Towards a Faster GNSS Interference Classification: a GRU-Based Approach using Spectrograms

Digital Twin Extension with Extra-Functional Properties

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***Abstract*—Digital twins of production lines do not focus solely on the management of the production process, they can also monitor and optimize other extra-functional aspects such as energy consumption and communications. This paper proposes the extension of digital twin concept in such directions. First, we extend the digital twin with models of energy consumption, that allow the monitoring of production line components throughout production lifetime. Then, we propose a flow to design the communication network starting from information obtained from the digital twin concerning the production, usage and flowing of information through the plant. All these methodologies start from the production line specification, then they enrich it with data collected during operation, and finally information is used to perform design and optimization. Results have been shown on a real Industry 4.0 research facility.**

***Index Terms*—Digital twin, Extra-functional properties, Cyber-Physical Production System (CPPS), Energy consumption monitoring and optimization, Network design**

I. Introduction

Digital twins of production lines and shop floors aim at connecting the manufacturing physical space with its virtual representation to improve the production process [1]. The virtual part records the historical evolution of the physical plant and predicts its evolution with the goal of identifying malfunctioning and possible optimizations. Meanwhile, the physical part provides sensed data and behaviors, to allow a continuous refinement and calibration of the virtual part.

The role of the digital twin in the lifetime of a production line is crucial at different stages [2], [3]:

- it acts as a *virtual prototype* of the production line, to evaluate its behavior before its actual implementation;
- it enables *effective decision making* to make informed data-driven decisions and reduce possible sources of inefficiencies;
- it *monitors line operation at run time* and predicts its behavior thus providing a reference golden model of its evolution for failure detection and possible optimizations.

During the construction of the digital twin of a production line, the focus is mostly on its *functional behavior*, i.e., on the interaction between human and equipment, on the movement of items on the production line, and on the manipulation of items by robots and machinery. Monitoring is indeed relevant to keep track of the evolution of the production line [4], [5].

However, this is only one aspect of the problem: other dimensions, hereby called *extra-functional*, can be considered

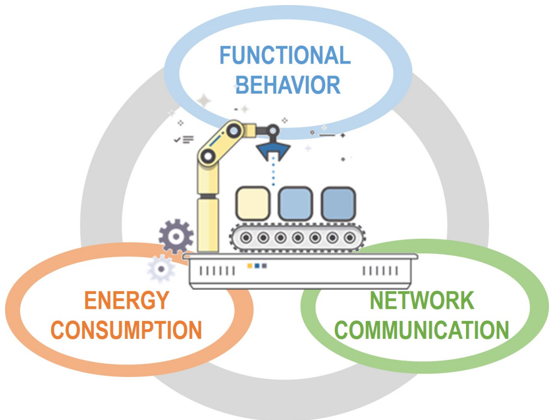


Figure 1. Dimensions considered for digital twin construction: monitoring of equipment and interaction with humans and produced items must be accompanied with energy consumption monitoring, and with network awareness.

with positive benefits on the effectiveness and efficiency of the production process. Figure 1 depicts this idea by showing the two extra-functional dimensions considered in this work: namely, energy consumption and communication.

Energy consumption monitoring, prediction and optimization is important to improve the cost effectiveness of a production line, to meet the emission goals and also to monitor the state of health of the equipment. Power models can be used both at design and configuration time, to identify efficient production recipes and to optimize energy waste [6], [7]. Additionally, power models included in the virtual part of the digital twin are extremely useful at run time, to detect any gradual increase of energy consumption as an effect of degradation of the equipment components, to detect the health of the production line, and to schedule maintenance operations [8].

