Living Lab Long-Term Sustainability in Hybrid Access Positive Energy Districts—A Prosumager Smart Fog Computing Perspective

Rudolf Vohnout, *Member, IEEE*, Ivo Bukovsky, *Senior Member, IEEE*, Shuo-Yan Chou, Jakub Geyer, *Graduate Student Member, IEEE*, Ondrej Budik, Rohit Sharma, *Senior Member, IEEE*, Milos Prokysek, Tomas Horvath, *Member, IEEE*, and Annemie Wyckmans

***Abstract*—Living lab, one of the recent emerging smart city concepts, faces long-term sustainability challenges associated with its complexity and breadth of use. To be efficient, it must rely on comprehensive set of information distributed appropriately among all stakeholders to unleash its full innovation potential. This is especially true in the case of positive energy districts (PEDs), where timely data dissemination is essential for prosumager decisions and their greedy behavior. This article interconnects intelligent information exchange, supported by ultralow latency hybrid access network infrastructure, with the clever use of available fog computing resources to properly disseminate complex energy details to all participating entities. As the optimal task offloading for effective information distribution constitutes the convergence problem, we reintroduced higher order neural units. These units contribute to sustaining both computational and energy efficiency, as well as the balance of the entire system. We have achieved a reliable hourly energy consumption prediction with a computationally very lightweight alternative to commonly used deep neural network approaches that can be deployed on available smart appliances with ease. The application and simulation were performed on the data set provided by one of Europe's smart city pioneers, where the prosumager PED transition has already started.**

***Index Terms*—Access network, fog computing, high order neural unit (HONU), living lab (LL), polynomial neuron, positive energy district (PED), prosumager, smart city, stability, tactile Internet (TI).**

Manuscript received 31 October 2022; revised 6 February 2023 and 14 April 2023; accepted 15 May 2023. Date of publication 29 May 2023; date of current version 24 October 2023. This work was supported in part by the Horizon 2020 Research and Innovation Program of the European Union under Grant 824260 (+CityXchange), and in part by the Interreg V 2014–2020 through BY-CZ Project 144, through FEKT-S-23-8189, and through Project–e-Infra under Grant LM2023054. *(Corresponding authors: Rudolf Vohnout; Rohit Sharma.)*

Rudolf Vohnout, Ivo Bukovsky, Jakub Geyer, Ondrej Budik, and Milos Prokysek are with the Department of Computer Science, Faculty of Science, University of South Bohemia in České Budějovice, 37005 České Budějovice, Czech Republic (e-mail: rvohnout@jcu.cz).

Shuo-Yan Chou is with the Department of Industrial Management, National Taiwan University of Science and Technology, Taipei 106, Taiwan.

Rohit Sharma is with the Department of Electronics and Communication Engineering, SRM Institute of Science and Technology, NCR Campus, Ghaziabad 201204, India (e-mail: rohitapece@gmail.com).

Tomas Horvath is with the Department of Telecommunications, Brno University of Technology, 61600 Brno, Czech Republic, and also with the Department of Optical Networks, CESNET a.l.e., 16000 Prague, Czech Republic.

Annemie Wyckmans is with the Department of Architecture and Planning, NTNU-Norwegian University of Science and Technology, 7491 Trondheim, Norway.

Digital Object Identifier 10.1109/JIOT.2023.3280594

I. Introduction

LIVING lab (LL) represents an emerging self-evolving entity within a smart city concept [1]. Sometimes referred to as the "Urban Lab," it allows its stakeholders to develop, operate, and evaluate smart city services with the main mission of innovation to ensure the continuous development and improvement of the "smart" ecosystem [2]. This not only assumes efficient sharing of common resources but also requires sustainable partnerships and cooperation strategies between the parties involved [3] bearing in mind that they are the real key players determining the direction of innovation. Technological readiness in LL areas is directly related to quality of life, where several evaluations have also been carried out in the past [4] in these types of urban areas.

In Europe, most LLs are united under the umbrella of the "European Network of LLs" [5] and provide added value services that allow selected parts of the city to be transformed into innovative and partially self-sustaining smart blocks or districts [6]. These smart city areas combine the uniqueness of the services offered with added value to the community, as an example of crowd sensing [7], smart water monitoring [8], or complex active control of all devices connected to a grid [9]. Efficiency in energy management has always been seen as a typical application and could lead, to some extent, to positive energy [10], or even off-grid urban areas [11]. The term positive energy district (PED) is often mentioned [12] as a synonym for the long-term sustainability of a smart grid [13] and is in line with the implementation of the LL concept. Although many "to-PEDs transition" projects are currently running [14], [15] the actual implementation of PED also requires a precise calculation of electricity consumption/demand and production/supply in a certain area, which is not easy to achieve [16]. Scaling down to positive energy blocks (PEBs) represented by the interconnection of several buildings in the PED area [17], the role of the prosumager is much more notable.

Another area in which PEBs/PEDs and LLs have in common is their high dependency on fog and cloud resources [18] and for these it is necessary to provide a sufficiently robust and reliable access and computing infrastructure with emphasis on stable jitter and low latency [19], especially for critical services [20]. From the point of view of the local government, every LL area presents valuable information where knowledge and especially its timely possession [21] mean an advantage for effective decision making [22]. Several LL technological foundations are considerably dependent on the Internet of Things (IoT) [23] or even the City of Things [24]. What these contributions have in common is the assumption that PEB/PED infrastructure must be designed to meet the scalability, information availability, and network latency requirements [25] to address the heterogeneity of a smart city between devices, data collections, and information security [26]. However, IoT is only the first step toward optimal behavior of the prosumager on the energy market within PEDs, even though an IOT role in smart energy systems is inevitable [27]. By accessing, controlling, and using smart devices, the prosumager can significantly influence the energy balance of the PEB (and figuratively also of the PED) in his favor to maximize his energy benefit. This entity focuses on greedy or selfish behavior, where self-benefit is always prioritized (maximized), it is necessary to connect the available edge/fog computing resources with a smart infrastructure [28] using elements of the tactile Internet (TI) or Tactile IoT [29].

Considering PED as a system that has to be stabilized in order to be sustainable in the long term, a complete information exchange is an essential prerequisite, especially considering the selfish manners of the energy market prosumers. A system that uses the shallow neural network apparatus to help optimally allocate available computing resources with a goal of prosumager efficient decision-making mechanism. The rapid distribution of information on the availability and consumption of energy will utilize the means of fog computing, in other words, moving the real-time data processing toward the edge of the network [30]. The possession of correct information on the energy demand response, which is even enhanced with energy supply and storage with complex knowledge of the status of other nodes that are active in the PED trading, is crucial [31]. Here, prediction systems play a vital role and are one of the key aspects in smart city infrastructure, taking into account optimal node task offloading in the fog environment [32] as well as its proper scheduling [33]. Therefore, prediction techniques shall play an important role not only for the prediction task but also for the system stability monitoring and predictability evaluation, anomaly detection, etc. However, the sufficient amount of training data can be achieved for deep learning techniques [34] and some prediction tasks may even require nondeep techniques, such as for highly nonstationary systems where only contemporary system behavior, can be used for real-time learning predictors. Shallow (nondeep) neural networks and real-time learning regressors can be utilized in such cases. However, the local minima is one of the practical issues with conventional neural networks (e.g., multilayer perceptron (MLP), alternatively with exponential linear unit (ELU)s and rectified ELU (RELU)s types of neurons) that results in performance variation of the same MLP instances when trained from different initial weights, for example, as studied on the prediction of mean power consumption [35].

II. Requirements

The optimal information exchange between the parties involved that has a direct influence on individual decision making depends on and contributes to the stability of the system is based in general on the following.

1) Infrastructure for the information sharing.
2) Decision-making process.
3) Available resources.
4) Timing of the information delivery.

There are two main topics that our contribution addresses.

1) The long-term sustainability of LL is based on the balanced behavior of the parties involved, which can be problematic in the long run. Our proposed approach addresses the decision process by optimizing the distribution of the computational problem and the timeliness distribution and availability of the resulting information to the end prosumager.
2) Optimal infrastructure concept for the given scenario. This includes a hybrid access infrastructure to minimize latency in communication between individual nodes and with the central workload forwarding coordinator (WFC) node. This will be further elaborated on in the methodology chapter. The conceptual design of the infrastructure is based both on the restrictive conditions of the area and on the feasibility study of the chosen smart city. The assumption is that the infrastructure must be complex and should not limit the decision-making and innovation potential of the LL complex in any way.

On the optimal information processing and distribution side, we utilize a class of shallow neural architectures that can be used as suitable learning predictors in the sense of fog computing [36]. These neural architectures are polynomial neural architectures, that is, higher-order neural units (HONUs) [37], [38] with customized order of polynomial are a subclass of in-parameter-linear nonlinear architectures (IPLNAs) [38] that have intriguing properties regarding computational efficiency and simultaneous weight convergence assurance [39] and stability monitoring of the underlying system represented by the training data. Recall that HONUs can also be viewed as energy-saving computing machine learning tools due to their properties and abilities to run efficiently on low power consumption devices.

