator Kubernetes k8s is deployed with mininet SDN framework.

- We propose a modified polynomial regression algorithm to predict the power consumption with minimal cloud dependency.
- We propose a traffic flow prediction algorithm for the SDN-GW cloud. The prediction is implemented using deep neural network to identify incoming traffic and control traffic routing accordingly. The optimization approach will reduce power consumption on networking equipment due to optimized traffic control.

The objective of this project is to reduce power consumption demands by intelligently predicting high power consumption by using self-optimized SDN meters. This approach will reduce the dependency on the core network as primary decision making and will be used as a data warehousing only with minimal processing. This eventually will lead to stabilize the grid cloud network, identify total demands and reduce power outages. Moreover, By decentralizing power prediction capabilities, the distributed SDN power meter system enhances grid resilience and reliability. In the event of network disruptions or communication failures, individual meters can continue to operate autonomously, ensuring uninterrupted power forecasting. Furthermore, the distributed nature of the system enables seamless scalability to accommodate growing grid infrastructures and evolving energy demands. New power meters can be easily integrated into the network without disrupting existing operations, allowing for flexible deployment and expansion. On the other hand, By minimizing reliance on the main grid network for data transmission and analysis, the distributed SDN power meter system reduces network congestion and latency. Localized data processing and prediction help optimize resource utilization and improve overall system efficiency.

The manuscript is structured as follows: Section I provides an introduction to the topic. Section II reviews related work in the field. Section III covers the presentation of the prediction model formulation. Section IV delves into the simulation and experimental results. Finally, Section V outlines the conclusions drawn from the research.

