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T6CONF: Digital Twin Networking Framework for IPv6-Enabled Net-Zero Smart Cities

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***Abstract*—An efficient serving of predictive management and what-if-analysis of smart cities is the only way to achieve a net-zero waste target. With the aid of the enhanced learning capabilities of digital twin (DT), net-zero aims of smart cities can be obtained with highly accurate results in the prediction of waste-to-energy and candidate truck paths. However, there is no unified communication model yet for a digital twin to maintain complete data and control flow in a fully-synchronized way. Without having a clear communication model for the digital twin, the interaction between the physical and digital replica cannot be sustained. To handle this, we propose a digital twin networking framework, called T6CONF, based on an IPv6 infrastructure to solve the end-to-end two-way communication and the synchronization problem of the resource-constrained Internet of Things networks. Besides, T6CONF serves two specific net-zero waste services, such as waste-to-energy and planned-truck-routing prediction services for the net-zero goal. We evaluate the proposed digital twin communication model with changing fidelity levels over the twinning rate and round-trip time. Additionally, we prove that the proposed T6CONF model increases the accuracy of service layer operations.**

***Index Terms*—Digital twin, two-way communication, synchronization.**

I. Introduction

IN the last few years, IN the last few years, digital twin networking has been seen as a strong candidate solution to better manage large- scaled Internet of Things (IoT) networks against rising smart city services. Especially for net-zero targets, monitoring metropolitan cities has increased the importance of digital twin networks. Concerning this, the report on the role of digital twins in sustainable cities highlights the economic and environmental benefits with 1.3 trillion of welfare, and 7.5 Gt CO2 emission reductions by 2030 [1]. At this point, several challenges need to be addressed to provide an underlying unified framework to implement digital twin networking in net-zero smart cities. Such a framework should address the following challenges:

- *Two-way communication:* Traditional one-way data acquisition approaches are insufficient to apply the planned net-zero actions due to lack of closed-loop automation. Having two parts of interactions, i.e., data flow and control flow, should be enabled without affecting the communication of IoT sensors.
- *High-fidelity modeling:* The DT representation of physical entities provides exact observability to measure net-zero results. However, there is a dilemma between near-realistic modeling and the digital data transfer. Thus, high-fidelity should be balanced during the twinning.
- *Fully-synchronized twinning:* Although synchronization is crucial in digital twinning, it is not always necessary to serve real-time interaction. When testing certain types of net-zero scenarios, the twins should be capable of reacting to synchronization triggers.
- *What-if & high-density triggers:* Since net-zero smart city environments are prone to topological changes, the fully- synchronized twinning should be robust against two triggers what-if activated and high-density.

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A. Related Works

In literature, there are significant efforts utilizing the DT to enhance the network management for resource-constrained environments. For instance, [2] proposes a DT assisted mobile edge computing (MEC) framework for industrial IoT (IIoT) architectures to reduce the end-to-end latency. Similarly, [3] and [4] investigate the DT of a MEC network to optimize resource allocation by a deep neural network. For smart city applications, [5] proposes a 3D DT model of a city; by overlaying the 5G network with the IoT data to improve traffic control and water management. Moreover, [6] proposes an IoT-based smart waste management framework to reduce the required time for truck routes. Likewise, [7] considers waste management in a LoRaWAN IoT scenario regarding the battery level of the sensors, and long- time data storage. Although there are several DT networking attempts for smart city applications, none of them focuses on the DT communication side to address the aforementioned challenges. Therefore, this study tries to answer "*How to serve (i) a robust fully-synchronized communication under various triggers, (ii) a two-way communication considering high-fidelity modeling, and (iii) a net- zero waste prediction accuracy, with the aim of high twinning rate, minimum round-trip-time?*" Therefore, we propose a novel DT networking framework, referred to as T6CONF, based on an IPv6 infrastructure to enable end-to-end fully-synchronized and two-way connectivity between DT layers. Thus, we elaborate the Yet Another Next Generation (YANG) which is a data modeling format to represent operational and configurational data of the core network [8].

