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Artificial Intelligence Signal Control in Electronic Optocoupler Circuits Addressed on Industry 5.0 Digital Twin

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Abstract: The paper is focused on the modeling of a digital twin (DT) through a circuit simulation and artificial intelligence (AI) analysis to determine the effects of disturbances and noise in optocoupler devices integrated into programmable logic controller (PLC) systems. Specifically, the DT analyzes the parametric and the predicted simulations about the sensitivity of the optocouplers versus noise and interference to provide possible corrective actions, compensating for the distortion of the output signal. The model is structured into two main data processing steps: the first is based on the circuit simulation of the optocoupler noise coupling by highlighting the time-domain sensitivity aspects and the frequency behavior of the coupled signals; the second one estimates the predicted disturbed signal by means of supervised random forest (RF) and unsupervised K-Means algorithms to provide further elements to prevent corrective solutions by means of risk maps. This work is suitable for Industry 5.0 scenarios involving machine control supported by AI-based DT platforms. The innovative elements of the proposed model are the DT features of scalability and modularity; the spatial multidimensionality, able to couple the effects of different undesired signals; and the possibility to simulate the whole PLC system, including its control circuits.

Keywords: digital twin; optocoupler circuits; optoelectronics; artificial intelligence; Industry 5.0



Citation: Massaro, A. Artificial Intelligence Signal Control in Electronic Optocoupler Circuits Addressed on Industry 5.0 Digital Twin. *Electronics* **2024**, *13*, 4543. <https://doi.org/10.3390/electronics13224543>

Academic Editors: Elias Stathatos and Spyros N. Yannopoulos

Received: 21 September 2024
Revised: 16 November 2024
Accepted: 18 November 2024
Published: 19 November 2024



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1. Introduction

Optocoupler devices are important electronic elements that are commonly integrated into programmable logic controller (PLC) systems and behave as isolation stages [1–10]. In optocouplers, light-emitting diodes (LEDs) and transistors are coupled to enable the command of a PLC by protecting the whole system. This protection could be violated by intentional or non-intentional disturbances acting on the software or on the hardware components. The possible causes of changes in the PLC control signals can be attacks, interference, or background noise involved during the production processes. When focusing our attention on intentional hardware modifications, possible attacks are classified as Hardware Trojan (HT) attacks [11–13], able to change the electrical parameters of the whole circuit, such as the electrical resistance or capacitance, due to the addition of further electronic components on the same board or to the changing of the environmental conditions, such as the working humidity or temperature, falsifying the sensor signals. Other forms of signal disturbances could be interference between different circuits (electromagnetic interference) [14–16], common noise having a specific carrier, or random noise such as white noise [17,18]. In the literature, different DT models in industry control systems have been proposed, including artificial intelligence (AI) tools for different applications [19–28]. Focusing our attention on PLC systems, some authors have analyzed DT-simulated production lines [29–31]. The DT models presented in the literature do not analyze in detail how these effects could contribute simultaneously to changes in the electrical signals of a circuit. In this direction, the goal of this paper is to simulate and combine different disturbances with different physical and spatial origins into a multidimensional DT model. Specifically, the proposed DT model, shown in Figure 1, behaves as a ‘black box’ defined by an input

port (signal enabling the optocoupler's switching) and an output port (voltage output signal controlling a PLC). Furthermore, the multidimensional model in Figure 1 takes into account the possibility to interact with different noise and interference (see green ports in Figure 1) coming from the 3D spatial domain and coupled with the spherical DT domain by means of circuital input ports (the sphere is able to simulate the disturbances coming from each direction of the 3D spatial domain). The DT model is interfaced with an AI engine executing supervised and unsupervised algorithms, able to predict the voltage output signal by comparing the threshold values of correct transmissions. In cases of possible mismatching with the threshold values, the system applies signal compensation or an adjustment by acting on a potentiometer, increasing the output voltage amplitude above the threshold.