II. RELATED WORK

In recent years, Software-Defined Networking (SDN) has emerged as a promising paradigm for enhancing the efficiency and flexibility of smart grid services. This section critically analyzes ten relevant papers that delve into various aspects of SDN's integration with smart grids. Each paper is discussed in detail, highlighting its contributions, benefits, and limitations. In [15] The study explores how SDN, with its centralized control and programmability, affects the performance and reliability of smart grid operations. By employing empirical data and simulations, the authors assess various scenarios to evaluate the effectiveness of SDN in managing and optimizing smart grid services. Moreover, The author provides valuable insights into the integration of SDN with smart grid systems. By empirically studying the influence of SDN controller interventions, the paper sheds light on the potential benefits such as improved network management and enhanced service delivery. However, limitations may arise in scalability and real-time responsiveness, particularly in large-scale smart grid deployments with high data volumes and stringent latency requirements. In [16] The focus of this paper is on revealing end-to-end delay characteristics in Software-Defined Networking (SDN) environments. Through experimental measurements and analysis, the authors investigate the factors contributing to delay in SDN architectures. They explore the impact of control plane communication, flow table lookup, and packet forwarding on overall delay performance. Furthermore, This research offers valuable insights into understanding the latency implications of SDN, which is crucial for applications requiring low-latency communication, such as smart grid control. However, the study's scope may be limited to specific SDN implementations and network configurations, warranting further investigation into the generalizability of the findings across diverse SDN deployments. While, in [17], the author conducts a comparative performance analysis between OpenFlow-based networks and traditional legacy switching networks. By evaluating metrics such as throughput, latency, and scalability, the authors aim to provide a comprehensive understanding of the performance trade-offs associated with transitioning to OpenFlow-based SDN architectures. The comparative analysis presented in this research offers valuable insights into the performance differences between OpenFlow-based SDN and legacy switching networks. However, the study's scope may be limited to specific network topologies and traffic patterns, necessitating further research to explore the scalability and robustness of OpenFlow-based SDN in complex network environments such as smart grids. In [18], the author investigates the design and implementation of an SDN network management architecture tailored for electric power communication systems. The authors propose novel approaches for orchestrating network resources, optimizing traffic routing, and ensuring reliability in power communication networks through SDN-based management frameworks. The research also addresses a crucial aspect of integrating SDN into electric power communication systems, highlighting the potential for enhancing network management efficiency and service reliability. However, challenges may arise in the practical deployment of the proposed architecture, including interoperability issues with existing infrastructure and the need for robust security mechanisms to safeguard critical power grid communications. In terms of intelligent SDN routing capabilities, the author in [19] presents a novel routing optimization algorithm for electric power communication networks using reinforcement learning techniques within an SDN framework. By leveraging reinforcement learning, the proposed algorithm dynamically adapts routing decisions based on network conditions and performance objectives, aiming to improve efficiency and reliability in power communication systems. The utilization of reinforcement learning in SDN routing optimization for power communication networks demonstrates innovative approaches to address dynamic network challenges. However, practical considerations such as the computational overhead and convergence speed of reinforcement learning algorithms may impact their scalability and real-time applicability in large-scale power grid deployments. Moreover, in [20] The author investigates the application of SDN in facilitating demand response mechanisms within smart grid infrastructures. By dynamically orchestrating network resources and communication pathways, SDN enables efficient demand management, load balancing, and integration of renewable energy sources, thereby enhancing the stability and sustainability of smart grid operations. Moreover, the integration of SDN with demand response mechanisms presents significant opportunities for optimizing energy consumption and improving grid reliability in smart grid environments. However, interoperability challenges, cybersecurity risks, and regulatory barriers may pose obstacles to the widespread adoption of SDN-based demand response solutions in complex energy ecosystems. Moreover, in [21] the author proposes a cross-domain resilience framework for SDN-enabled smart power grids, focusing on enhancing information sharing and coordination across diverse domains. By leveraging dataspaces as a unified data management paradigm, the framework facilitates real-time data exchange, situational awareness, and collaborative decision-making to enhance grid resilience and reliability. The proposed cross-domain resilience framework offers a holistic approach to addressing the complex challenges of smart power grid management through SDN-enabled information sharing. However, practical implementation considerations such as data privacy, scalability, and interoperability with legacy systems may require further exploration to ensure the effectiveness and feasibility of the proposed approach. Moreover, the author in [22] explores the intelligent scheduling of both business and traffic activities within power communication networks using SDN technologies. By integrating SDN control capabilities with intelligent scheduling algorithms, the authors aim to optimize resource utilization, prioritize critical communications, and enhance overall network performance in support of power grid operations. it is worthily to mention that the integration of SDN with intelligent scheduling mechanisms offers promising avenues for enhancing the efficiency and reliability of power communication networks. However, challenges may arise in balancing the diverse communication requirements of power grid applications, necessitating careful design considerations to ensure optimal resource allocation and prioritization. In [23], the author comprehensively investigates the current and forthcoming communication solutions tailored for smart grid applications. The authors embark on an intricate journey through the landscape of communication technologies pertinent to smart grids, providing invaluable insights into the state-of-the-art and future prospects. Moreover, The paper dives into the technical intricacies of various communication solutions, encompassing both wired and wireless technologies. It meticulously dissects the functionalities, strengths, and limitations of each approach, shedding light on their applicability in the context of smart grids. For instance, the discussion on wired communication protocols such as Ethernet and Power Line Communication (PLC) delves into their robustness in terms of reliability and data throughput, while also addressing challenges like susceptibility to interference and scalability issues. Similarly, the examination of wireless technologies like WiMAX, LTE, and Zigbee ventures into their suitability for different smart grid use cases. It meticulously evaluates parameters such as coverage, latency, and energy efficiency, offering a nuanced understanding of their performance in dynamic grid environments. Moreover, the paper elucidates emerging paradigms such as 5G and IoT, exploring their potential to revolutionize smart grid communications by enabling massive device connectivity and ultra-low latency communication. The author in [24] presents a formal synthesis model aimed at the resiliency-aware deployment of Software-Defined Networking (SDN) in Smart Grid Supervisory Control and Data Acquisition (SCADA) systems. It delves into the intricacies of leveraging SDN to enhance the resilience of SCADA networks, offering a formal framework for synthesizing resilient deployment strategies. Moreover, The paper navigates through the technical nuances of SDN deployment in SCADA systems, elucidating the benefits of decoupling control plane from data plane and centralizing network management functions. It provides a rigorous formal model, rooted in mathematical principles such as formal synthesis, to optimize the deployment of SDN controllers in smart grid environments. This model takes into account various parameters including network topology, traffic patterns, and criticality of SCADA components to synthesize deployment strategies that maximize resiliency. Moreover, the paper explores the intricacies of SCADA system architecture, dissecting the interplay between legacy infrastructure and emerging SDN paradigms. It delves into the challenges of integrating SDN into existing SCADA networks, highlighting issues such as backward compatibility, protocol interoperability, and real-time control constraints. Furthermore, in [24], the paper delves into the intricacies of Wide Area Measurement Systems (WAMS) and the critical role they play in ensuring the stability and efficiency of smart grid operations. It provides a comprehensive overview of SDN-enabled architectures for WAMS, elucidating how centralized control and programmable dataplanes facilitate dynamic network management and real-time data processing. Moreover, the paper introduces the concept of fast failover mechanisms within the SDN dataplane, enabling rapid rerouting of traffic in the event of link failures or network disruptions. It discusses various strategies for implementing fast failover, including backup path computation, packet redirection, and flow table manipulation, highlighting their effectiveness in minimizing service disruption and ensuring continuous data delivery in WAMS environments. The author also addresses key challenges such as packet loss, latency, and control overhead associated with failover events, offering insights into optimization techniques to mitigate these issues. To the best of our knowledge, none of the previous research discuses distributed SDN meter system. Therefore, we propose a distributed SDN power meter system operates autonomously within a smart grid environment, consisting of a network of power meters deployed across different locations within the grid infrastructure. Unlike traditional centralized approaches that rely heavily on the main grid network for data transmission and analysis, the distributed SDN power meter system operates independently, leveraging local data processing and prediction capabilities to forecast power dynamics.

III. PREDICTION MODELS FORMULATION

We have developed an intelligent SDN control power meter as a distributed IoT system to be implemented as in-home intelligent power meter that minimum communication with the core network and can provide power predictions on-site accordingly. The overall structure consists of three layers: the power meter layer that consists of IoT hardware with the intelligent process for power prediction. Second is the SDN-GW cloud layer that consists of an intelligent gateway with link optimizer to reduce data congestion of the cloud due to the high volume of incoming sensor data. The third layer is the servers and data warehousing layer that is used to process data and generate billing and notification information. The neural network model that we propose uses power consumption historical data for each household. The historical data will be used to train the network and validate the prediction model so that a better accuracy can be achieved with minimum error. Fig 3 represents our proposed deep neural network system with multiple layers. The optimization algorithms are presented in Pseudo code: Algorithm 1 and Algorithm 2.