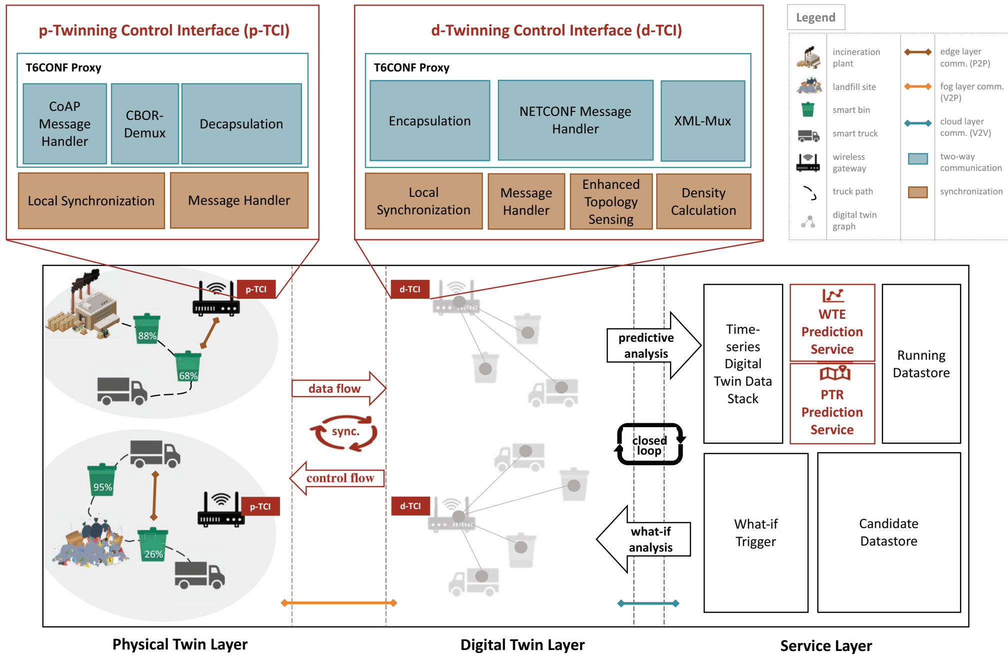


Fig. 1: The proposed digital twin networking architecture for net-zero waste management.

B. Contributions

Contributions of this study are as follows:

- To enable two-way communication considering high-fidelity modeling, we propose the Network Configuration Protocol (NETCONF) based Constrained Application Protocol (CoAP) protocol stack. For this, we are using YANG data model to Concise Binary Object Representation (CBOR) data mapping, called as T6CONF Proxy. Further, we evaluate it through round-trip-time (RTT) and twinning rate with changing fidelity levels.
- To provide a fully-synchronized and robust twinning, we derive a synchronization behavior with the ability of enhanced topology sensing and reacting according to the calculated request density. Then, we investigate the twinning rate performance of the synchronization against two external triggers; what-if and high-density.
- To measure the performance of the service layer of DT, we focus on waste management considering the waste-to-energy (WTE) and planned truck routing (PTR) services. Then, we perform machine learning (ML) approaches and compare their prediction accuracy.

The remainder of the article is organized as follows: Section II explains the proposed T6CONF framework with the service layer of the DT through net-zero waste management. The performance of the proposed T6CONF is evaluated in Section III. Finally, we conclude the paper in Section IV.

II. The T6CONF Framework

The proposed T6CONF DT networking framework for net-zero waste management comprises three layers:

- **Physical Twin Layer:** This layer operates waste management IoT sensors and several wireless communication technologies to underlay smart city applications. The IoT gateways where sensors directly communicate include a physical side of the twinning control interface (p-TCI) to transfer physical twin data to a DT environment.
- **Digital Twin Layer:** Digital replica of the real-world waste management represents the middle layer of the DT network. It comprises digital entities of IoT sensors and the digital side of TCI (d-TCI) to regulate synchronization and two-way data transfer issues.
- **Service Layer:** Net-zero-oriented waste management applications with pre-defined ML models run on the service layer. It includes a time-series data stack, prediction models, running and candidate datastores, and a what-if trigger.