III. Methodology

Smart PED and LL ecosystems that rely on the optimal decision making of the citizen, here represented as a prosumager entity that utilizes fog computing nodes capabilities to support a strict multicriteria analysis and load balancing [40]. The computational infrastructure uses intelligent and cooperative fog computing task offloading [41] and taking into account the available computing and energy resources [42] to balance the workload processed and further reduce the service response time, and improve the overall efficiency. Our approach is based on decentralization control systems [43] and enhanced with the cooperative fog computing network [44] and further elaborated in [45]. For a particular size of the fog infrastructure [46] we introduce a fog node cooperation strategy, called offload forwarding. In this strategy, each fog node can forward a part or all of its offloaded workload to multiple neighboring fog nodes in the fog and/or help multiple other fog nodes process their workload. Task offloading is based on the distributed alternating-direction method of multipliers by means of the variable splitting (ADMM-VS) algorithm. Here, the WFC is defined as the entity deployed as the part of the fog/edge or cloud infrastructure that coordinates workload among fog nodes through a dual variable for optimization of all nodes workload subproblems, as well as optimal node placement [47]. The flowchart of the node optimization problem is depicted in Fig. 1.

The fog computing node optimization problem to be solved is then defined as

$$\boldsymbol{\phi}^{t+1} = \arg\min_{\boldsymbol{\phi}} \mathcal{L}_{\rho}\left(\phi_{\bullet 1}, \phi_{\bullet 2}, \ldots, \phi_{\bullet N}, \boldsymbol{\psi}^{t}, \Lambda^{t}\right). \tag{1}$$

Based on this, $\boldsymbol{\psi}$ as a node updating optimization problem can be defined as

$$\boldsymbol{\psi}^{t+1} = \arg\min_{\boldsymbol{\psi}} \frac{\rho}{2}\left\|\boldsymbol{\phi}^{t+1} - \boldsymbol{\psi}^{t} + \boldsymbol{\Lambda}^{t}\right\|_2^2 + \mathbf{I}_{\mathcal{G}_c}(\boldsymbol{\psi}) \tag{2}$$

where i is the ith fog computing node, N represents the number of individual subproblem, ϕ represents the vector of workloads (optimization problems) with λi workload value for the ith node, $\mathcal{L}$ is Lagrangian form with ρ as the augmented parameter, and $\boldsymbol{\Lambda}$ is the vector of the dual variables. The $\mathbf{I}\mathcal{G}_c(\boldsymbol{\psi})$ is indicator function which is defined as

$$\mathbf{I}_{\mathcal{G}_c}(\boldsymbol{\psi}) = \begin{cases} 0, & \boldsymbol{\psi} \in \mathcal{G}_c \\ +\infty, & \boldsymbol{\psi} \notin \mathcal{G}_c. \end{cases} \tag{3}$$

The dual variable update subproblem can then be written as follows:

$$\Lambda^{t+1} = \Lambda^{t} - \rho\left(\phi^{t+1} - \boldsymbol{\psi}^{t+1}\right). \tag{4}$$

The optimization of subproblems is equivalent to the form of the traditional ADMM with two random variables: ϕ and ψ. In distributed ADMM-VS, each fog node i will calculate the optimal service vector $\phi^{*}_{\bullet i}$ by solving the following subproblem:

$$\phi^{t+1}_{\bullet i} = \arg\min_{\phi_{\bullet i}} \mathcal{L}'_{S_i}\left(\phi_{\bullet i}, \boldsymbol{\psi}^{t}_{i}, \Lambda^{t}_{i}\right). \tag{5}$$

Based on the above mathematical constructions, it is possible to define an optimization algorithm for fog computing task offloading [47].

To ensure ultralow latency and stable jitter, the concept is inspired by selected elements of the TI approach [48]. For this work, TI nodes in each residential unit, which represents a prosumager entity in the energy market, are used directly for demand-response and energy supply management in order to optimize greedy behavior in favor of the prosumager. For the purpose of this article each residential unit, where the passive optical network is terminated (see Section V), is considered as IoT network entity with fog resources.

A. Polynomial Neural Architectures for Efficient Fog Computing

The mathematical aspect of convergence, which can be beneficial in fog computing, is also recalled. This concept in the

---

Distributed ADMM-VS Algorithm

Initialization: Each fog node i chooses an initial service vector $\phi^{0}_{\bullet i}$ and WFC chooses an initial dual variable $\boldsymbol{\Lambda}^{0}$.

WHILE t = 0, 1, ...

↓

Fog node updating: Each fog node i calculates $\phi^{t+1}_{\bullet i}$ by solving 5 and then sends the resulting $\phi^{t+1}_{\theta i}$ and λ_k to the WFC,

↓

WFC Updating: WFC calculates $\psi^{t^{t+1}}$ by solving the ψ-updating problem in 2.

↓

Dual Variable Updating: WFC updates dual variables $\boldsymbol{\Lambda}^{t+1} = \boldsymbol{\Lambda}^{k} - \rho\left(\boldsymbol{\phi}^{t+1} - \boldsymbol{\psi}^{t+1}\right)$ and sends $\boldsymbol{\phi}^{t+1}_{i}$ and Λ^{t+1}_{i} to fog node i.

↓

ENDWHILE

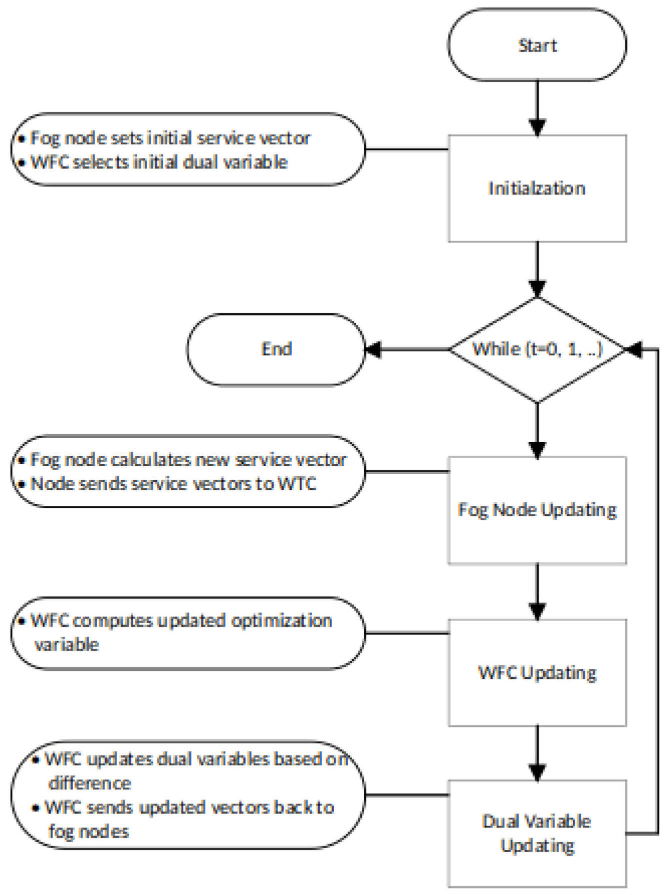

Fig. 1. Flowchart scheme of the distributed ADMM-VS algorithm.

IOT-cloud-fog-edge has recently already been elaborated in greater detail and gives great insight into optimal resource utilization [49], [50]. Furthermore, this section recalls HONUs as a subclass of IPLNAs for monitoring the stability of the underlying data-generating process. These exclusive aspects of HONUs can be evaluated for batches of data or even for individual data samples during real-time learning. The demonstration is based on a real example of energy consumption data. We propose that these aspects of HONUs are intriguing for (nondeep) fog computing in IoT applications.

The mathematical architecture of HONUs for prediction is as follows:

$$\tilde{y}(k+h) = \mathbf{w}(k)^T \cdot \mathrm{col}^r(\mathbf{x}(k)) \tag{6}$$

where $\tilde{y}$ is the neural output, h is the prediction horizon in samples [hours], $\mathbf{x}$ is a columnwise vector of features augmented with unit as its first element, i.e., $x_0 = 1$, and $\mathrm{col}^r(.)$ is a columnwise polynomial kernel of polynomial order r, and $\mathbf{w}$ is a columnwise vector of neural weights whose length is the same as the length of the columnwise vector $\mathrm{col}^r(.)$, k is a discrete index of time, and upper T stands for vector transposition (for more details, see [38]).

Let us emphasize that the IPLNA form (6) of HONUs means that each neural weight in w is unique for each polynomial term in $\mathrm{col}^r(\mathbf{x})$. Additionally, training HONUs represents a linear optimization problem that prevents HONUs from a local minima problem such that it is common for conventional types of neural networks, for example [35].

Moreover, gradient and stochastic incremental learning and its modifications, including ADAM [51] and recursive least squares (RLS, originating from [52] and [53]), allow us to analyze the convergence of neural weights in the sense of bounded-input bounded-state (BIBS) which serves to avoid the divergence of this machine learning tool in real time. Recall briefly the gradient incremental learning rule of HONU, which is in its general form as follows:

$$\mathbf{w}(k+1) = \mathbf{w}(k) - \mu(k)\frac{\partial Q(k)}{\partial \mathbf{w}} \tag{7}$$

where μ is the learning rate that can vary over time depending on the applied form of learning, and Q is the error criterion $Q(k) = e(k)^2$. It is shown in [39] that for IPLNAs, including HONUs, the weight-update system in (7) can be expressed in the linear time-variant state-space representation form

$$\mathbf{w}(k+1) = \mathbf{A}(k) \cdot \mathbf{w}(k) + \mathbf{B}(k) \cdot \mathbf{u}(k) \tag{8}$$

where the eigenvalues of the local dynamics matrix $\mathbf{A}$ and its relevant state transition matrix $\mathbb{A}_k = \prod_{j=0}^{k-k_0} \mathbf{A}(k-j)$ determine the BIBS stability of the weight system (7) during learning (see [39] for further details). The relevant experimental study can be found in [38], where the most strict condition of the spectral radius $\rho(\mathbf{A}(k)) < 1$ is demonstrated when weight convergence is evaluated in every individual data sample (of a time series).