Another important dimension is *networking and communication*. Today's factory machines are ever more connected with PLC, SCADA, MES, ERP applications as well as external systems for data analysis. Communications have different types of requirements: control communications at the lowest level are susceptible to delays and errors, while monitoring data to be used by machine learning procedures require large network capacity but with not particularly short latency constraint. The spatial features (i.e., walls and distances) may block communications or impact on cabling costs. No automatic technique is currently available in the context of Industry 4.0 to choose

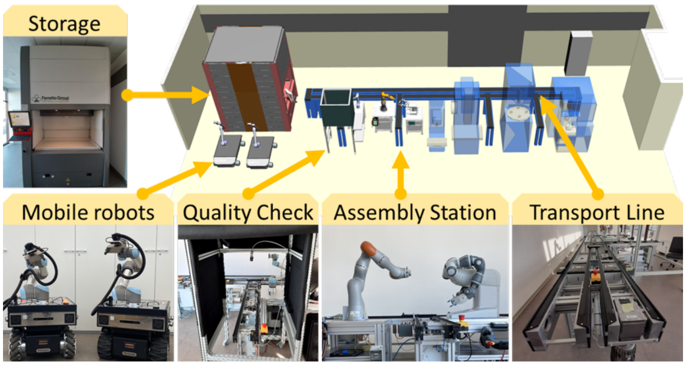


Figure 2. Structure of the ICELab production line.

the best mix of (wired and wireless) network architectures according to spacial constraints, cost, and quality-of-service requirements.

This paper outlines how such extra-functional aspects can be put in relationship with digital twin to improve the design and maintenance of the production plant. The concepts are exemplified on a real setup in an Industry 4.0 research facility.

II. ICE LABORATORY CASE STUDY

The reference production line for this work is an Industry 4.0 research facility called *Industrial Computer Engineering (ICE) Laboratory (ICELab)* [9]. The general structure of the ICELab includes a fully fledged production line (Figure 2):

- a vertical warehouse for storing materials and products;
- two collaborative Autonomous Mobile Robots (AMRs), i.e., two Robotnik RB-Kairos AMR [10] equipped with anthropomorphic manipulators, that can load and unload materials from the warehouse to a dedicated point on the conveyor belt, actively cooperate with an operator, and perform advanced and cooperative handling tasks;
- a quality check station;
- a collaborative robotic assembly station, comprising two lightweight collaborative robots: an ABB Yumi [11], and a Kuka Lightweight Robot [12];
- two 3D printers: a stereolithography mono material 3D printer and a multi-material polijet 3D printer;
- a milling machine;
- an electronic automatic tester;
- a complex transportation system composed of a main conveyor belt that spans across the entire laboratory in a ring configuration, and an unloading conveyor bay for each machine and for the AMRs.

This particular structure of the laboratory allows to represent the most modern automation technologies adopted in production processes. This paper focuses on a subset of the equipment, specifically, the parts labeled in Figure 2.

The considered production process is divided into four phases. First, a set of LEGO-like blocks is transported from the vertical warehouse to the assembly station by means of the transport belts. Second, the pieces are assembled by the two cooperating robotic arms, i.e., Kuka and ABB. Third, the assembled product is transported to the quality check station by means of the same transportation belts used before. At the quality check station, a robotic arm rotates the assembled piece and exposes all the critical parts to the cameras: if the quality standards are achieved the piece is then put back on the belt and transported to the vertical warehouse for storage.

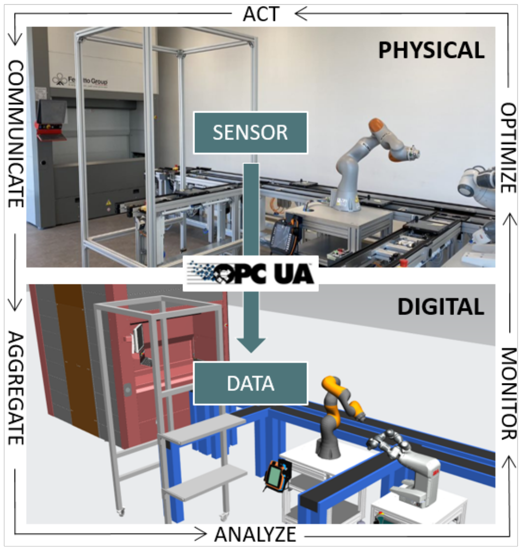


Figure 3. ICELab digital twin.