In T6CONF framework, there are three communication links shown in brown, orange, and blue color for P2P, P2V, and V2V in Fig. 1, respectively.

- **P2P:** Physical-to-physical link exists within the physical twin layer and represents communication links for IoT sensors. It is the edge layer communication including sensor-to-sensor or sensor-to-gateway links.
- **P2V:** Physical-to-virtual (or vice versa) link symbolizes the communication between the physical and DT. This link is established among gateways; it refers to fog layer communication in the IoT glossary.
- **V2V:** Virtual-to-virtual data transfer is placed between two virtual layers: the digital twin layer and the service layer. It represents the cloud-layer communication.

The unified DT network architecture and proposed T6CON are presented in Fig. 1. Accordingly, light blue-boxes indicate the operations of two-way communication and light brown-boxes denominate synchronization tasks within physical twin and DT.

A. Two-way Communication

The data flow from physical twins to digital twins and the control flow in the reverse direction form a two-way communication between two layers. Unlike simulation platforms where the data flow exists in one-way, the DT network supplies control flow through digital entities. To deal with two-way communication, YANG models are used. The tree-like structure of the YANG model describes a schema to state how operational data (i.e., status data of the network node) and configurational data (i.e., network command to be sent to the device) look like. Two data models exist in YANG: operational data (i.e., sensor data) and configurational data (i.e., control data). The ability to send sensor data to replicate physical entities; and send back the related control data from digital replicas ensures interactive management and data-driven automation.

Besides, YANG models can be encoded with the extensible markup language (XML) when used with NETCONF. Pure IoT-based infrastructures cannot handle heavy XML format with the NETCONF protocol due to their power constraint. Therefore, the YANG models used in the core network telemetry are not suitable for IoT edge. Thus, we have introduced the CoAP with YANG data modeling. As seen in Fig. 1, there is Twinning Control Interface (TCI) on both the physical side (p-TCI) and the digital twin side (d-TCI) to realize the fog layer communication. The pipeline for the operational data from p-TCI to d-TCI is as follows:

- *CoAP Message Handler:* IoT messages coming to the IoT gateway first are met here. The CoAP protocol operates the user datagram protocol (UDP) in the transport layer regardless of the wireless protocol utilized in the lower layers. Then, it sends CBOR data to the next submodule.
- *CBOR-Demux:* The Concise Binary Object Representation (CBOR) is a data format that aims to be light and tiny messaging in constrained IoT devices. The IoT message is interpreted and extracted from the CBOR format.
- *Decapsulation:* The message is decapsulated to obtain the IPv6 packet format.
- *Encapsulation:* The IPv6 packet format is now encapsulated with new transport and application layer protocols, SSH/TLS and NETCONF, respectively.
- *XML-Mux:* The IoT message is formatted with the XML data format.
- *NETCONF Message Handler:* The NETCONF message is generated for the operational data, and is processed in the DT layer to be later sent to the service layer.

The reverse operations are valid for the configurational data, where control flow messages are generated. The complete CoAP-based IoT communication enhanced with the YANG data model induces a new protocol stack shown in Fig. 2. The links (P2P, V2P, and V2V) are shown with the same colors as in Fig. 1. Moreover, the alignment of the proposed T6CONF with the TCP/IP protocol stack is shown on the left.

B. Synchronization

Time synchronization between the physical twin layer and the DT layer ensures that all sensor nodes are aware of their time difference with regard to a reference point. For traditional IoT applications, physical gateways and several physical sensors behind the gateway constitute an edge and a fog layer. Moreover, considering edge and fog layers, we refer to intralayer synchronization as local synchronization and interlayer synchronization as global synchronization. When modeling the synchronization behavior of this end-to-end system, we follow the one-to-many pattern rather than one-to-one. Namely, there is one replica or root node that sends the synchronization packets to the other entities.