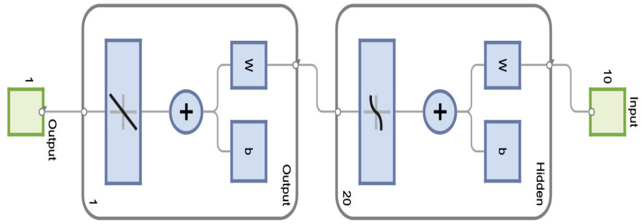

FIGURE 3. Proposed deep neural model schematics.

Algorithm 1 Pseudo Code for Traffic Prediction: SD-GW

$t \leftarrow$: time steps from 1 to 2000
INPUT: traffic generated from power meters T_{in} $\triangleright$ traffic flow data
$noiseMagnitude \leftarrow 0.1$ $\triangleright$ Adjust traffic noise magnitude
$noisyTrafficFlow \leftarrow trafficFlow + noiseMagnitude \times$ Gaussian noise
$trainRatio \leftarrow 0.7$ $\triangleright$ Set training and testing split
$numTrain \leftarrow \text{Round}(trainRatio \times \text{Length}(noisyTrafficFlow))$
$trainData \leftarrow noisyTrafficFlow[1 : numTrain]$
$testData \leftarrow noisyTrafficFlow[numTrain + 1 : \text{End}]$
$inputSequenceLength \leftarrow 10$
$outputSequenceLength \leftarrow 1$
$XTrain \leftarrow []$, $YTrain \leftarrow []$
for $i = 1$ to $(numTrain - inputSequenceLength - outputSequenceLength + 1)$ **do**
  Append $trainData[i : i + inputSequenceLength - 1]$ to $XTrain$
  Append $trainData[i + inputSequenceLength + outputSequenceLength - 1]$ to $YTrain$
end for
$net \leftarrow \text{CreateFeedforwardNet}(20)$
$net \leftarrow \text{Train}(net, XTrain, YTrain)$
$XTest \leftarrow []$
for $i = 1$ to $(length(testData) - inputSequenceLength - outputSequenceLength + 1)$ **do**
  Append $testData[i : i + inputSequenceLength - 1]$ to $XTest$
end for
$predictedTest \leftarrow net(XTest)$
CalculateMSE($predictedTest$, $testData$)
Check overall Accuracy
Re–ROUTE traffic abd load balance

The most important factor when implementing a polynomial regression is to reduce the error levels of inaccurate predictions. The errors can be represented in different forms such as Mean Square Error (MSE), Root Mean Square Error

Algorithm 2 Pseudo Code for Power Consumption Prediction

1: INPUT: dataset -: provided by cloud initially
2: Split data into training and testing sets (80% training, 20% testing)
3: Set polynomial degree: degree = 3
4: Create polynomial features for training set: $X_{\text{train}} = [\mathbf{1}, x_{\text{train}}, x_{\text{train}}^2, x_{\text{train}}^3]$
5: Calculate coefficients using least squares: $\boldsymbol{\beta} = (X_{\text{train}}^T X_{\text{train}})^{-1} X_{\text{train}}^T y_{\text{train}}$
6: Create polynomial features for test set: $X_{\text{test}} = [\mathbf{1}, x_{\text{test}}, x_{\text{test}}^2, x_{\text{test}}^3]$
7: Predict values for test set: $\hat{y}_{\text{pred}} = X_{\text{test}} \cdot \boldsymbol{\beta}$
8: Calculate RMSE: RMSE $= \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_{\text{test},i} - \hat{y}_{\text{pred},i})^2}$
9: Calculate R-squared: R-squared $= 1 - \frac{\sum_{i=1}^{n} (y_{\text{test},i} - \hat{y}_{\text{pred},i})^2}{\sum_{i=1}^{n} (y_{\text{test},i} - \bar{y}_{\text{test}})^2}$
10: Calculate overall accuracy: Overall Accuracy $= \left(1 - \frac{\text{RMSE}}{\text{std}(y_{\text{test}})}\right) \times 100$

(RMSE), Mean Absolute Error (MAE) and confusion matrix. We intend to reduce the error to a very minimum level so that the proposed system can be reliable and accurate in power consumption prediction. The difference between them is that RMSE is used to optimize outputs with high errors by implementing large weights; whereas, MAE is used to compute the average with all weights are provided equally. It is worthy to mention that there are some major factors that could effect the operation of the SDN power meter in terms of storage size denoted as $S_{storage}$, controller processing denoted as $\Delta_{cprocess}$. These values are required to be tuned for efficient performance. Since there is large volume of sensor traffic that is generated every few seconds, there must be a model that the system has to reflect on in case of congestion and overflow storage. Storage requires efficient management as storage increase within time t. We can express the storage with regards to time in Eq 1 as follows:

$$\frac{dS_{storage}}{dt} = \alpha S_{storage} \tag{1}$$

where α is the storage management constant. Solving Eq 1 using the separation of variables rule method, we can express Eq 1 in the following form of Eq 2 as follows:

$$S_{storage}(t) = S_{in} \exp^{\alpha t} \tag{2}$$

where S_{in} is the initial storage value. The sensor value samples are feed into the proposed intelligent model stack. However, after t iteration, the storage has to be partially cleared for efficient space utilization. Therefore, the used samples in prediction after specific time slot are cleared and replaced with new measurements. Assuming that we clear the storage when storage reach 1000 samples, then, we can express the new samples allocations in Eq 3 as follows:

$$S_c = clearold(\sum_{p=1}^{1000} S_p) + \sum_{n=1}^{1000} S_n + \delta \sum_{r=1}^{u} S_r \tag{3}$$