Newly, we highlight the connotation of the weight convergence rule [39] with the famous Levenberg–Marquardt batch learning algorithm (LM, with origins in [53] and [54]) as follows. Recall the fundamental form of the L–M algorithm as follows:

$$\Delta\ \mathbf{w}^T = \left(\mathbf{J}^T \cdot \mathbf{J} + \frac{1}{\mu} \cdot \mathbf{I}\right)^{-1} \cdot \mathbf{J}^T \cdot \mathbf{e} = \mathbf{L_M} \cdot \mathbf{e} \tag{9}$$

where $\mathbf{I}$ is the identity matrix, $\mathbf{L_M}$ is the $M \times n_w$ matrix (M is the duration of the training batch and n_w is a number of neural weights), $\mathbf{J}$ is the Jacobian, and the upper "-1" denotes matrix inversion; for the HONU feedforward (and the IPLNA feedforward in general), the Jacobian J is constant because its rows are directly the feature vectors processed by the kernel as follows:

$$\mathbf{J} = \mathbf{colX} = \begin{bmatrix} \mathrm{col}^r(\mathbf{x}(k=1))^T \\ \mathrm{col}^r(\mathbf{x}(k=2))^T \\ \vdots \\ \mathrm{col}^r(\mathbf{x}(k=M))^T \end{bmatrix} \tag{10}$$

where the $\mathbf{colX}$ notation for HONUs is from [38], and $\mathbf{e}$ in (9) is the $M \times 1$ error vector as follows:

$$\mathbf{e} = \mathbf{y} - \tilde{\mathbf{y}} = \mathbf{y} - \mathbf{colX} \cdot \mathbf{w} \tag{11}$$

where $\mathbf{y}$ is the vector of all real outputs (targets). Then, the convergence rule of the batch weight updates

$$\mathbf{w}(\epsilon + 1) = \mathbf{w}(\epsilon) + \Delta\mathbf{w} \tag{12}$$

where ϵ is the index of the training epoch, which is as follows. By substituting (9) and (11) into (12), the batch learning (12) yields

$$\mathbf{w}(\epsilon + 1) = (\mathbf{I} - \mathbf{L_M} \cdot \mathbf{J}) \cdot \mathbf{w}(\epsilon) + \mathbf{L_M} \cdot \mathbf{y}. \tag{13}$$

Thus, the eigenvalues of the resulting local dynamics matrix $\mathbf{I} - \mathbf{L_M} \cdot \mathbf{J}$ determine the convergence (stability) of the weight-update system for the L–M batch algorithm. For feedforward IPLNAs, the weight-update system (13) is a linear time-invariant dynamical system (LTI) because the Jacobian $\mathbf{J}$ is constant with respect to the epoch index ϵ. For recurrent IPLNAs with the L–M algorithm, system (13) is a dynamical linear time variable (LTV) system, and the BIBS stability paradigm shall be used as in [39].

In addition to ensuring weight convergence, the polynomial architecture of HONUs allows us exclusively to apply the stability of the BIBS concept to HONU as a dynamical system that approximates the dynamics of the underlying data [55], [56]. Thus, by learning, HONU approximates (predicts) the dynamics of the underlying system and that naturally reflects the stability of the underlying system. Recall from [55] and [56] that the long-vector form of HONU in (6) can also be expressed in its corresponding time-variant state space forms as follows:

$$\chi(k+1) = \hat{\mathbf{A}}(k) \cdot \chi(k) + \hat{\mathbf{B}}(k) \cdot \hat{\mathbf{u}}(k) \tag{14}$$

where χ is the state vector of HONU, and the hat sign in $\hat{\mathbf{A}}, \hat{\mathbf{B}}, \hat{\mathbf{u}}$ indicates that the arrays are different from the ones in (3). Then, the eigen values of $\hat{\mathbf{A}}(k)$ determine the stability of HONU BIBS that reflects the stability of the approximate dynamical system (similarly to the proof in [39]). Notice that for merely time series prediction, the input gain matrix $\hat{\mathbf{B}}(k)$ and input vector $\hat{\mathbf{u}}(k)$ either disappears or represents only the augmenting bias with its weight, i.e., $w_0, w_{0,0}, w_{0,0,0}, \ldots,$ respectively, as for HONUs of polynomial order $r = 1$, $r = 2$, $r = 3, \ldots,$ respectively.

This section introduces the mathematical architecture of HONUs, their absence of the local minima problem, and their weight update convergence for real-time gradient and stochastic learning. Exclusively for HONUs, the stability monitoring of the underlying data generation system was introduced through HONU, which predicts the data, for example, time series.

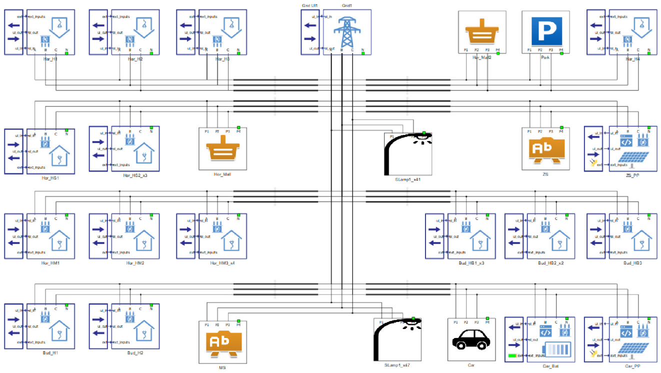

Fig. 2. Schematic representation of the model of the energy district of the city of Pisek. Each node represents a different home complex, business, school, public lighting, or cumulative positive energy sources. Each of these node's appliances' behavior is controlled individually on lower level of the simulation.

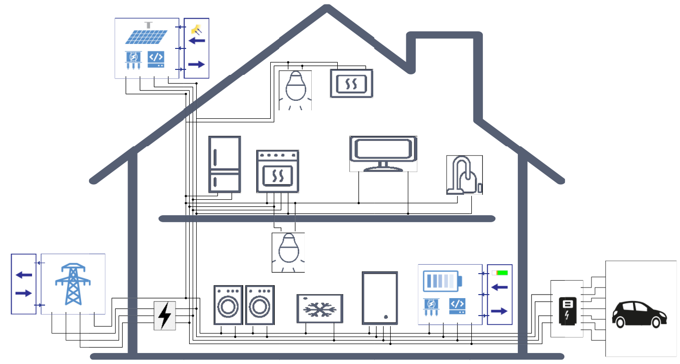

Fig. 3. Overview of the prosumager's home loads (smart appliances) and resources (grid, photovoltaic, battery, and EV). Designed in Typhoon HIL real-time simulator.

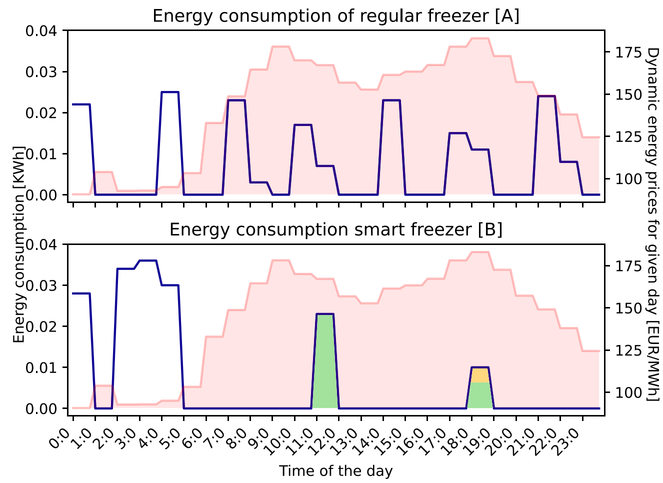

Fig. 4. Energy consumption comparison between a regular chest freezer at −18 °C and a smart freezer (blue lines) that over freezes to −32 °C during cheap energy periods (see red line), using accumulated cold later. The smart freezer consumed 0.16 KWh, while the regular one used 0.14 KWh, however, saving 10% in costs (due to energy price difference). The smart freezer can also draw energy from wall batteries (green fill) or EV batteries (orange fill) when available and price is above selected threshold. In the first spike during the day, only the wall battery was used; in the second, 65% wall battery and 35% EV battery energy were utilized, further decreasing operating costs.

IV. SMART BEHAVIOR SIMULATION

Simulation of the real use case scenario of all relevant stakeholders in the PED has been carried out using the Smart Grid Typhoon HIL simulator,[1] the HIL 602 + appliance type. This simulator allows us to analyze the behavior of the part of the grid [57] in real time based on the collected data or by real-time inputs from distributed sensors. It also enables validation of the performance and control of the grid in virtual environment [58] before deploying new distributed energy resources (DERs).

This simulation contains 51 housing units clustered into 14 load groups, two schools, two shopping centers, a garage parking lot and a car dealership. It also contains two smart public light connection points (with 130 public light passive optical network endpoints as distribution nodes for each residential house), two photovoltaic power plants and one high capacity battery with EV charger. 3-phase 400V/50Hz distribution network is used with assumed 10% nominal voltage drop of 10% over underground powerlines. This scenario inspired by the real use case is depicted in Fig. 2 above. The smart appliances behavior is simulated within a Python environment of Typhoon HIL, where the main operation criterion is the current dynamic energy price.