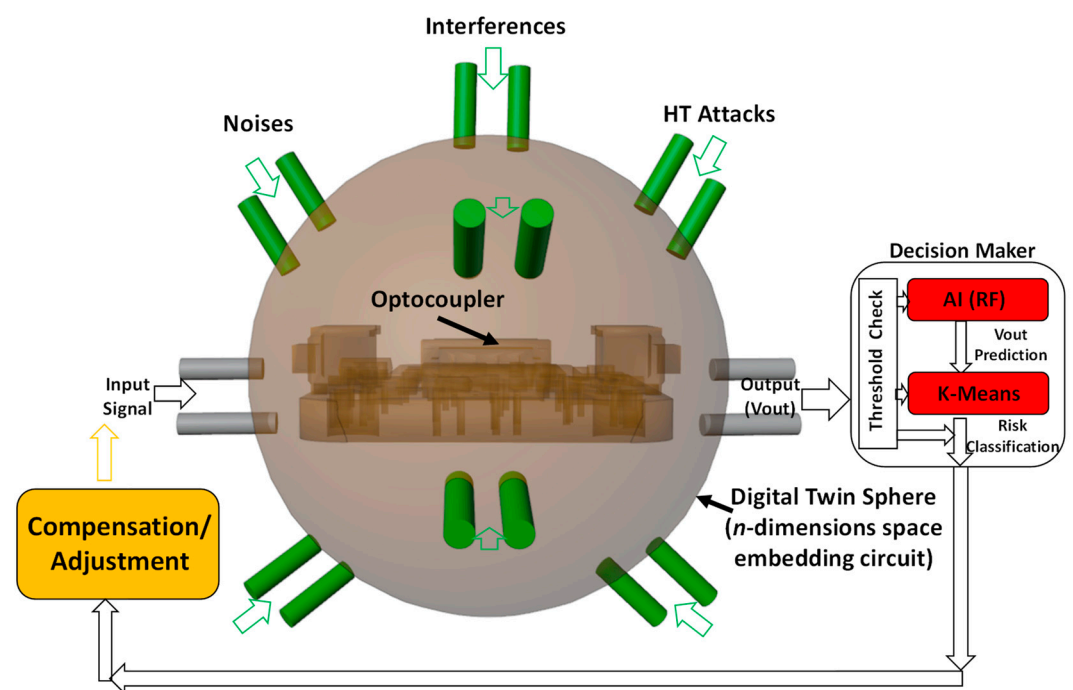


Figure 1. Theoretical multidimensional AI-based DT model simulating optocoupling optimization in Industry 5.0 PLC systems. The AI framework is the decision maker, able to compensate for the circuit disturbed by interference, attacks, and noise (inputs denoted by the green ports).

In order to explain the application of the AI-based DT model in Figure 1, we simulate a circuit integrating an optocoupler influenced by one type of white noise and an interference signal (only two green ports are considered in the model of Figure 1). This paper is structured as follows.

- **Materials and Methods:** A description of all of the tools adopted to implement the DT model in Figure 1 by describing the electrical signals and the sensitivity response of a control circuit integrating an optocoupler; a description of the AI framework predicting the output signals and supporting the corrective actions by analyzing the risk of incorrect transmission (risk maps).
- **Results:** A discussion of the circuit simulations and of the AI results estimating the DT performance, as well as providing criteria to compensate for the disturbed output signal.
- **Discussion:** An explanation from the perspectives of the Industry 5.0 applications, limitations, advantages, and disadvantages of the proposed DT model.
- **Conclusions:** A summary of the results presented in this paper.

2. Materials and Methods

The DT model in Figure 1 is structured by integrating two main simulation parts: the first one is the circuit simulation framework, and the second one is the AI engine supporting the definition of the possible risks of uncorrected signal reading and signal transmission. For all simulations, we use a Core i5 2.4 GHz/16 GB RAM processor.