As seen from Fig. 2, there are two types of physical nodes (PNi) on the edge, such as bins and trucks in waste management. Moreover, there is a physical gateway (PG) to handle communication between the sensors and the servers. On the DT side, there is a digital replica of the physical gateway, that is twin gateway (TG), and the replica of physical sensors, twin nodes (TNi). In T6CONF synchronization, we take PG as the reference point. Thereby, PG maintains local synchronization and performs message handling considering the synchronization request of PNi and TG. Namely, PNi and TG send REQ messages to the PG to get the current timestamp of the reference point. After, they wait till SYNC message arrives. After the synchronization response, nodes set up their local clock time with respect to the reference clock timestamp. On opposite, the local synchronization of TNi and TG is conducted with a control mechanism, including enhanced topology sensing and density calculation to give proactive responses and maintain robust twinning. When a REQ message comes from TNi with a timeout occurrence, TG does not go to the reference point; it just realizes a self- update and sends back its current timestamp to the TNi , and the local synchronization process ends. If no timeout occurs, TG observes the synchronization request of all TNi 's and calculates a request density. After that, TG sends synchronization requests to the reference point with a frequency regarding the density value. After, TG calculates its local timestamp and forms a CORR message to relay the current timestamp of the reference point to the virtual edge layer. With the performed local synchronization processes, the DT topology has become a globally synchronized end-to-end model. Consequently, T6CONF synchronization behavior is prone to sense physical and virtual topology changes by listening the IoT topology.

C. Net-Zero Waste Services

The service layer conducts predictive and what- if analysis, and evaluates them within the close-loop. The first step is collecting time-series data, referred to as *time-series digital twin data stack* in Fig. 1. Then, predictive services operate by using the collected data, and current constraints held in *running datastore*. According to predictive decisions, what-if scenarios observe DTs using a new set of configurations and restrictions which are kept in the *candidate datastore*. If what-if scenarios are accepted, the running datastore is overwritten with the *candidate datastore*.

1) WTE Prediction: In net-zero waste management, WTE plays a crucial role in balancing internal equity. The first step