Smart appliances (Fig. 3) connected to a fog environment will optimize their energy consumption. Not all appliances can be adjusted accordingly to energy prices without causing discomfort for home users. However, some tasks could be postponed or prestock (for example, preheating/precooling). Prosumagers can apply various models to optimize their power consumption based on the available energy price and the variable power demand of their appliances [31]. Data on long-term measured consumption characteristics of the chest freezer have been used as input for the simulation. Using a smart freezer it is possible to store energy directly (Fig. 4), which allows for the further use of excess power and, at the same time, reduces overall cost.

The simulation setup and the simulated behavior of all elements are based on the greed/selfish strategy due to absence of any central management system. Households or even appliances are seen as individual rational energy users who want to reduce their electricity costs [59]. The entire behavior of the system is then influenced only by the billing rules and the price of energy in the spot market in a given network. Because saving money is one of the most important reasons for the transition of prosumagers [60], it is natural to expect that prosumers and their households will selfishly share energy with their neighbors and also schedule their energy storage systems to maximize profits.

The district simulation (Fig. 5) allows us to monitor and analyze the behavior of each component with the 1-s time step and 100 steps-per-second in real time or 15-min time step in virtual simulation. DER can be individually controlled and optimized based on the grid demands. Data from all smart meters (mainly nominal active power and nominal apparent power) and IoT sensors (grid state) are stored separately and loaded within SCADA initialization. Using component scripting, the data are normalized to correspond

[1]https://www.typhoon-hil.com/

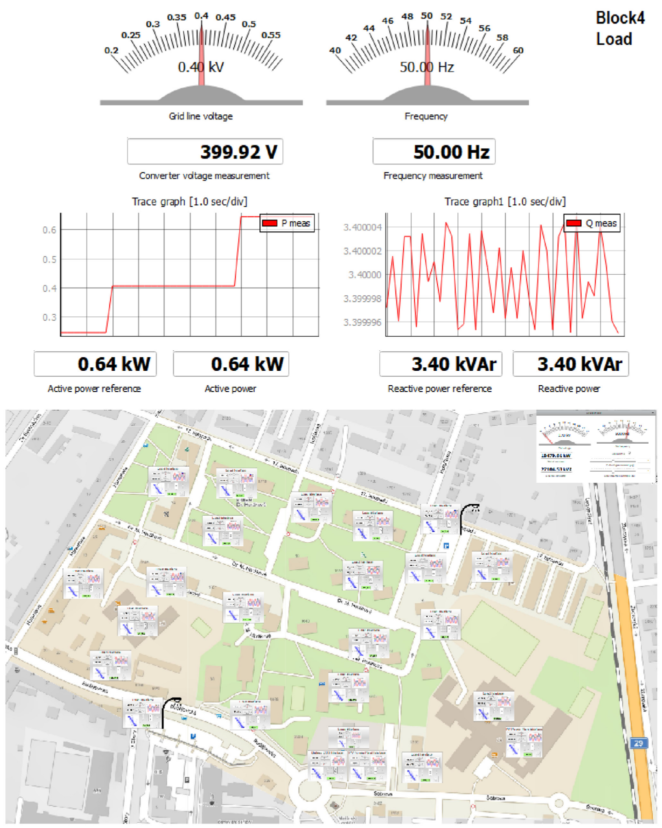

Fig. 5. Simulation of the overall consumption in a PED running in the Typhoon HIL environment. Overview map in the HIL SCADA environment is shown (bottom) with the available controls allowing access to the details of the power consumption and setup of individual parts (top).

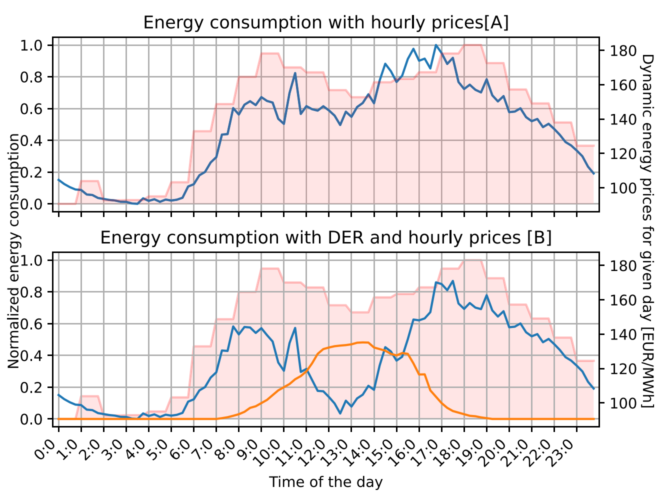

Fig. 6. Energy consumption of the district power grid in one day with dynamic hourly prices. On graph A, we can see normalized energy consumption of the grid without its DER. On graph B, we see the consumption of the power grid (blue) with its DER (orange). As we can see, the energy consumption on this sample winter day is nearly covered by DER around noon, which is more than satisfactory result for its winter behavior.

to the timings. When running the long-term virtual simulation (with various DERs), the input and output values have to be adapted accordingly.

The graphs depicted in Fig. 6 illustrates the total power consumption of the district for 1 day in winter with low utilization of renewable energy resources and higher

Fig. 7. Real situation of a energy positive block in the city of Pisek, where the black lines represent the chart skeleton of the LL infrastructure and black circles represent the nodes.

consumption related to the heating of the building. Graph A shows the total power consumption of the district without DER. Graph B shows the total district power with DER (photovoltaic power plants, battery). An average of four days from consecutive four weeks is used.

V. Positive Energy District Local Government Infrastructure

The area is represented by a pilot smart city in the Czech Republic, Pisek, which was one of the partners of the Horizon 2020 project entitled Positive City ExChange (+CityxChange).[2] Here, based on the feasibility study, an optimal public hybrid access infrastructure is proposed to support the long-term sustainability of a PED concept. Beyond the scope of this study, infrastructure is designed with respect to the methodology chapter, where energy-efficient infrastructure design is based on a hybrid model of an optical access network with fog computing nodes. It is based on the application of gradient learning cleverly distributed among the computational nodes available in a given residential unit, as well as other unused parts of the network, using the efficient TI traffic flow algorithm [61]. This results in intelligent leverage of the fog computing nodes offloading with a real smart city application. The situation is depicted in Fig. 7.

Based on the penetration of commercial optical links that already exist in the area and the feasibility study recommendations, a subset of nodes is eligible for the LL infrastructure. The technology used will be the gigabit-capable passive optical network (GPON) which represents an energy-efficient solution [62] with low power consumption in optical distribution networks (ODNs). The architecture is based on [62] and allows edge-to-edge connections between fog computing nodes. The fiber distribution will be in HDPE microtubes of diameter 40/33 mm containing 19 microtubes, always in pairs, one active, another backup. The installed fiber will be SM 9/125, G.652 D type and/or SM 9/125, G.657 family should be considered for in-house deployments due to higher band tolerance.

[2] https://cityxchange.eu/

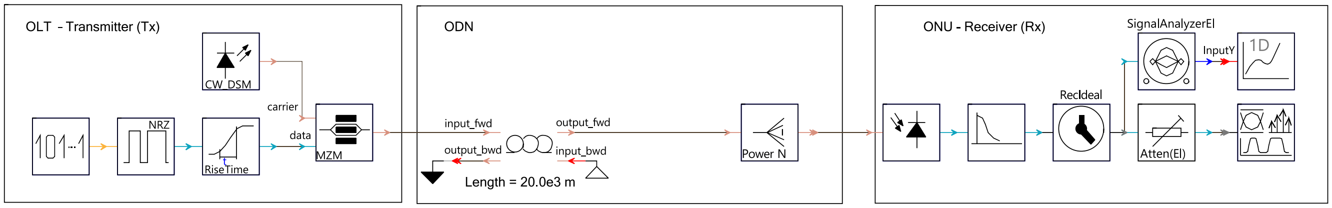

Fig. 8. Simulation scheme of the proposed topology in the smart city Pisek.

TABLE I
TABLE OF NUMBER OF ENDPOINT NODES

OLT	Branches	Endpoints
A	4	27 + 32 + 25 + 32
B	2	10 + 13

The proposed scheme of the GPON network was simulated in the VPIphotonics Design Suite (see Fig. 8). Due to the many buildings and end units, the cascade connection of the splitters is necessary, and the class C attenuation of the GPON was selected. This allowed us to ensure an attenuation range in the ODN of 15 to 30 dB. Fig. 8 shows the simulation topology consisting of the OLT, ODN, and ONU. The OLT launches with a power of 6.5 dBm (class C defines a power of 5 to 9 dBm). Data transmission was performed with 2.488 Gbit/s. The ODN contains 20 km of single mode fiber (G.652D) and one splitter, which is the worst case of ODN length. The type of splitter was changed from 1:2 to 1:128. The customer's part had an ONU network with bit error rate (BER) evaluation.

On the customer side (public lightning lamp), the optical network unit (ONU) will be used. To ensure power efficiency on the customer side, the ONU is equipped with power management. The ONUs should move to cyclic sleep mode, where the transmitting and receiving sides are turned off for a specific period, and then the ONU just checks the status of the link. Periodic link status is necessary due to loss of frame LoF and loss of signal LoS timer expiration, which will lead to deactivation of the ONU. The PON-based solution also offers the minimum latency for data transmission [63]. The fiber infrastructure footprint will have two separate central distribution units A and B, (see Table I).