As depicted in Figure 3, all the active entities of the production line are instrumented to provide the IT office with real-time data by using OPC-UA protocol with end-to-end encryption [13]. Each sensor implements an OPC-UA server that exposes some relevant parameters of the equipment.

III. FUNCTIONAL DIGITAL TWIN

A. *State-of-the-art*

Digital twins can be used in very different contexts, *e.g.*, manufacturing, cities, transportation and energy sector [14]. Moreover, the nature of a digital twin can be manifold, and can consider different aspects, *e.g.*, visualize, identify, predict and control [15]. The digital twin of each production line is designed for a specific target, and thus, is different from one factory to another, depending on the factory, on the level of detail of information and on the desired twin accuracy. Different typologies of digital twin are reviewed in [16] and [17].

B. *Case study: ICE laboratory twin*

The digital twin of the functional behavior of the ICELab plant has been implemented in Tecnomatix Plant Simulation [18], an industrial-grade tool with a strong manufacturing-oriented focus and wide popularity among industrial actors [19] (Figure 3). The digital twin includes a discrete-event simulation, reproducing the behavior of the real production line, plus collects data coming from the real equipment and sends commands to influence production [20].

The virtual part of the digital twin is described in Plant Simulation by using the simTalk object-oriented programming language [21]. It reproduces the movement of pallets carrying the pieces in the production line towards the different bays and the processing performed by each equipment.

The digital twin communicates with the actual production line via the OPC-UA communication protocol: the digital twin acts as an OPC-UA client, communicates with the OPC-UA servers located on the equipment, and is able make asynchronous calls of the methods exposed by the servers to actively control the actions of the production line. Data related to production and machine operation are retrieved by subscribing to the servers variables, and is used to update the virtual replica of the digital twin and to perform analysis on the production line, *e.g.*, tracing power consumption and evaluating equipment reliability.

IV. ENERGY CONSUMPTION MONITORING AND MODELING

Energy consumption is an important aspect of any manufacturing process, and it is tightly dependent on the operation of the equipment: different activation sequences and different equipment configurations may lead to very different energy consumption. For this reason, energy monitoring and modeling can be fruitfully included in the digital twin of the plant (Figure 4):

- the *physical part* of the digital twin can be enriched with sensors monitoring energy consumption and equipment-relevant parameters, useful to determine the operating conditions and the corresponding functional behavior;
- the *virtual part* can be extended with models of energy consumption, either developed a priori, based on the equipment specifications, or from available historical data.

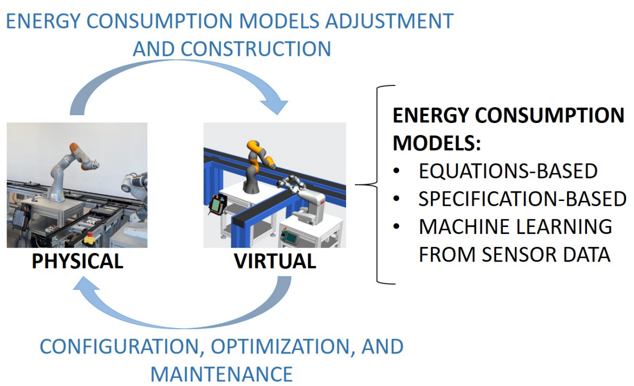


Figure 4. Role of the digital twin for energy consumption monitoring and modeling, with mutual impact of the physical part and the virtual part.

The models of energy consumption implemented by the virtual part can be of very heterogeneous nature, ranging from energy consumption equations based on mechanical models of the equipment [22], [23] to machine learning algorithms applied to historical sensor data [24].

The virtual part and the physical part mutually influence each other. Sensory devices are attached to the physical equipment, to measure both energy consumption and parameters related to the functional operation (*e.g.*, vibrations, speed, load) [25]–[27]. Such measurements can be used to adjust the virtual part at run time to the evolving conditions of the production line: as an example, any gradual increase of energy consumption induced by equipment degradation (*e.g.* wear, corrosion and crack) can be used to adjust the models of power consumption [8]. On the other hand, the configuration and design of the physical part can be influenced by simulations run on the virtual part, to identify optimal configurations and settings and to optimize energy waste through a careful management of active and idle times of the equipment [6], [7], [24], [27], [28].