where S_c represents the current samples, S_p represents the old samples used in the prediction, S_n represents the new current samples plus the remaining samples represented with S_r with size factor of δ. Moreover, the controller processing has to accommodate the sensor traffic. We can express the correlation of processing with time in Eq 4 as follows:

$$\frac{d\Delta_{cprocess}}{dt} = \eta \Delta_{cprocess} \tag{4}$$

where η is the initial constant. Solving Eq 4 using the separation of rule method, we get Eq 5 as follows:

$$\Delta_{cprocess}(t) = \Delta_{int} \exp^{\eta t} \tag{5}$$

where Δ_{int} is the initial processing utilization of the controller. Respectively, we can express the total power consumed in the SDN power controller in Eq 6 as follows:

$$P_{SDNtotal} = \sum_{a=1}^{g} P_{process}^{g} + \sum P_{switch} + \sum_{b=1}^{4} P_{rpi} + \sum_{c=1}^{2} P_{powerhub} + P_{NAS} \tag{6}$$

where g is the processes that run at a specific time and NAS is the network attache storage. The SDN-GW is used as an aggregate condensing device to collect power meter information, statistics profiles and events periodically using wireless communications such as Zigbee, LoRa or WiFi. The SDN-GW is mainly used to balancing the traffic on the southbound interface links using link optimizer algorithm as shown in Algorithm 2 pseudo code. The link optimizer uses deep neural network model to predict the incoming traffic based on data collected from metering nodes. Furthermore, our proposed hardware components of our smart power meter system comprise of hardware that is microcontroller, analog current and voltage sensors. The readings will be based on specific time slot with measurements of every 5 seconds. All data will be serially transferred to a higher computational module that is RPI4 stack. The RPI4 stack will be running neural prediction model that will be used to predict the power consumption on consumer site. The data can be displayed on an LCD screen as a user interface. The data then is transferred to the SDN-GW. Moreover, we have added an initial storage unit of 500GB for testing and an additional RPI4 module as a fail-over controller in case the first one fails. Furthermore, we have installed a managed switch to provide interconnected communications to all running modules in case management configuration is needed. The link optimization of the cloud is running on a separate desktop python server. The proposed SDC power meter hardware cluster is shown in Fig 4. The system consists of RPI4 cluster with L-2 switch and WLAN capabilities. The orchestrator is Kubernetes k8s and mininet is used as the SDN framework.

The deployment of the proposed intelligent power meter is intended to enhance the electric grid by adding intelligent components with self-optimization. The proposed architecture will allow consumers to have direct awareness of how