The smart district of the city of Pisek consists of six areas with two central office points. Point A controls four branches of the smart district and point B controls two branches. There will be four distribution branches (depicted as green, brown, blue, and purple) originating at optical network termination (OLT) A (see Fig. 9) and two branches (gray and pink) originating at OLT B. OLT will be located at both points. OLT at point A manages four branches of the district via 4 GPON ports with a split ratio up to 1:64 physical reach. Note that the transmission convergence layer supports up to 1:128. The splitters may be connected in cascade, or the operator may use one splitter with a higher split ratio (up to 1:64) in the first distribution box of anchorage. In our case, cascade connection of splitters is a better solution, and the first splitter (with a lower split ratio) should be located at the base of the first house on the street.

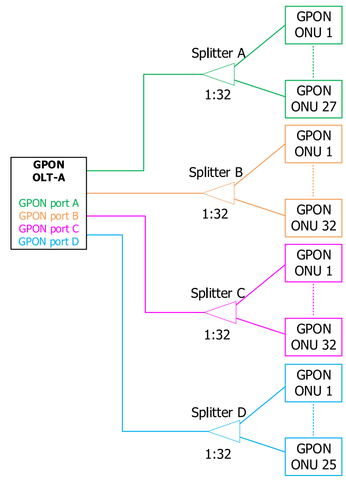

Fig. 9. Proposed GPON setup for the public lightning infrastructure of the OLT A.

TABLE II
SIMULATION RESULTS OF GPON SYSTEM WITH VARIOUS SPLIT RATIO

Split ratio	BER
1:2	5.7×10^{-54}
1:4	4.62×10^{-52}
1:8	7.03×10^{-50}
1:16	3.68×10^{-45}
1:32	1.86×10^{-34}
1:64	6.22×10^{-22}
1:128	4.29×10^{-12}

Table II shows the simulation results of the proposed GPON topology. The proposed topology supports a split ratio up to 1:128 without reaching the threshold value of BER (1×10^{-10}). On the other hand, the scheme did not consider the forward error correction (FEC) algorithm, which can move the threshold below (1×10^{-4}). The simulation included that split ratio for demonstration usage or future expansion in a real scenario with selected attenuation classes.

VI. APPLICATION OF HONUS TO ENERGY CONSUMPTION PREDICTION

Here, the application of real-time gradient learning of HONUs is demonstrated in the short-term (hour) real-time prediction of building energy consumption for one year recordings [64]. We limit the data set to contain hourly measurements of one predicted variable y, which is energy consumption [kWh], and two external input variables u_1 and u_2 representing outside temperature [C°] and wind speed [m/s], respectively.

TABLE III
CONFIGURATION OF APPLIED HONU AND LEARNING ALGORITHMS FOR 3-H PREDICTION WITH REAL-TIME RETRAINING (RANDOM WEIGHT INITIALIZATION AT THE BEGINNING)

1-st Order HONU	Feature vector $\mathbf{x}(k)$	Learning Rule	$\Delta\mathbf{w}$	setups
$\tilde{y}(k+h) = \mathbf{w}^T \cdot col^r(\mathbf{x})$ $r = 1$ $h = 3$	$\begin{bmatrix} 1 \\ y(k-n_y+1) \\ \vdots \\ y(k) \\ u_1(k-n_{u1}+1) \\ \vdots \\ u_1(k+h) \\ u_2(k-n_{u2}+1) \\ \vdots \\ u_2(k+h) \end{bmatrix}$	NLMS (incremental)	$\Delta\mathbf{w}(k) = \frac{\mu}{\lvert\lvert\mathbf{x}\rvert\rvert^2} \cdot e(k) \cdot \mathbf{x}(k)$	$n_y = 24, n_{u1}$ $n_{u2}, \mu = 1$
		L-M (batch)	$\Delta\mathbf{w}(k) = \mathbf{L_M} \cdot \mathbf{e}(k)$ $\mathbf{e}(k) = \begin{bmatrix} e[k-M+1] \\ e[k-M+2] \\ \vdots \\ e(k) \end{bmatrix}$	$n_y = 24, n_{u1} = 12$ $n_{u2} = 12, \mu = 1$ $epochs = 10$ $M = 27 \cdot 7[hrs]$ $(= 1week)$

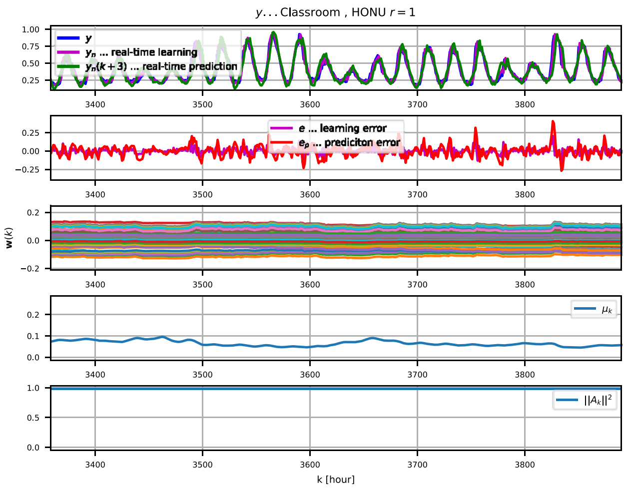

Fig. 10. Adaptive prediction with NLMS incremental learning (top, y is the real energy consumption), where prediction error (second top), the weight behavior (third top), normalized learning rate (second bottom), and spectral radius of the matrix of dynamics (bottom) is shown for a selected interval of a year, all values are min-max normalized (see Fig. 12 for full view).

The first-order HONU with real-time retraining was used. Two learning algorithms were applied. First, the incremental learning rule of gradient descent with normalized learning rate was used, also known as the normalized least mean square (NLMS, [65], [66]). Second, the batch L–M algorithm was applied, where the sliding window of the last measured data samples M was used for retraining as in the real-time application. The characteristic vector $\mathbf{x}$ of HONU contained current and past energy consumption values, as well as future values of the predicted outside temperature and wind speed. The configuration of applied HONUs and the learning algorithms is in Table III.

The min-max normalized plots for real-time predictions of a residential unit energy consumption with measured and (accurately) predicted both outside temperature and wind speed are shown in Figs. 10 and 11 with full views of the figures in the appendix. The incremental NLMS preserves the constant spectral radius (estimated using the Frobenius norm $|A||^2$) of the matrix dynamics due to the normalization of the normalization of the learning rate Table III, while the L–M batch retraining maintains a constant learning rate and $|A||^2$ is well below 1. The full view of Fig. 10, illustrates the prediction with NLMS incremental learning for the entire year of data samples. The full view of Fig. 13, is showcasing the prediction with batch L–M retraining for all the year's data samples.

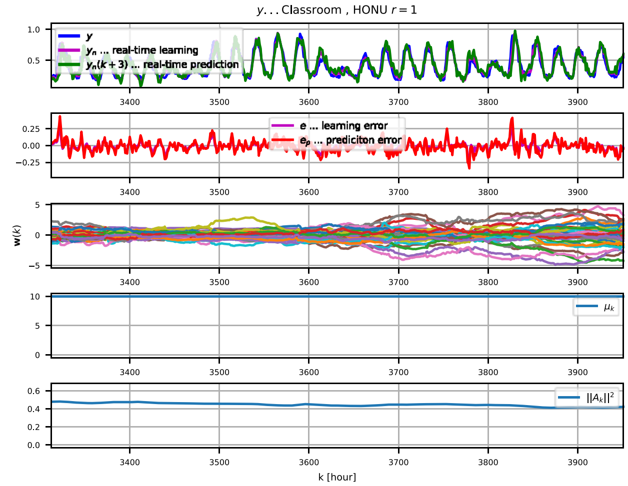

Fig. 11. Adaptive prediction with L–M (mini) batch retraining (top, y is the real energy consumption), prediction error (second top), weight behavior (third top), normalized learning rate (second bottom), and spectral radius of the matrix of dynamics (bottom) are shown for a selected interval of a year, all values are min-max normalized (see Fig. 13 for full view).

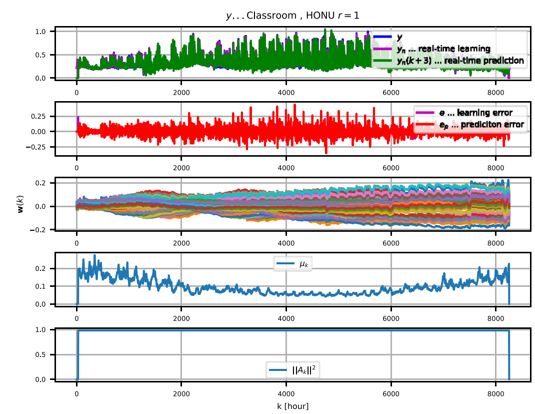

Fig. 12. Full view for Fig. 10 of prediction with NLMS incremental learning, where prediction error (second top), the weight behavior (third top), normalized learning rate (second bottom), and spectral radius of the matrix of dynamics (bottom) is shown for all the year data samples.

VII. FUTURE WORK

The involvement of prosumager in the innovative smart city concepts is relatively new and not well mapped, even in the literature currently available. The challenge of electricity storage, as a commodity used to maximize the utility function, is the key to the long-term sustainability of all innovative (electricity-using) efforts within LLs. Although energy-positive districts already have the tools to incorporate prosumagers' greedy behaviors, LLs, which may be constrained by lack of available electricity in advancing their innovative potential are not nearly as far. The question for future work, then, is to focus on holding electricity beyond own need and the resulting maximization of profit at the cost of slowing the pace of innovation creation within LLs or even stagnating it.