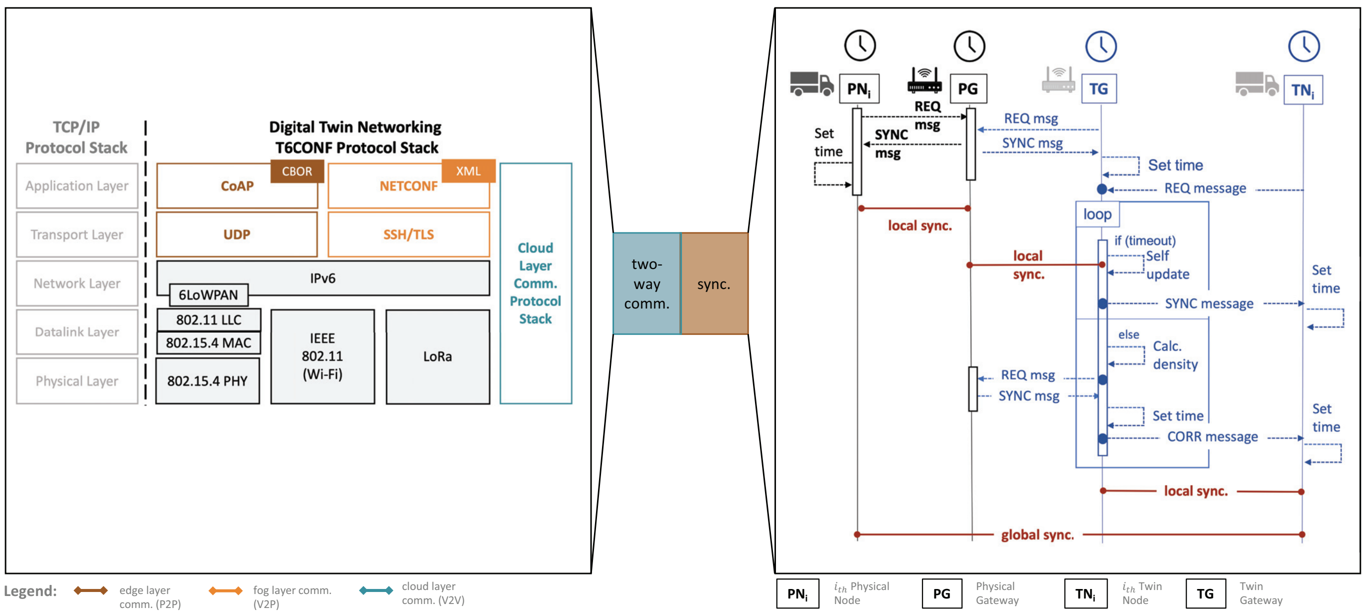


Fig. 2: T6CONF two-way communication (on the left) and synchronization model (on the right).

is to predict the amount of municipal solid waste (MSW) and use colorific values to obtain the expected amount of energy. Colorific values are the findings in waste characterization, which is out of the scope of this research. We assume that we know the colorific index values of some districts in Istanbul city calculated by fourteen various MSW [9]. Thanks to the T6CONF DT data pipeline, we have IoT waste sensor data to predict the amount of MSW by the district. Then, we have obtained the total predicted energy from waste. New configurations are set to come in net-zero aims using the T6CONF control flow through the YANG configurational data.

2) PTR Prediction: Transportation of trucks in net-zero constitutes a significant amount of CO2 emission regarding the transportation time and path length. Moreover, several factors affect the waste collection and truck routing, such as population density, waste generation, the capacity of bins and trucks, etc. In such a multi-factor environment, dynamic decision-making for the truck ride has the advantage of net-zero aim. The PTR service takes bin and truck data from time-series digital twin data stack. The bin data includes bin ID, bin capacity, bin level, bin location, etc. Truck data includes truck ID, truck capacity, and truck fuel level. With this, PTR outputs the estimated truck paths. After, the trucks update their paths to be followed with better utilization of the truck capacities regarding the PTR output.