2.1. LTSpice Circuit Modeling

The circuit simulations are performed by the SPICE-based open-source LTSpice tool [32,33]. In Figure 2, we illustrate the simulated LTSpice circuit layout, defining the application field of the DT model. Specifically, the circuit is composed of the following components:

- A 4N25 optocoupler [34,35] (U1 optocoupler embedded into a 6-pin package) connected to a single output port;
- A pulsed input signal generator (generating the input voltage signal) defined by the following parameters (see Figure 3a): $V_{\text{initial}} = 0$ V (initial value), $V_{\text{final}} = 5$ V (pulse final value), $T_{\text{delay}} = 0$ s. (delay of the first pulse), $T_{\text{rise}} = 1$ μ s (pulse rise time), $T_{\text{fall}} = 1$ μ s (pulse descent time), $T_{\text{on}} = 100$ μ s (pulse duration), $T_{\text{period}} = 200$ μ s (pulse period);
- A fixed output resistance ($R2 = 330$ Ω) connected to the output port, allowing the correct reading of the output signal that is properly scaled;
- A DC voltage generator ($V2 = 5$ V), enabling the electrical current of the BJT transistor constituting the optocoupler (current passing after the correct transmission of the input pulse);
- A white noise voltage generator (B1) with a series resistance ($R_{\text{noise}} = 250$ Ω fixed to observe the significant ripple variation in the input signal), modulating the noise amplitude (white noise is a typical type of noise analyzed in Industry 4.0 environments, able to model generic background noise);
- A voltage generator (V3), modeling an interference as a superimposed pulsed signal having the following parameters: $V_{\text{initial}} = 0$ V, $V_{\text{final}} = 5$ V, $T_{\text{delay}} = 0$ s, $T_{\text{rise}} = 1$ μ s, $T_{\text{fall}} = 1$ μ s, $T_{\text{on}} = 50$ μ s, $T_{\text{period}} = 200$ μ s;
- A parametric resistance RN1, modulating the interference amplitude ($RN1 = 3$ Ω , 300 Ω , 3000 Ω);
- A potentiometer that is able to change the resistance value R1, matching with the predicted signal and with the threshold comparison (the corrective actions are performed by changing the potentiometer resistance).

The simulations are performed in the time domain (transient analysis with a stop time of 2000 μ s, with a maximum time step of μ sec) and in the frequency domain by means of the Fast Fourier Transform (FFT). A threshold value of 2 Volts is supposed to distinguish good transmission conditions (voltage higher than the threshold) from strong transmitted conditions (voltage lower than the threshold).

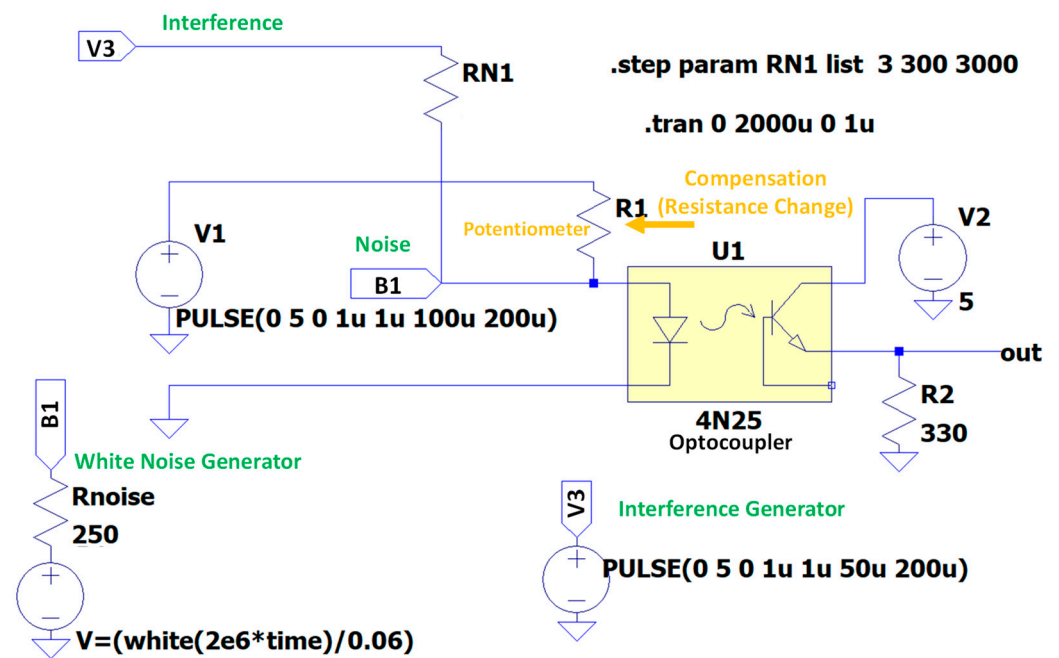


Figure 2. LTSpice circuit model simulating the optocoupler and possible interferences and noise (see green descriptions) entering from the green ports in Figure 1. The 4N25 optocoupler is highlighted by the yellow box.