VIII. CONCLUSION

Two directly interconnected topics have been merged to uniformly contribute to the long-term sustainability of the

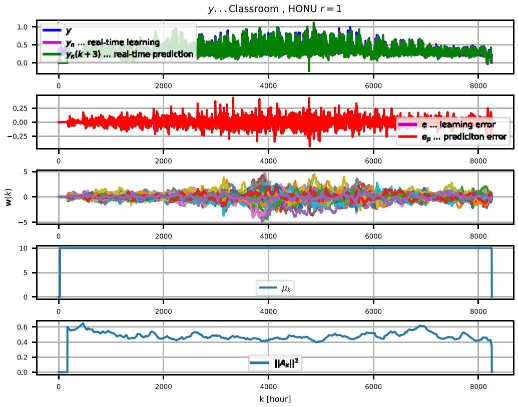

Fig. 13. Full view for Fig. 11 of prediction with batch L–M retraining, where prediction error (second top), the weight behavior (third top), normalized learning rate (second bottom), and spectral radius of the matrix of dynamics (bottom) is shown for all the year data samples.

special smart city use case—an LL as a potential complementary innovation linkage to a PED. We contributed to the stability of such districts by leveraging smart energy components and available fog computing resources to support optimal prosumager decision making and proper energy information dissemination. The decision model is based on the distribution of computational complexity using smart fog computing resource allocation. The clever application of shallow neural networks help prosumagers to predict electricity prices and apply greedy/selfish techniques to maximize their utility. For this purpose, distributed workload allocation vectors among individual compute nodes were used exploiting a central WFC controller. This approach is further supported by a hybrid access architecture, which, by adopting elements known from the tactile IoT concept, guarantees very low latency and stable jitter. The foundation of this architecture is an energy-efficient public optical access network that runs up to each residential unit. Design and simulation were performed based on a data set provided by a pilot PED smart city environment that was part of the Horizon 2020 Positive City ExChange project.

References

[1] P. Althaus, F. Redder, E. Ubachukwu, M. Mork, A. Xhonneux, and D. Müller, "Enhancing building monitoring and control for district energy systems: Technology selection and installation within the living lab energy campus," *Appl. Sci.*, vol. 12, no. 7, p. 3305, Mar. 2022. [Online]. Available: https://doi.org/10.3390/app12073305

[2] B. Robaeyst, B. Baccarne, W. Duthoo, and D. Schuurman, "The city as an experimental environment: The identification, selection, and activation of distributed knowledge in regional open innovation ecosystems," *Sustainability*, vol. 13, no. 12, p. 6954, Jun. 2021. [Online]. Available: https://doi.org/10.3390/su13126954

[3] Á. Oliveira and M. Campolargo, "From smart cities to human smart cities," in *Proc. 48th Hawaii Int. Conf. Syst. Sci.*, Jan. 2015, pp. 2336–2344. [Online]. Available: https://doi.org/10.1109/hicss.2015.281

[4] F. D. Filippi, C. Coscia, and R. Guido, "From smart-cities to smart-communities," *Int. J. E-Plan. Res.*, vol. 8, no. 2, pp. 24–44, Apr. 2019. [Online]. Available: https://doi.org/10.4018/ijepr.2019040102

[5] G. Nesti, "Living labs: A new tool for co-production?" in *Smart and Sustainable Planning for Cities and Regions* (Green Energy and Technology), A. Bisello, D. Vettorato, R. Stephens, P. Elisei, Eds. Cham, Switzerland: Springer Int., Nov. 2016, pp. 267–281. [Online]. Available: https://doi.org/10.1007/978-3-319-44899-2_16

[6] C.-A. Papadopoulou and M. Giaoutzi, "Crowdsourcing and living labs in support of smart cities' development," *Int. J. E-Plan. Res.*, vol. 6, no. 2, pp. 22–38, Apr. 2017. [Online]. Available: https://doi.org/10.4018/ijepr.2017040102

[7] G. Cardone, A. Cirri, A. Corradi, and L. Foschini, "The participact mobile crowd sensing living lab: The testbed for smart cities," *IEEE Commun. Mag.*, vol. 52, no. 10, pp. 78–85, Oct. 2014. [Online]. Available: https://doi.org/10.1109/mcom.2014.6917406

[8] L. Gabrielli, M. Pizzichini, S. Spinsante, S. Squartini, and R. Gavazzi, "Smart water grids for smart cities: A sustainable prototype demonstrator," in *Proc. Eur. Conf. Netw. Commun. (EuCNC)*, Jun. 2014, pp. 1–5. [Online]. Available: https://doi.org/10.1109/eucnc.2014.6882685

[9] S. Carillo-Aparicio, J. R. Heredia-Larrubia, and F. Perez-Hidalgo, "SmartCity Málaga, a real-living lab and its adaptation to electric vehicles in cities," *Energy Policy*, vol. 62, pp. 774–779, Nov. 2013. [Online]. Available: https://doi.org/10.1016/j.enpol.2013.07.125

[10] S. Soutullo, L. Aelenei, P. S. Nielsen, J. A. Ferrer, and H. Gonçalves, "Testing platforms as drivers for positive-energy living laboratories," *Energies*, vol. 13, no. 21, p. 5621, Oct. 2020. [Online]. Available: https://doi.org/10.3390/en13215621

[11] N. Martínez-Bello, M. J. Cruz-Prieto, D. Güemes-Castorena, and A. Mendoza-Domínguez, "A methodology for designing smart urban living labs from the university for the cities of the future," *Sensors*, vol. 21, no. 20, p. 6712, Oct. 2021. [Online]. Available: https://doi.org/10.3390/s21206712

[12] O. Lindholm, H. ur Rehman, and F. Reda, "Positioning positive energy districts in European cities," *Buildings*, vol. 11, no. 1, p. 19, Jan. 2021. [Online]. Available: https://doi.org/10.3390/buildings11010019

[13] E. Derkenbaeva, S. H. Vega, G. J. Hofstede, and E. van Leeuwen, "Positive energy districts: Mainstreaming energy transition in urban areas," *Renew. Sustain. Energy Rev.*, vol. 153, Jan. 2022, Art. no. 111782. [Online]. Available: https://doi.org/10.1016/j.rser.2021.111782

[14] S. Bossi, C. Gollner, and S. Theierling, "Towards 100 positive energy districts in Europe: Preliminary data analysis of 61 European cases," *Energies*, vol. 13, no. 22, p. 6083, Nov. 2020. [Online]. Available: https://doi.org/10.3390/en13226083

[15] X. Zhang, S. R. Penaka, S. Giriraj, M. N. Sánchez, P. Civiero, and H. Vandevyvere, "Characterizing positive energy district (PED) through a preliminary review of 60 existing projects in Europe," *Buildings*, vol. 11, no. 8, p. 318, Jul. 2021. [Online]. Available: https://doi.org/10.3390/buildings11080318

[16] A. G. Moreno, F. Vélez, B. Alpagut, P. Hernández, and C. S. Montalvillo, "How to achieve positive energy districts for sustainable cities: A proposed calculation methodology," *Sustainability*, vol. 13, no. 2, p. 710, Jan. 2021. [Online]. Available: https://doi.org/10.3390/su13020710

[17] D. Ahlers, P. Driscoll, H. Wibe, and A. Wyckmans, "Co-creation of positive energy blocks," in *Proc. IOP Conf. Ser. Earth Environ. Sci.*, vol. 352, Oct. 2019, Art. no. 12060. [Online]. Available: https://doi.org/10.1088/1755-1315/352/1/012060

[18] C. Perera, Y. Qin, J. C. Estrella, S. Reiff-Marganiec, and A. V. Vasilakos, "Fog computing for sustainable smart cities: A survey," *ACM Comput. Surv.*, vol. 50, no. 3, pp. 1–43, May 2018. [Online]. Available: https://doi.org/10.1145/3057266

[19] B. Ali, M. A. Pasha, S. ul Islam, H. Song, and R. Buyya, "A volunteer-supported fog computing environment for delay-sensitive IoT applications," *IEEE Internet Things J.*, vol. 8, no. 5, pp. 3822–3830, Mar. 2021. [Online]. Available: https://doi.org/10.1109/jiot.2020.3024823

[20] S. Troia, M. Mazzara, M. Savi, L. M. M. Zorello, and G. Maier, "Resilience of delay-sensitive services with transport-layer monitoring in SD-WAN," *IEEE Trans. Netw. Service Manag.*, vol. 19, no. 3, pp. 2652–2663, Sep. 2022. [Online]. Available: https://doi.org/10.1109/tnsm.2022.3191943

[21] I. Martinez, A. S. Hafid, and A. Jarray, "Design, resource management, and evaluation of fog computing systems: A survey," *IEEE Internet Things J.*, vol. 8, no. 4, pp. 2494–2516, Feb. 2021. [Online]. Available: https://doi.org/10.1109/jiot.2020.3022699

[22] E. Cosgrave, K. Arbuthnot, and T. Tryfonas, "Living labs, innovation districts and information marketplaces: A systems approach for smart cities," *Procedia Comput. Sci.*, vol. 16, pp. 668–677, Feb. 2013. [Online]. Available: https://doi.org/10.1016/j.procs.2013.01.070

[23] L. Manman et al., "Distributed artificial intelligence empowered sustainable cognitive radio sensor networks: A smart city on-demand perspective," *Sustain. Cities Soc.*, vol. 75, Dec. 2021, Art. no. 103265. [Online]. Available: https://doi.org/10.1016/j.scs.2021.103265