A. *Construction of the models of energy consumption*

Energy efficiency is one of the main goals of the ICELab production line, thus the extra-functional dimension was considered as relevant as the functional perspective. To allow a simulation-based estimation of energy consumption, we thus adapted an ESL paradigm to production line modeling and simulation. We measured typical values of power consumption of each equipment in the different operation states. Energy consumption data has been recovered through measurements performed in isolation on each machine, directly within ICELab. This allowed the construction of a power state machine (PSM) [29] of each equipment of the production line. These models are then merged in the digital twin of the production line to monitor its overall energy consumption as a function of the different operations.

To construct a PSM, the designer shall identify the most relevant states of each equipment item, typically including one or more active states and an idle state. Then, each state is associated with a value of power consumption, that can be taken from a measurement or from technical documentation. In our case, the value was measured with power consumption sensors when operating each item separately from the production line. Figure 5 shows an exemplification of power modeling for the collaborative robotic assembly station: each robot has one active state, a hold state, and an idle state; the belt is modeled with only one active state and an idle state; each state is annotated with the corresponding power consumption. The evolution of the power state machines is controlled by the operation of the production line, either as events from the simulated Plant Simulation model, or as data collected from the real plant. The power consumption of the production line at any instant is given by the sum of the power consumption of each equipment item, estimated as the power consumption of the current state of its power state machine.

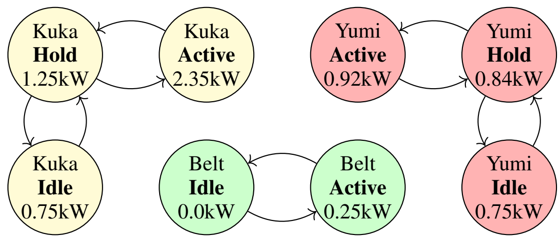
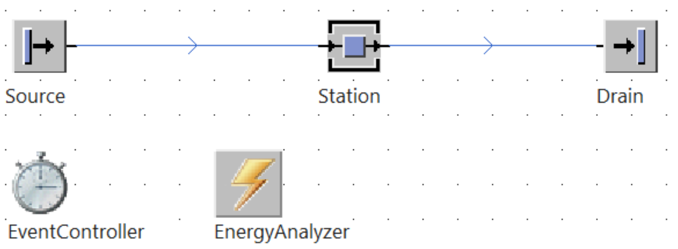


Figure 5. Example of PSM model for the collaborative robots in the assembly station and the transport belt.

As an example, power consumption of the collaborative robotic assembly station is given by the consumption of the Kuka robot (e.g., $Active = 2.35kW$), of the Yumi robot (e.g., $Hold = 0.84kW$) and of the belt (e.g., $Idle = 0kW$, overall $3.19 kW$). Figure 6 describes how the PSM of the Kuka robot is implemented inside the digital twin created with Plant Simulation by adding one block to the simulation setup (top, *EnergyAnalyzer* block) and its corresponding implementation code (bottom).

As a next step, the production line equipment will be equipped with external sensors of power consumption for each machine of the production line. In the medium term, these sensors will be used to collect historical data, to infer a more accurate model through machine learning and statistical techniques [24], [27], when coupled with information on the equipment operational state gathered from the physical plant and from the Plant Simulation traces. In the long term, sensor data is compared at run time with the evolution of the power state machines, to rapidly detect malfunctioning and unexpected conditions.




```
var currentPowerState := KukaSensor.readPSMState()
if currentPowerState = KUKA_STATE_IDLE
    Kuka.PowerInputWorking := 0.75
elseif currentPowerState = KUKA_STATE_HOLD
    Kuka.PowerInputWorking := 1.25
elseif currentPowerState = KUKA_STATE_ACTIVE
    Kuka.PowerInputWorking := 2.35
else
    Alert("Wrong Kuka State")
end
```

Figure 6. Implementation of the Kuka PSM inside Plant Simulation: dedicated *EnergyAnalyzer* block (top) and corresponding code (bottom).