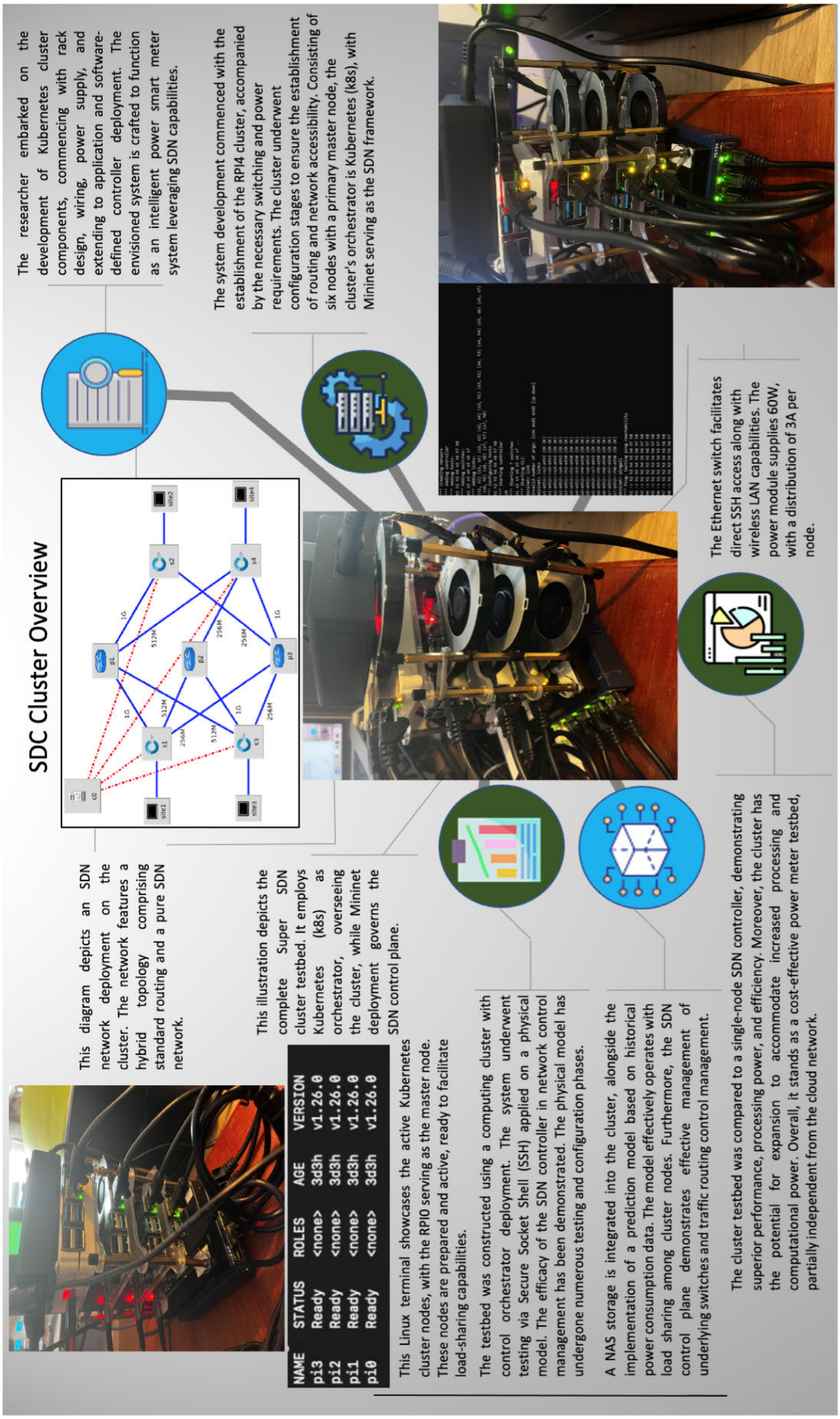

FIGURE 4. Software Defined Control (SDC) cluster details.

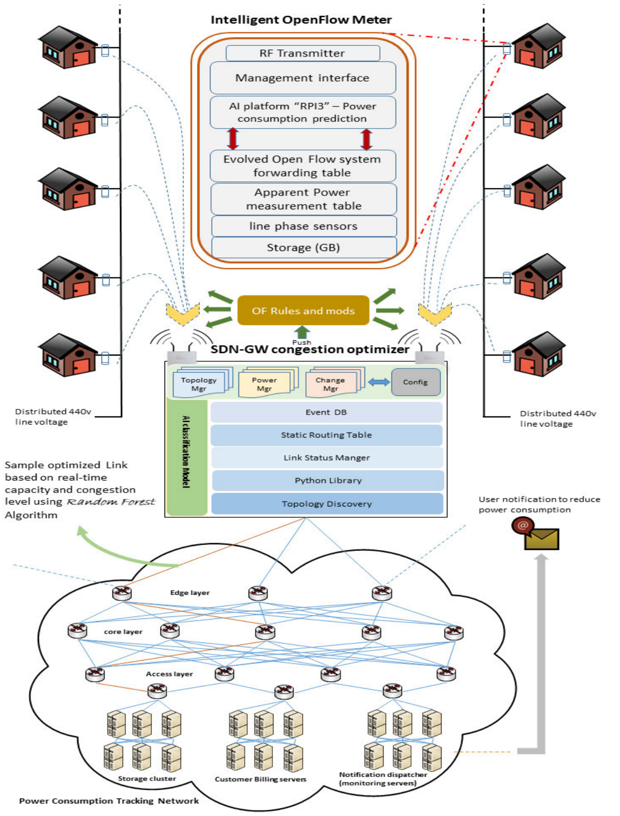

FIGURE 5. Proposed meter deployment architecture and integration with the cloud.

much power they are consuming and what are the predictions of their power usage during the next days. This will help in reducing power demands, thus fewer outages may occur. The on-site optimization meter is a novel technique that we are proposing to reduce dependency on the electric grid network which will be used as a data warehouse only. Furthermore, overall prediction requires large computation processing that is power-hungry, thus, decentralizing the power optimizer in each meter will reduce power consumption of the cloud core processing and minimize failure in links and network equipment. The proposed architecture is shown in Fig 5.

IV. EXPERIMENTAL AND SIMULATION RESULTS

Predicting consumer power consumption based on machine learning is an intelligent approach that constitutes successive benefits both for consumer and utility management. As we mentioned earlier that we are focusing on extending this system as a case study to help simplify measurement and logging of power usage. In furtherance of building our proposed intelligent agent in the power meter, we have used measurements of electrical power consumption for one household with 1-minute sampling for about 45 months worth of data to train our neural network platform. The data consist of many fields such as voltage, current intensity and active/reactive power that were logged for 3 types of loads of home appliances. Additionally, the total consumed active

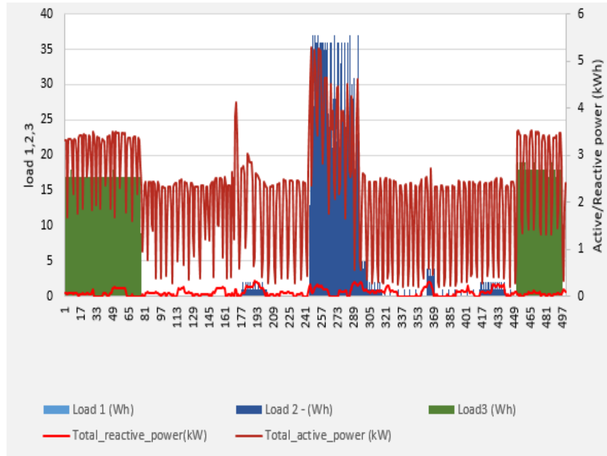

FIGURE 6. Sample power consumption parameters for a home.

and reactive power is noted. Moreover, we used this data to train our model so that the intelligent SDN meter can provide an estimate of power consumption prediction. For the SDN-GW deep neural model, all weights are initialized randomly at the first stage. The weights are tuned using a gradient descent approach to reduce the error rate and provide an efficient preliminary prediction. For the power prediction, we have implemented polynomial regression to predict the power consumption levels. Fig 6 shows data set that we have used for a 1-minute sampling measurement. The figure represents three types of load with respect to active and reactive power measurements.