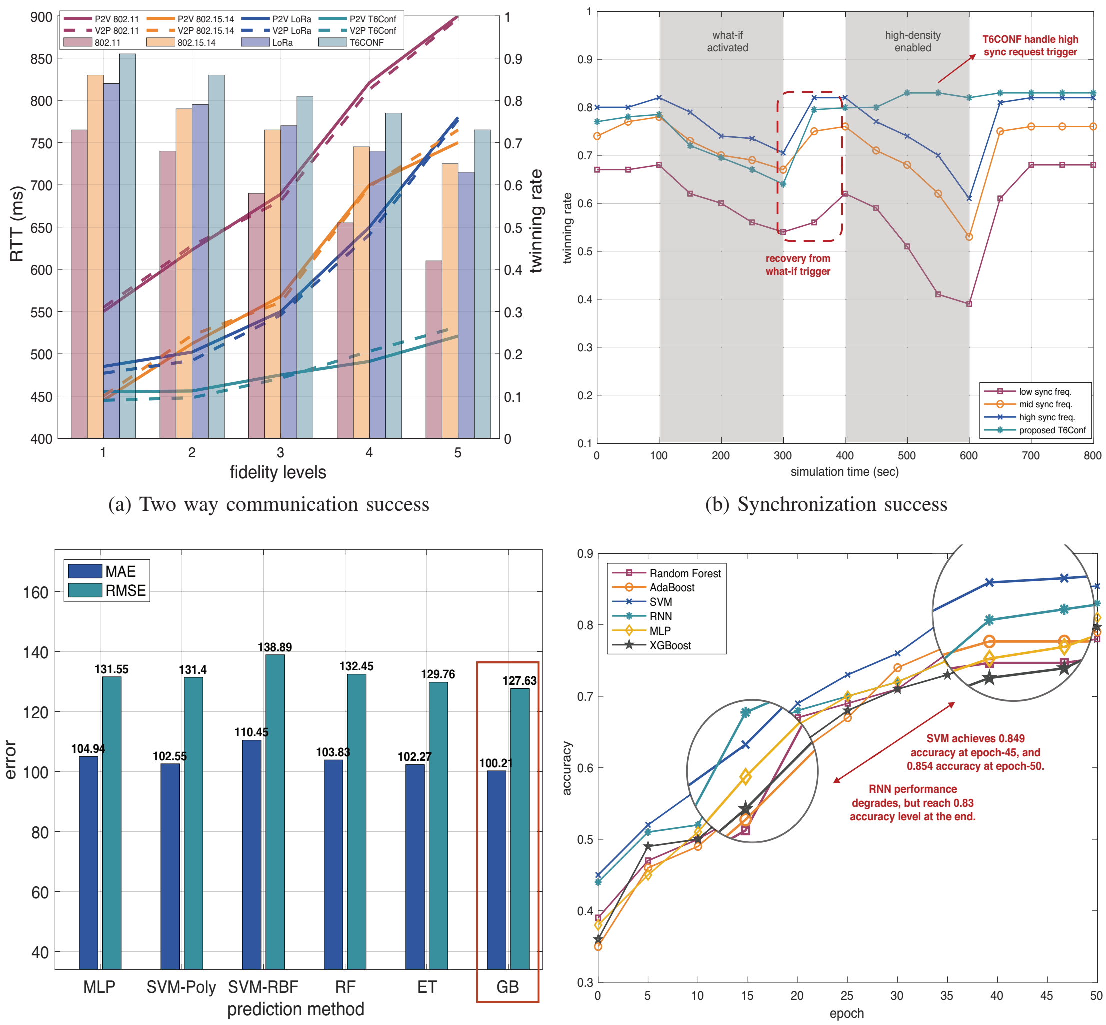
III. Performance Evaluation

We investigate the efficiency of the T6CONF by considering, (i) two-way communication success according to changing fidelity levels and twinning rates, (ii) synchronization success related to twinning rate, (iii) waste-to-energy prediction success, and (iv) truck path prediction accuracy. We have used two DT-specific metrics commonly used in DT studies: twinning rate and fidelity [10]. The twinning rate implies the frequency with which synchronization occurs between the physical entity and the corresponding virtual entity. It lies in the interval of [0, 1], in which 0 means no synchronization and 1 means real-time synchronization. We have used timestamps in the twins and the delay passed during the transmission to calculate the twinning rate. Moreover, the fidelity level shows how much the twins are similar. Since the fidelity level might change according to the use case, its scale varies from abstract (low level) to precise (high level) [10]. Thus, we have used the number of YANG sensor paths as the decision criteria of fidelity level, that is if more of YANG sensor paths are used for a replica, the fidelity level will be high.

A. The Performance of the T6CONF Communication Model

1) Two-way Communication: We have used RTT and twinning rate to evaluate the two-way communication performance of T6CONF. We have considered both P2V and V2P directions. As a baseline, we choose the applied protocol stack as (i) 802.11 wireless, (ii) 802.15.14 Zigbee, and (iii) LoRa. NS-3 simulation environment is used to perform wireless protocol stacks. Since the proposed T6CONF makes a contribution on top of the underlying wireless communication link and offers a two-way and synchronized data transmission for digital twinning, it operates regardless of the wireless protocol utilized in the first two layers. Simply, in T6CONF, we have used IEEE 802.11ac for the physical and datalink layer communication. Besides, we have depicted the fidelity levels on the x-axis. With changing fidelity levels, we measure how two-way communication is affected under different communication models. Line charts show RTT values on the left y-axis, while the bar charts where the twinning rate is computed are shown on the right y-axis.