B. Simulation in the digital twin

The power-enriched digital twin can be used to simulate different production recipes and find the best trade-off between peak power absorption, energy consumption and production throughput. The graphs in Figure 7 reproduce the evolution of simulated power consumption (in kW) for the production of two pieces by following two different recipes; a simple recipe, with one single piece being handled by the production line at any time, is compared to a more complex recipe handling two pieces simultaneously. The handling of the first piece and of the second piece is denoted by the blue arrow and the red arrow, respectively. The curves reported in these graphs do not exhibit abrupt variations since the change from low current consumption to high current consumption follows a smooth trend, as typical in industrial machines. The most relevant phases from the point of view of power consumption are carried out by the *Assembly station* and the *Quality check station*, respectively (see labels on top): the former includes the operation of the collaborative robots (Yumi and Kuka), that are the most consuming equipment of the production line; the latter involves a robotic arm to rotate the assembled piece exposing it to the cameras for quality assessment. In both recipes the total *energy consumption* is 0.41 kWh, but in the first one the peak of power is 6.67 kW, while for the second one it is 7.02 kW. The simulation shows that when more pieces are handled in parallel (bottom), there is an increase in peak power consumption ($+5\%$) with respect to sequential production, but at the same time it is possible to reduce idle times and thus overall production time (-16%).

As exemplified by these graphs, digital twin simulation allows to explore the impact of different production recipes on industrial parameters such as cost due to energy and production time. Power peaks may also be analysed and optimized, as they have a strong impact on machine aging [30].

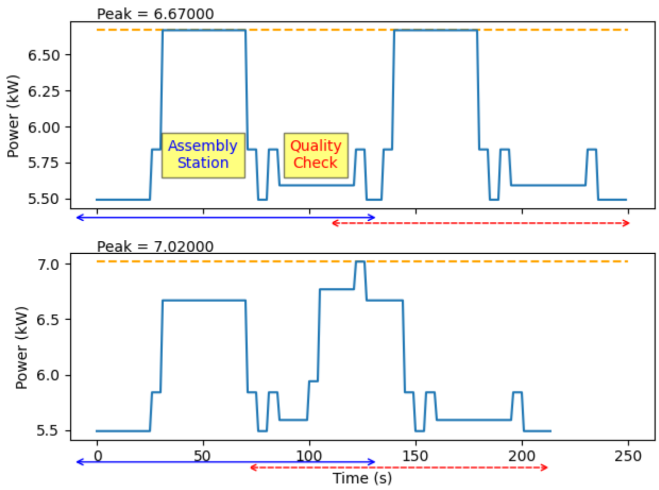


Figure 7. Power behavior of the plant for the production of two pieces sequentially (top) or in parallel (bottom). The production of the first/second piece is highlighted by the blue/red arrow, respectively. The plot on top also highlights the two most important phases of production carried out by the assembly station and the quality check station, respectively.

V. Communications

Machine-to-machine communications as well as interactions with applications outside the plant (*e.g.*, the digital twin) are crucial in smart manufacturing. To support the designer in managing communication complexity we need an approach for the computer-aided design of the physical network infrastructure by satisfying plant constraints (*e.g.*, required quality of service) and optimizing a given metric (*e.g.*, overall cost).

The starting point is the *identification of communication flows* involving the plant. Currently, this activity is performed manually by asking directly to people who designed or manage the plant. This approach is time-consuming and may lead to an inconsistent set of information. We propose to extract communication requirements automatically from the digital twin.