[24] S. Latre, P. Leroux, T. Coenen, B. Braem, P. Ballon, and P. Demeester, "City of things: An integrated and multi-technology testbed for IoT smart city experiments," in *Proc. IEEE Int. Smart Cities Conf. (ISC2)*, Sep. 2016, pp. 1–8. [Online]. Available: https://doi.org/10.1109/isc2.2016.7580875

[25] K. Shahzad, S. Iqbal, and H. Mukhtar, "Optimal fuzzy energy trading system in a fog-enabled smart grid," *Energies*, vol. 14, no. 4, p. 881, Feb. 2021. [Online]. Available: https://doi.org/10.3390/en14040881

[26] O. B. Mora-Sánchez, E. López-Neri, E. J. Cedillo-Elias, E. Aceves-Martínez, and V. M. Larios, "Validation of IoT infrastructure for the construction of smart cities solutions on living lab platform," *IEEE Trans. Eng. Manag.*, vol. 68, no. 3, pp. 899–908, Jun. 2021. [Online]. Available: https://doi.org/10.1109/tem.2020.3002250

[27] T. Ahmad and D. Zhang, "Using the Internet of Things in smart energy systems and networks," *Sustain. Cities Soc.*, vol. 68, May 2021, Art. no. 102783. [Online]. Available: https://doi.org/10.1016/j.scs.2021.102783

[28] L. U. Khan, I. Yaqoob, N. H. Tran, S. M. A. Kazmi, T. N. Dang, and C. S. Hong, "Edge-computing-enabled smart cities: A comprehensive survey," *IEEE Internet Things J.*, vol. 7, no. 10, pp. 10200–10232, Oct. 2020. [Online]. Available: https://doi.org/10.1109/jiot.2020.2987070

[29] P. P. Ray, "A review on tactile IoT: Architecture, requirements, prospects, and future directions," *Trans. Emerg. Telecommun. Technol.*, vol. 33, no. 4, p. e4428, Apr. 2022. [Online]. Available: https://doi.org/10.1002/ett.4428

[30] F. Haider, D. Zhang, M. St-Hilaire, and C. Makaya, "On the planning and design problem of fog computing networks," *IEEE Trans. Cloud Comput.*, vol. 9, no. 2, pp. 724–736, Apr.–Jun. 2021. [Online]. Available: https://doi.org/10.1109/tcc.2018.2874484

[31] A. Violi, P. Beraldi, and G. Carrozzino, "Dealing with the stochastic prosumager problem with controllable loads," *Soft Comput.*, to be published. [Online]. Available: https://doi.org/10.1007/s00500-022-06809-2

[32] S. Vakilian, A. Fanian, H. Falsafain, and T. A. Gulliver, "Node cooperation for workload offloading in a fog computing network via multi-objective optimization," *J. Netw. Comput. Appl.*, vol. 205, Sep. 2022, Art. no. 103428. [Online]. Available: https://doi.org/10.1016/j.jnca.2022.103428

[33] M. Aqib, D. Kumar, and S. Tripathi, "Machine learning for fog computing: Review, opportunities and a fog application classifier and scheduler," *Wireless Pers. Commun.*, vol. 129, no. 2, pp. 853–880, Dec. 2022. [Online]. Available: https://doi.org/10.1007/s11277-022-10160-y

[34] H. Luo, H. Cai, H. Yu, Y. Sun, Z. Bi, and L. Jiang, "A short-term energy prediction system based on edge computing for smart city," *Future Gener. Comput. Syst.*, vol. 101, pp. 444–457, Dec. 2019. [Online]. Available: https://doi.org/10.1016/j.future.2019.06.030

[35] I. Bukovsky, N. Homma, L. Smetana, R. Rodriguez, M. Mironovova, and S. Vrana, "Quadratic neural unit is a good compromise between linear models and neural networks for industrial applications," in *Proc. 9th IEEE Int. Conf. Cogn. Inform. (ICCI)*, Beijing, China, Jul. 2010, pp. 556–560. [Online]. Available: http://ieeexplore.ieee.org/document/5599677/

[36] S. Yi, Z. Hao, Z. Qin, and Q. Li, "Fog computing: Platform and applications," in *Proc. 3rd IEEE Workshop Hot Topics Web Syst. Technol. (HotWeb)*, 2015, pp. 73–78. [Online]. Available: http://ieeexplore.ieee.org/document/7372286/

[37] M. M. Gupta, N. Homma, Z.-G. Hou, A. M. G. Solo, and I. Bukovsky, "Higher order neural networks: Fundamental theory and applications," in *Artificial Higher Order Neural Networks for Computer Science and Engineering: Trends for Emerging Applications*. Hershey, PA, USA: IGI Global, 2010, pp. 397–422. [Online]. Available: www.igi-global.com/chapter/higher-order-neural-networks/41676

[38] I. Bukovsky and N. Homma, "An approach to stable gradient-descent adaptation of higher order neural units," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 28, no. 9, pp. 2022–2034, Sep. 2017.

[39] I. Bukovsky, G. Dohnal, P. M. Benes, K. Ichiji, and N. Homma, "Letter on convergence of in-parameter-linear nonlinear neural architectures with gradient learnings," *IEEE Trans. Neural Netw. Learn. Syst.*, early access, Nov. 15, 2021. [Online]. Available: https://ieeexplore.ieee.org/document/9614673/

[40] R. Beraldi, C. Canali, R. Lancellotti, and G. P. Mattia, "Distributed load balancing for heterogeneous fog computing infrastructures in smart cities," *Pervasive Mobile Comput.*, vol. 67, Sep. 2020, Art. no. 101221. [Online]. Available: https://doi.org/10.1016/j.pmcj.2020.101221

[41] M. Mukherjee, M. Guo, J. Lloret, and Q. Zhang, "Leveraging intelligent computation offloading with fog/edge computing for tactile Internet: Advantages and limitations," *IEEE Netw.*, vol. 34, no. 5, pp. 322–329, Sep./Oct. 2020. [Online]. Available: https://doi.org/10.1109/mnet.001.2000004

[42] Y. Xiao and M. Krunz, "Distributed optimization for energy-efficient fog computing in the tactile Internet," *IEEE J. Sel. Areas Commun.*, vol. 36, no. 11, pp. 2390–2400, Nov. 2018. [Online]. Available: https://doi.org/10.1109/jsac.2018.2872287

[43] A. Giordano, G. Spezzano, and A. Vinci, "Smart agents and fog computing for smart city applications," in *Smart Cities* (Lecture Notes in Computer Science, 9704), E. Alba, F. Chicano, and G. Luque, Eds. Cham, Switzerland: Springer Int., 2016, pp. 137–146. [Online]. Available: https://doi.org/10.1007/978-3-319-39595-1_14

[44] Y. Dong, S. Guo, J. Liu, and Y. Yang, "Energy-efficient fair cooperation fog computing in mobile edge networks for smart city," *IEEE Internet Things J.*, vol. 6, no. 5, pp. 7543–7554, Oct. 2019. [Online]. Available: https://doi.org/10.1109/jiot.2019.2901532

[45] I. A. Ridhawi, M. Aloqaily, F. Karray, M. Guizani, and M. Debbah, "Realizing the tactile Internet through intelligent zero touch networks," *IEEE Netw.*, early access, Oct. 17, 2022. [Online]. Available: https://doi.org/10.1109/mnet.117.2200016

[46] I. Martinez, A. Jarray, and A. S. Hafid, "Scalable design and dimensioning of fog-computing infrastructure to support latency-sensitive IoT applications," *IEEE Internet Things J.*, vol. 7, no. 6, pp. 5504–5520, Jun. 2020. [Online]. Available: https://doi.org/10.1109/jiot.2020.2979705

[47] F. Faticanti, F. D. Pellegrini, D. Siracusa, D. Santoro, and S. Cretti, "Throughput-aware partitioning and placement of applications in fog computing," *IEEE Trans. Netw. Service Manag.*, vol. 17, no. 4, pp. 2436–2450, Dec. 2020. [Online]. Available: https://doi.org/10.1109/tnsm.2020.3023011

[48] V. Fanibhare, N. I. Sarkar, and A. Al-Anbuky, "A survey of the tactile Internet: Design issues and challenges, applications, and future directions," *Electronics*, vol. 10, no. 17, p. 2171, Sep. 2021. [Online]. Available: https://doi.org/10.3390/electronics10172171

[49] F. Firouzi, B. Farahani, and A. Marinšek, "The convergence and interplay of edge, fog, and cloud in the AI-driven Internet of Things (IoT)," *Inf. Syst.*, vol. 107, Jul. 2022, Art. no. 101840. [Online]. Available: https://doi.org/10.1016/j.is.2021.101840

[50] M. K. Pandit, R. N. Mir, and M. A. Chishti, "Adaptive task scheduling in IoT using reinforcement learning," *Int. J. Intell. Comput. Cybern.*, vol. 13, no. 3, pp. 261–282, Jun. 2020. [Online]. Available: https://doi.org/10.1108/ijicc-03-2020-0021

[51] D. P. Kingma and J. Ba, "Adam: A method for stochastic optimization," Dec. 2014, *arXiv:1412.6980v9*.

[52] H. S. Shapiro, "Least-square smoothing and prediction of noisy linear and polynomial data," unpublished.