As seen in Fig. 3a, with the increasing fidelity levels, RTT is also increasing. The least rise is observed in the proposed T6CONF communication model; we achieve the worst RTT results in WiFi (i.e., 802.11) and an almost similar RTT



(a) Two way communication success

(b) Synchronization success

(c) Waste to energy prediction success

(d) Planned truck route prediction success

Fig. 3: Performance comparison of the proposed digital twin networking framework.

increase in Zigbee and LoRa. Finally, growing fidelity levels, and a minor decrease in the twinning rate, are observed in the T6CONF model. This is because the proposed IoT-compatible data modeling induces less RTT and more twinning rate, which are two crucial criteria in digital twinning models.

2) Synchronization: We evaluate the synchronization performance of T6CONF via the twinning rate metric. In our experiments, we consider two distinct external trigger mechanism such as what-if activated, and high-density enabled. The first one means stopping the synchronization for a certain amount of time and working on the operational data. The latter one means several IoT sensor nodes want to synchronize with the reference clock. In addition, we assume that the external triggers occur separately. To measure the robustness against the two triggers, we apply the proposed T6CONF model and a manual synchronization frequency set in which there are three levels of synchronization such as low, medium, and high. We set the frequency values of these levels as 5s, 100ms, and 10ms respectively. Moreover, in the sensor density estimation, we allow maximum 1% duty cycle for each of the sensor nodes to minimize the effects of spectrum sharing limitation. Also, we set a limit on the amount of transferred data as 8 bytes in total both in uplink (UL) and downlink (DL) direction. Namely, UL traffic is to notify the virtual sensor gateway regarding synchronization requests by using 2 bytes of data; DL traffic is to convey the current timestamp of the reference clock by using maximum 6 bytes of data. Then, we observe the twinning rate oscillations to decide on a more robust synchronization model.

As seen from Fig. 3b, the time intervals regarding the trigger mechanisms are highlighted with gray shadows. When no distinct trigger occurs, the manual frequency set model tends to have a twinning rate behavior directly proportional to the previously set frequency level. If a high-frequency level is set, we observe high twinning rate results of around 0.83. Likewise, low and medium-level frequency sets result in average 0.77 and 0.66 twinning rates, respectively. The proposed T6CONF model gives an average 0.84 twinning rate if there is no external trigger. When the what-if occurs, the twinning rate for all models decreases which is the natural result of stopping the synchronization for a certain time period. When the trigger ends after the 300s, the models start to recover twinning rates till another external trigger. Within the recovery interval ([300 s, 400 s]), we see that the T6CONF model tries to recover its twinning rate more rapidly, with a value of 24.2% increase compared to the manual synchronization. This is due to T6CONF conducts topology listening and sensing by performing proactive synchronization. Conversely, when high-density occurs, the manual synchronization responses with a decreasing twinning rate. This is because the manual model cannot afford to handle an increasing IoT topology synchronization needs. However, the proposed T6CONF responds to a high-density enabled trigger by adapting to the IoT topology changing. For this reason, T6CONF results in a more robust synchronization owing to its enhanced density calculation ability.

Besides, propagation and processing delay are two issues in synchronization. To conclude a common output from Fig. 3a and Fig. 3b, the proposed T6CONF synchronization model shows the best twinning rate performance (on average 0.7) under the two triggers. At fidelity level 5, the only approach giving more than 0.7 twinning rate is just T6CONF with approximately 525ms RTT value. These supplementary results show that 500-550ms RTT values (or approximately 250ms propagation delay) do not affect the proposed synchronization and still give higher twinning rates even if external triggers. On the other hand, increasing the fidelity level means increasing the data. Moreover, different communication protocols with various packet sizes and headers also affect the processing delay. To conclude, the experiments verify the robustness of the proposed T6CONF model under various circumstances, which affect both the processing and propagation delay.

B. The Performance of the T6CONF Services

We have provided a set of experiments with various ML algorithms to emphasize how prediction performance might be applicable for net-zero activities. Traditional IoT networks are capable of collecting data but lack two-way links where what-if scenarios can not be applicable. Using the prediction results, what-if scenarios (out of the scope of this study) could be observed with the proposed T6CONF digital twin stack.