A. Automatic extraction of communication requirements

Figure 8 shows the graph created in Plant Simulation to model the movement of pieces between the different entities

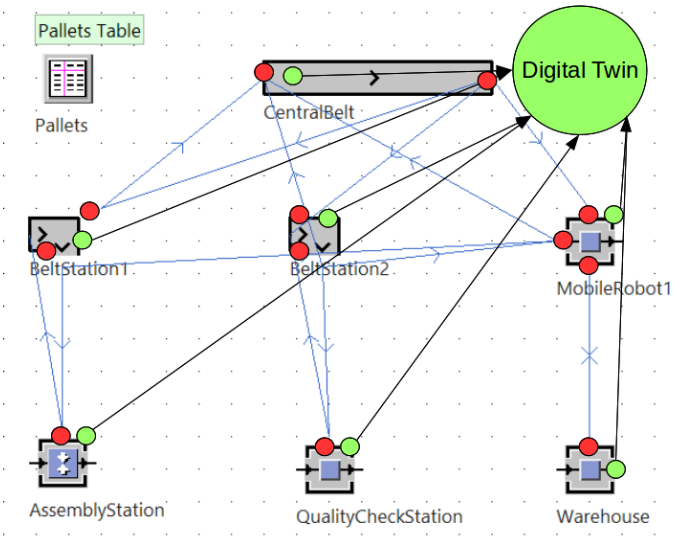


Figure 8. Plan Simulation model of the ICELab production line with highlights on data flows that are represented as arrows between source and destination tasks (red and green circles).

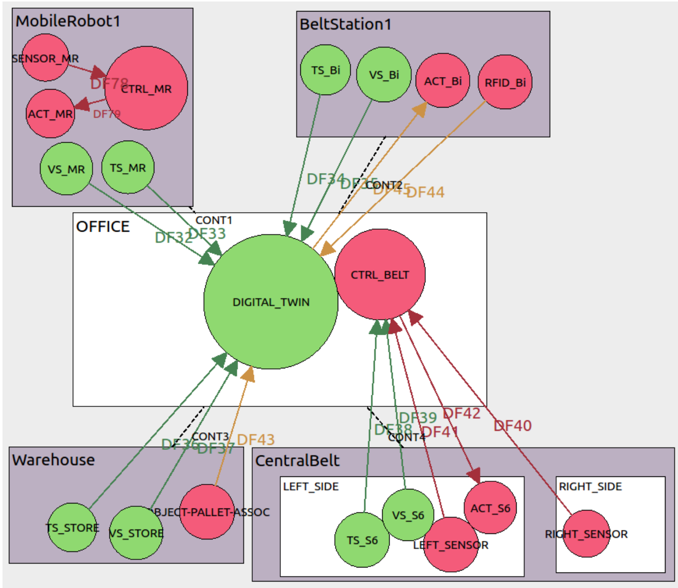


Figure 9. Network synthesis problem statement for the ICELab.

of the ICELab plant. For instance, the mobile robot takes the raw pieces from the warehouse and puts the finished ones there.

It is reasonable to assume that the movement of a piece between two machines is associated to a communication flow between them and, eventually, a third agent acting as coordinator. Since the simulation model describes all these interactions, we propose to *extract data flows from simulation code*. Without loss of generality, let us assume that each blue arrow in Figure 8 represents also a data flow between the machines involved in the exchange of pieces. We also highlighted by red circles the tasks that act as sources and destinations of such data flows. The figure also reports tasks (denoted by green circles) that send data (black arrows) to the digital twin through OPC-UA as explained in Section III-B.

B. Synthesis of the physical network infrastructure

The physical network infrastructure can be considered as a container of the data flows extracted with the previously described approach. The problem of the automatic allocation of data flows into physical channels and network protocols can be seen as a *network synthesis* problem as stated in [31]. For this purpose, the designer should map the communication requirements of the plant onto the set of entities formalized in the network synthesis approach, *i.e.*, tasks, data flows, abstract channels, zones and contiguity relationships.

We already discussed how *tasks* and *data flows* can be extracted from the digital twin. They should be annotated with computational and communication requirements, respectively. Groups of tasks belonging to the same machine can be mapped onto *zones* which can be nested to represent not only rooms but also a machinery inside the room of even different parts of a machinery. Network solutions (from the physical channel up to transport layer), to be chosen at the end, can be mapped onto the concept of *Abstract channel*. The designer should also provide the Network Synthesizer with a catalog of network architectures to be used as abstract channels (*e.g.*, Ethernet, WiFi, CAN bus). *Contiguity relationship* ties two zones and an abstract channel. It can be used to model the impact of the environment between the two given zones on the behavior of the given network architecture (*e.g.*, bandwidth reduction or cabling cost). Such information can be specified by performing a site survey of the shop floor.