Extensive testing was undertaken on the measured data to predict the power consumption and to predict the power consumption levels. After training the network with 1000 rounds of (Epochs), we were able to achieve an accuracy of 97.75% using the proposed optimization algorithm. Fig 7 and Fig 8 shows the model prediction versus the actual data. The trend of the data is polynomial so the best option was to use polynomial model to fit the data.Moreover, Fig 9 illustrates the error variations and Fig 10 shows the RMS, R^2 and the overall accuracy of the model.

Moreover, Fig 11, Fig 12, Fig 13 and Fig 14 provide different aspects of the neural network's performance and behavior, offering insights into its accuracy, generalization capabilities, and convergence during training. The error histogram illustrates the distribution of errors across the dataset. It shows how many data points fall within specific error ranges. A well-performing network would ideally have a histogram that's centered around zero or with most errors clustered close to zero, indicating accurate predictions. While RMS provides an overall measure of the model's prediction accuracy. Lower RMS values indicate better performance, implying that the model's predictions are closer to the actual values on average. On the other hand, R-squared measures the proportion of the variance in the dependent variable (output) that is predictable from the independent variables (inputs). We can see that form the results that the R^2 value is very near to 100%. Moreover, gradient plot represents the slope

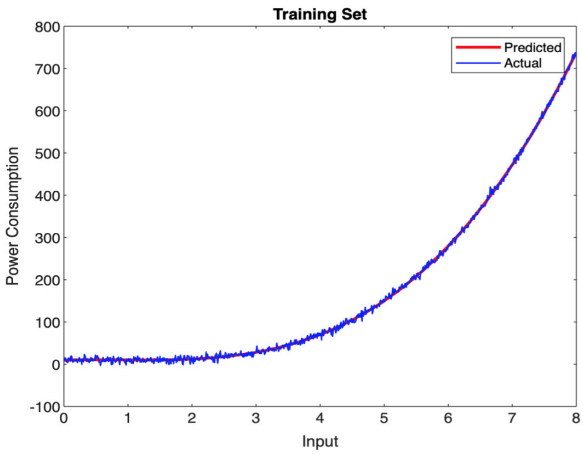

FIGURE 7. Predicted vs. actual power consumption: training.

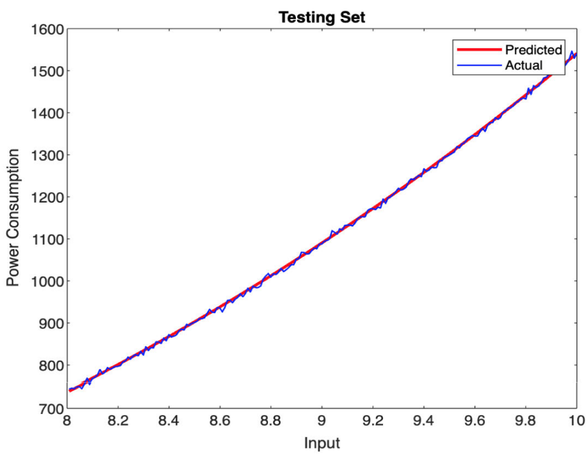

FIGURE 8. Predicted vs. actual power consumption: testing.

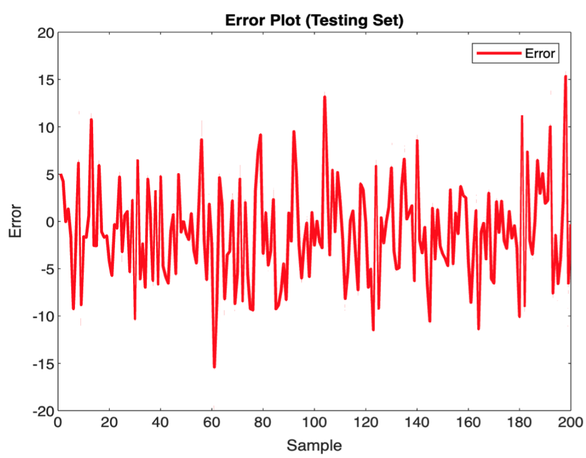

FIGURE 9. Error: testing phase.

of the error surface and indicates the direction and steepness of the error function with respect to the network's weights. Monitoring the gradient helps in understanding how the weights are being updated during training. After extensively training the deep learning model, the model is able to achieve a 98.79% accuracy in predicting the best the overall inbound traffic. Predicting the inbound traffic is very important for the type of cloud that is dynamically changing over time with continuous physical layer upgrades (heterogeneous). Moreover, based on prediction analysis, the SDN-GW can effectively control routing based on load-balancing criteria. Alternatively, since the distributed SDN power meter reduce dependency on the cloud and most computation intelligence is perform on the distributed SDN meters, the servers' power consumption will reduce significantly and less subject to failure or reboot. Fig 17 shows a rack server power consumption with high computation load versus less traffic when using effective routing control. It is noted that the server power consumption is less with using our proposed model as it require less power for computational resources. The load of computation is distributed along the proposed meters which result in a significant power reduction in the main grid cloud network. Edge computing significantly enhances the functionality and performance of smart meters

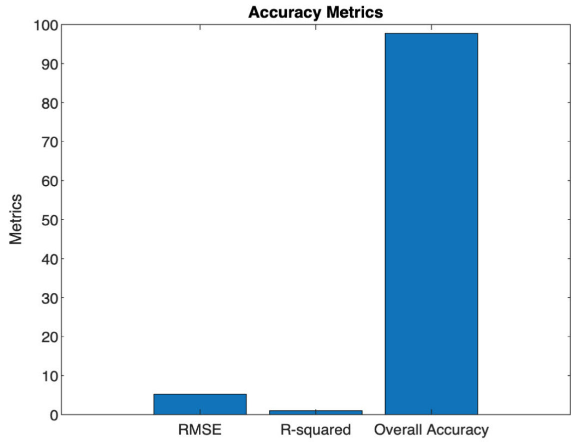

FIGURE 10. Accuracy metrics: RMSE, R^2, accuracy.