[53] N. Levine, "A new technique for increasing the flexibility of recursive least squares data smoothing," *Bell Syst. Tech. J.*, vol. 40, no. 3, pp. 821–840, May 1961. [Online]. Available: https://ieeexplore.ieee.org/document/6773640

[54] D. W. Marquardt, "An algorithm for least-squares estimation of nonlinear parameters," *J. Soc. Ind. Appl. Math.*, vol. 11, no. 2, pp. 431–441, 1963. [Online]. Available: https://www.scienceopen.com/document?vid=a1e9765d-fecb-4600-bfe0-d15b908f4a35

[55] P. Benes and I. Bukovsky, "On the intrinsic relation of linear dynamical systems and higher order neural units," in *Automation Control Theory Perspectives in Intelligent Systems*, vol. 466, R. Silhavy, R. Senkerik, Z. K. Oplatkova, P. Silhavy, and Z. Prokopova, Eds. Cham, Switzerland: Springer, 2016, pp. 235–246. [Online]. Available: https://doi.org/10.1007/978-3-319-33389-2_23

[56] P. Benes and I. Bukovsky, "An input to state stability approach for evaluation of nonlinear control loops with linear plant model," in *Cybernetics and Algorithms in Intelligent Systems* (Advances in Intelligent Systems and Computing), vol. 765, R. Silhavy, Ed. Cham, Switzerland: Springer Int., 2019, pp. 144–154. [Online]. Available: https://doi.org/10.1007/978-3-319-91192-2_16

[57] P. Maloney. "Building a better microgrid with hardware in the loop." Microgrid Knowledge. 2019. [Online]. Available: https://info.typhoon-hil.com/lp-mgk-whitepaper-building-a-better-microgrid-with-hardware-in-the-loop

[58] S. K. Bagudai, O. Ray, and S. Samantaray, "Evaluation of control strategies within hybrid DC/AC microgrids using typhoon HIL," in *Proc. 8th Int. Conf. Power Syst. (ICPS)*, 2019, pp. 1–6. [Online]. Available: https://ieeexplore.ieee.org/document/9067331/

[59] P. A. Schirmer, C. Geiger, and I. Mporas, "Reducing grid distortions utilizing energy demand prediction and local storages," *IEEE Access*, vol. 9, pp. 15122–15132, 2021. [Online]. Available: https://doi.org/10.1109/access.2021.3053200

[60] P. Zuk and P. Zuk, "Prosumers in action: The analysis of social determinants of photovoltaic development and prosumer strategies in Poland," *Int. J. Energy Econ. Policy*, vol. 12, no. 4, pp. 294–306, Jul. 2022. [Online]. Available: https://doi.org/10.32479/ijeep.13124

[61] V. Fanibhare, N. I. Sarkar, and A. Al-Anbuky, "Toward a fog-based traffic flow framework for tactile Internet," *IEEE Internet Things J.*, vol. 9, no. 13, pp. 10718–10731, Jul. 2022. [Online]. Available: https://doi.org/10.1109/jiot.2021.3126758

[62] A. Helmy and A. Nayak, "Fog integration with optical access networks from an energy efficiency perspective," in *Proc. IEEE INFOCOM Conf. Comput. Commun.*, Jul. 2020, pp. 2639–2647. [Online]. Available: https://doi.org/10.1109/infocom41043.2020.9155289

[63] H. Chung, H. H. Lee, K. O. Kim, K.-H. Doo, Y. Ra, and C. Park, "TDM-PON-based optical access network for tactile Internet, 5G, and beyond," *IEEE Netw.*, vol. 36, no. 2, pp. 76–81, Mar./Apr. 2022. [Online]. Available: https://ieeexplore.ieee.org/document/9785743/

[64] S.-Y. Chou, A. Dewabharata, F. E. Zulvia, and M. Fadil, "Forecasting building energy consumption using ensemble empirical mode decomposition, wavelet transformation, and long short-term memory algorithms," *Energies*, vol. 15, no. 3, p. 1035, 2022. [Online]. Available: https://www.mdpi.com/1996-1073/15/3/1035

[65] B. Widrow and S. D. Stearns, *Adaptive Signal Processing*. Englewood Cliffs, NJ, USA: Prentice-Hall, 1985.

[66] D. P. Mandic, "A generalized Normalized gradient descent algorithm," *IEEE Signal Process. Lett.*, vol. 11, no. 2, pp. 115–118, Feb. 2004. [Online]. Available: http://ieeexplore.ieee.org/document/1261952/

Rudolf Vohnout (Member, IEEE) received the master's degree from the Faculty of Transportation, University of Pardubice, Pardubice, Czech Republic, in 2005, and the Ph.D. degree in computer science from the Faculty of Statistics and Informatics, Prague University of Economics, Prague, Czechia Republic, in 2014.

Since then, he has been focussing on computer networks, their security aspects, network optimization, optical transmission systems, and quantum key distribution. He was a Ph.D. Visiting Researcher with Jožef Stefan Institute in Ljubljana, Ljubljana, Slovenia, from 2006 to 2007. He is currently the Head of the Department of Computer Science, Faculty of Science, University of South Bohemia České Budějovice, České Budějovice, Czech Republic, as well as partially involved in network research activities with CESNET, Prague, and Czech National Research and Educational Network Operator.

Dr. Vohnout is an Active Member of ComSoc Society.

Ivo Bukovsky (Senior Member, IEEE) received the master's degree and Ph.D. degree in control and systems engineering from Czech Technical University in Prague, Prague, Czechia Republic, in 2002 and 2007, respectively.

He is with the Department of Computer Science, Faculty of Science, University of South Bohemia České Budějovice, České Budějovice, Czech Republic. He was a short-term Visiting Researcher with the University of Saskatchewan, Saskatoon, SK, Canada, in 2003, and with the University of Manitoba, Winnipeg, MB, Canada, in 2010. Since 2009, he has been cooperating with Tohoku University, Sendai, Japan. His research interests include novelty detection, multiscale analysis approaches, dynamical systems and data analysis, adaptive control with in-parameter-linear nonlinear neural architectures, and novel information theory through machine learning.

Dr. Bukovsky has served as an Associate Editor for IEEE TRANSACTIONS ON NEURAL NETWORKS AND LEARNING SYSTEMS, IEEE TRANSACTIONS ON NEURAL NETWORKS AND LEARNING SYSTEMS, and IEEE TRANSACTIONS ON CYBERNETICS, as well as PC for numerous IEEE conferences.

Shuo-Yan Chou received the Ph.D. degree in industrial and operations engineering from the University of Michigan at Ann Arbor, Ann Arbor, MI, USA, in 1992.

He is a Distinguished Professor of Industrial Management and the Director of the Center for Internet of Things Innovation with the National Taiwan University of Science and Technology (Taiwan Tech), New Taipei, Taiwan. His research interests include Internet of Things innovation, technology-enabled services, sustainability, smart energy, smart logistics, AI, blockchain, as well as various applications in the context of smart city and Industry 4.0 development.

Dr. Chou has served as the Editor-in-Chief of the *Journal of the Chinese Institute of Industrial Engineers* (Taylor and Francis) as well as on the editorial boards of *International Journal of Fuzzy System*, *ASCE Journal of Energy Engineering*, *Journal of Engineering Design*, *PLOS One* and *Wind*, among other academic and public services.

Jakub Geyer (Graduate Student Member, IEEE) was born in Czech Republic, in 1987. He received the master's degree in applied computer science from the Faculty of Science, University of South Bohemia, České Budějovice, Czech Republic, in 2015.

He joined the Department of Computer Science, University of South Bohemia in 2017 as an Assistant Professor. His main areas of interest and expertises are database systems, software development, simulations, and additive manufacturing.

Ondrej Budik received the B.S. and M.S. degrees from the Faculty of Mechanical Engineering, Czech Technical University in Prague, Prague, Czechia Republic, in 2019 and 2021, respectively, where he is currently pursuing the Ph.D. degree.

His research is focused on designing hardware-accelerated neural network algorithms for detection and prediction tasks in industrial applications, with a focus on ensuring stability and providing explainability.

Rohit Sharma (Senior Member, IEEE) received the Ph.D degree from Teerthanker Mahaveer University, Moradabad, India, the M.Tech. degree from Shobhit University, New Delhi, India, and the B.Tech. degree from Uttar Pradesh Technical University, Lucknow, India.

He is currently an Associate Professor with the Department of Electronics and Communication Engineering, SRM Institute of Science and Technology, NCR Campus, Ghaziabad, India.

He serves as a Book Editor for seven different titles to be published by CRC Press, Taylor & Francis Group, USA, and Apple Academic Press, CRC Press, Taylor & Francis Group, USA, Springer.

Dr. Sharma is an Editorial Board Member and Reviewer of more than 12 international journals and conferences, including the topmost journal IEEE ACCESS and IEEE INTERNET OF THINGS JOURNAL. He is an Active Member of ISTE, ICS, IAENG, and IACSIT.

Milos Prokysek was born in Jindrichuv Hradec, Czech Republic, in 8 May 1980. He received the master's degree in physics and information technology from the University of South Bohemia České Budějovice, Cesk Budejovice, Czech Republic, in 2003, and the Ph.D. degree in pedagogy from Charles University, Prague, Czech Republic, in 2009.

In 2004, he joined the Department of Information Technology, Faculty of Education, University of South Bohemia Cesk Budejovice, where he joined the Department of Computer Science as an Assistant Professor in 2010.

Tomas Horvath (Member, IEEE) was born in Havirov, Czech Republic, in 1989. He received the Ph.D. degree in communications and informatics from Brno University of Technology, Brno, Czechia Republic, in 2017.

He is a Researcher with Brno University of Technology and with CESNET, Prague, Czechia Republic. His record shows more than 70 peer-reviewed proceedings and journal papers. His current research interests include passive optical networks, sensing, and QKD.

Annemie Wyckmans, photograph and biography not available at the time of publication.