Starting from this formalization, network synthesis consists in finding the solution of an optimization problem which describes the communication infrastructure in terms of mapping of data flows onto abstract channels taken from a catalog.

C. Application to ICELab

Figure 9 shows the details of the network synthesis problem for some items of Figure 8. Tasks are denoted by circles whose radius is proportional to their computational complexity. Zones are denoted by boxes. They are used to group tasks belonging to the same item, *i.e.*, warehouse, office, robot and belt (as well as parts of it). Data flows are denoted by arrows. Green data flows are generated by OPC-UA monitoring tasks, that require a high bitrate without constraints on delay. Red data flows convey control loop information with low bitrate but a strict constraint on delay. Brown data flows are used for plant coordination with medium bitrate and a moderate constraint on delay. Task `VS_MR` and `TS_MR` are mobile with respect to the communication with other tasks since they are executed on the mobile robot.

Listing 1 shows the output of the Network Synthesizer. The most relevant result is the allocation of data flows to the network architectures provided as catalog to the optimizer. Most of the data flows have been assigned to Ethernet, which provides high capacity without strong guarantees on delay. Data flows related to control loops have been assigned to CAN bus. Data flows involving mobile tasks have been assigned to WiFi as expected. The tool also provides statistics on relevant metrics for the infrastructure such as cost, energy consumption, sum of delay values and error rate values.

```
* List of activated channels:
*    Use    3 channels of type Ethernet
*    Use    1 channels of type WiFi
*    Use    2 channels of type CAN
* Data-Flows allocation:
*    Dataflow DF32 inside c WiFi.1
*    Dataflow DF33 inside c WiFi.1
*    Dataflow DF34 inside c Ethernet.3
*    Dataflow DF35 inside c Ethernet.3
*    Dataflow DF36 inside c Ethernet.1
*    Dataflow DF37 inside c Ethernet.1
*    Dataflow DF38 inside c Ethernet.2
*    Dataflow DF39 inside c Ethernet.2
*    Dataflow DF40 inside c CAN.1
*    Dataflow DF41 inside c CAN.2
*    Dataflow DF42 inside c CAN.2
*    Dataflow DF43 inside c Ethernet.1
*    Dataflow DF44 inside c Ethernet.3
*    Dataflow DF45 inside c Ethernet.3
* Economic Cost        : 9031
*    2442 (Nodes) + 1201 (Wireless) + 5388 (Channels)
* Energy Consumption :  581
*    42 (Nodes) + 201 (Wireless) + 338 (Cable)
* Total Delay          :  128
*    80 (Wireless) + 48 (Cable)
* Total Error          :   16
*    4 (Wireless) + 12 (Cable)
* Elapsed Time : 1.20 s
*    File parsing            : 0.02 s
*    Structure creation      : 0.12 s
*    Constraints definition : 0.63 s
*    Optimization            : 0.42 s
```

Listing 1. Network synthesis output for the ICELab.

Network design, that is currently performed manually, will benefit from this approach especially in case of complex infrastructures and continuous plant reconfiguration.

VI. Conclusions

This paper highlighted that the digital twin concept can have an even more effective role in smart manufacturing if extra-functional properties are taken into account. First, overall *energy consumption* has been modeled by associating a power state machine to each equipment item, as currently done in embedded system modeling. This extension allows to explore the effect of different production recipes on energy consumption and production throughput by using simulation before a real commissioning of the plant. Furthermore, by feeding the digital twin with real-time energy data it is possible to highlight deviations with respect to the energy model witnessing aging and faults of machines. Second, the digital twin can be used to extract *communication flows* that can be used to synthesize the optimal physical network topology, if not yet available.

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