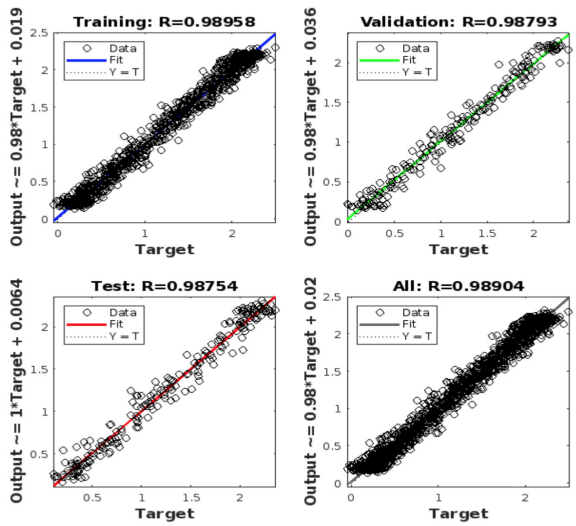

FIGURE 11. Training, testing and validation phases with R score.

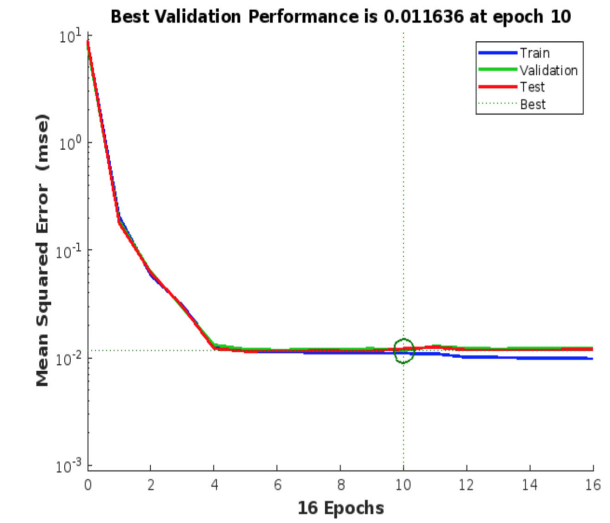

FIGURE 12. RMS.

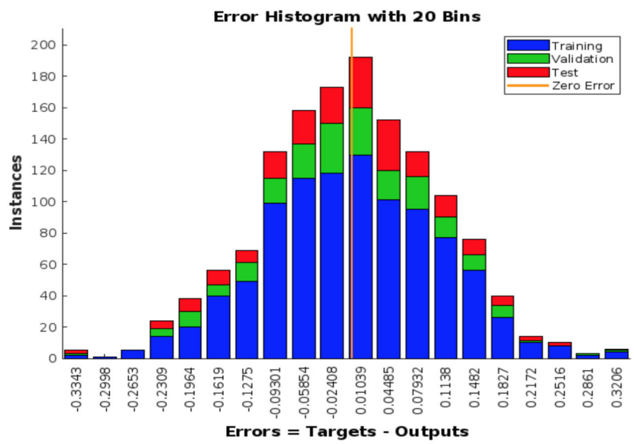

FIGURE 13. Error histogram for all phases.

embedded with machine learning by enabling real-time data processing and analysis. By processing data locally at the meter, latency is reduced compared to sending data to a centralized cloud, allowing for immediate decision-making and responses to events. This capability provides instant insights into energy usage patterns, facilitating quicker anomaly detection and more efficient energy management. Additionally, edge computing improves privacy and security by keeping sensitive data localized, minimizing the risks associated with transmitting data over networks. Furthermore, it optimizes bandwidth usage by reducing the volume of data sent to the cloud, resulting in lower communication costs and improved network efficiency. The combination of edge computing and machine learning at the smart meter level supports more intelligent and autonomous energy systems, leading to enhanced operational efficiency, better demand response, and more personalized energy services for consumers.

We can summarize the implications of introducing SDN in our project is: (a) Decoupling the control plane from the data plane, allowing centralized control of network devices.

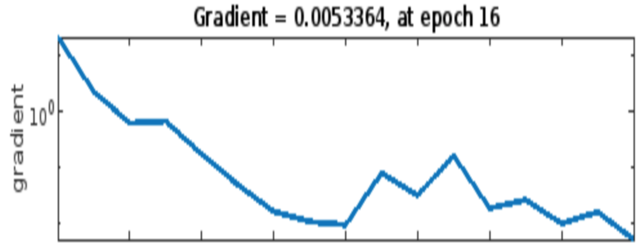

FIGURE 14. Gradient over testing phase.

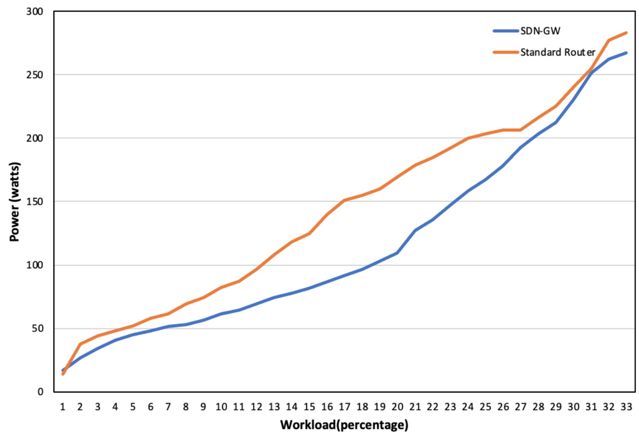

FIGURE 15. Server vs. SDN-GW power consumption showing the proposed model effect with 29.37% power consumption rate.