1) WTE Prediction: We perform multi layer perceptron (MLP), support vector machines (SVM) with a polynomial kernel and radial basis function (rbf) kernel which is implemented by distances from the central point, random forest (RF), extra trees (ET) and gradient boosting (GB) to measure the performance of the WTE prediction. For the MLP, we created six different architectures, and we decided on a 4-layered 16-8-4-8 architecture according to the results. For SVM, we performed polynomial-SVM and rbf-SVM by setting the upper bound on the fraction of margin errors to 0.2, kernel coefficient to 1, degree to 2, regularization parameter to 0.1. We applied 10 fold cross validation and Scikit-learn library. We have used i) temperature (°C), ii) wind speed (m/s), iii) humidity (%), iv) min. pressure (hPA) v) socio-economic level of the district (low income, high income, and commercial area), and vi) amount of daily waste (in tonnes) for the prediction of 14 different waste types (e.g., paper, glass, plastic, metal etc.) Since the generated energy and calorific index values vary according to waste types, it is crucial to forecast the amount of waste separately in the DT city to increase prediction accuracy. Moreover, when we investigate the descriptive properties of the data, the minimum, maximum, average, and standard deviation values for MSW are 1806, 3187, 2587, and 189, respectively. We have noted the mean absolute error (MAE) and the root mean squared error (RMSE) values for each of the prediction. As seen from Fig. 3a, the GB method results in at most 19% improvement. Therefore, the service layer of the DT could be choosen as GB for the WTE prediction.

2) PTR Prediction: We perform RF, adaptive boosting (AdaBoost), SVM with a polynomial kernel, recurrent neural network (RNN), extreme gradient boosting (XGBoost), and MLP. For RF, we assume the number of estimators as 50, and loss function as Gini. For AdaBoost, we set the number of estimators to 50, and learning rate as 0.8. For SVM-poly, we use the polynomial kernel as the default that is 3. For RNN, we use *Adam* optimizer and the sigmoid activation function. For XGBoost, we set the number of estimators to 50, learning rate as 0.8, and the regularization term to 10. For MLP, we use a 3-layered 10-6-3 architecture. It is proved that in some dataset, tree-based ensemble algorithms gives higher accuracy in time-series predictions. Therefore, we have considered AdaBoost, RF, and XGBoost beside the time-series naive models such as SVM and RNN. In AdaBoost, RF, and XGBoost, we have used *sliding window approach* (or called as a *rolling window*) and then *TimeSeriesSplit* to remove randomness and enable walk-forward validation. We evaluated the performance of ML algorithms through increasing epoch values to see the learning curve. Namely, epoch shows how many times the dataset is iterated through and, at some point, the line flattens when ML algorithm learns. As seen from Fig. 3d, SVM results best training accuracy at epoch- 45 with the value of 0.854. Thereby, the candidate paths are chosen according to the SVM outcomes. Conversely, the accuracy of predicted paths with RF, AdaBoost, XGBoost, and MLP are low compared to SVM and RNN. Furthermore, as seen from the zoomed circles in Fig. 3d, RNN performance degrades at first but reaches an approximate training accuracy of 0.83 at epoch-50, similar to SVM. Therefore, another service layer prediction function of the DT for PTR could be applied as RNN.

IV. CONCLUSION

We have focused on two main problems of DT networks: two-way communication and full-synchronization. Considering the resource-constrained environments of IoT devices and net-zero waste management, we have proposed a DT networking framework, named T6CONF. The proposed framework comes in predictive analysis and what- if scenarios through DT. The results have showed 42% less RTT on average and 12% more twinning rate for the two-way communication model. Moreover, we have evaluated the robustness of the synchronization model against two triggers: what-if activated and high-density enabled. The proposed T6CONF model responds to two triggers rapidly compared to baselines. Finally, we have evaluated net-zero services through waste-to-energy and planned-truck routing case studies. We have showed that the proposed T6CONF DT framework is a vital enabler of the net-zero waste targets.

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