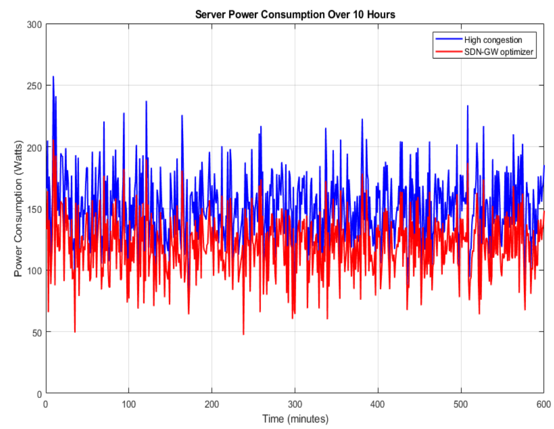

FIGURE 16. Standard routing engine vs. SDN-GW power consumption for 10 hours.

This simplifies network management and configuration per each site. (b) Dynamically adjust network configurations and policies to meet changing needs without physically modifying hardware. (c) We can enable the implementation of custom policies and protocols through software rather than hardware, allowing more tailored and innovative network solutions. (d) Network tasks such as routing, load balancing, and security can be automated, reducing the potential for human error and increasing operational efficiency. (e) We can manage and balance loads dynamically, ensuring optimal performance and reducing the risk of overloads. Moreover, by reducing the need for proprietary hardware and allowing

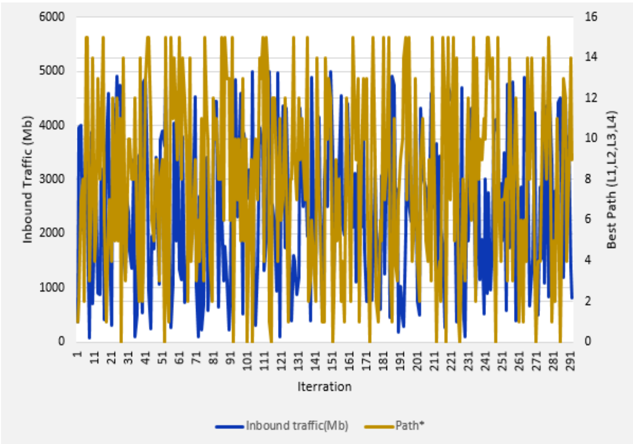

FIGURE 17. Inbound traffic with best link selection by the SDN-GW.

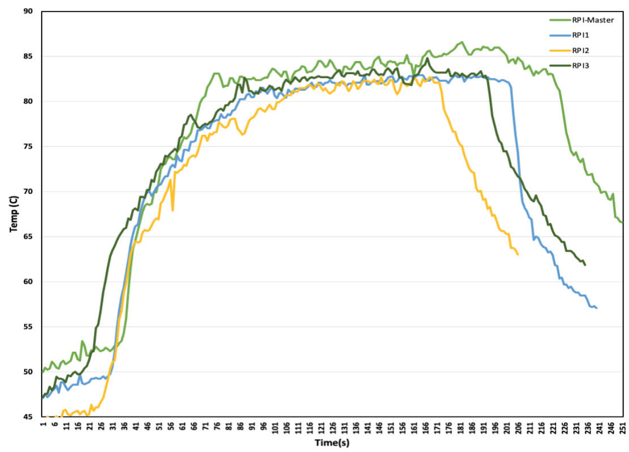

FIGURE 18. Cluster peak load CPU temperature.

for more efficient use of existing resources, SDN can lower operational costs in both domains.

V. CONCLUSION

In this paper, we introduce a novel super Software-Defined Control power prediction system that incorporates an intelligent agent within the meter infrastructure. The model is developed as an experimental testbed for effective validation of the research proposal. contrast to traditional power meter platforms, this prototype effectively addresses the limitations found in them, enabling seamless integration between power consumers and grid suppliers. It ensures accurate meter readings, prevents billing errors, and enables homeowners to monitor their energy consumption on a regular basis. In addition, it provides grid suppliers with a comprehensive view of peak periods, enabling proactive measures during times of high demand. In addition, our system proposes traffic control and inbound prediction mechanisms to reduce the reliance on cloud services and minimize power consumption. As a result of rigorous experimental and simulation testing, we were able to demonstrate 97.75% accuracy for our SDN meter and 98.79% accuracy of for the deep learning traffic optimizer. Through the effective management of high power demands and the implementation of precise power predictions and consumption control, this proposed system holds the potential to significantly mitigate the effects of power grid outages. In addition, the intelligent platform ensures the reliability of the grid communication core network by decentralizing it from the primary grid network, resulting in minimal equipment failures and reduced computational stress.

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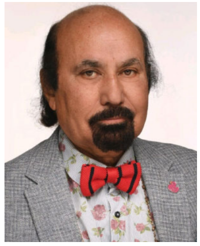

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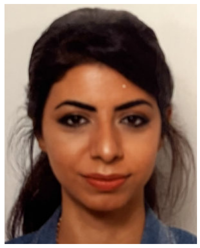

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