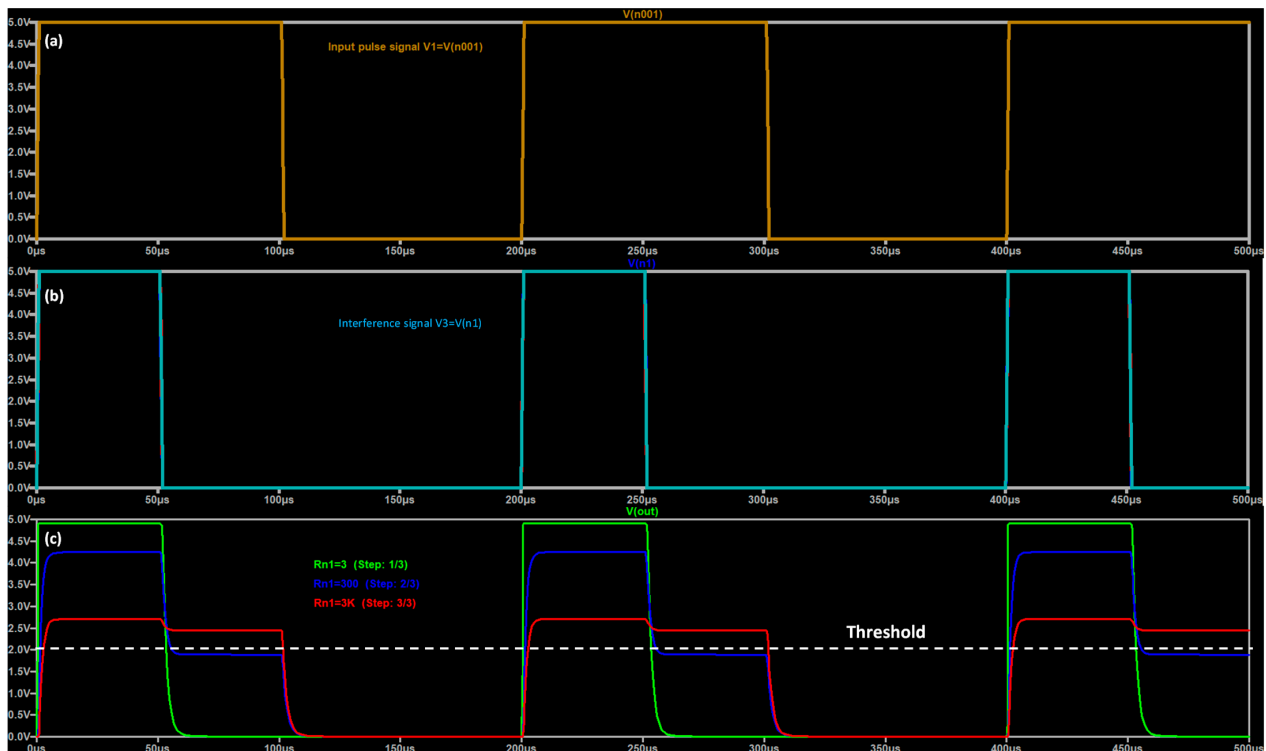


Figure 3. LTSpice parametric simulation of the circuit sensitivity versus the interference: (a) input pulse signal V1; (b) interference signal V3; (c) time responses of output voltage signal (V_{out}) when varying the electrical resistance R_{n1} , modulating the interference effects ($R_{n1} = 3 \Omega$, 300Ω , $3 \text{ k}\Omega$) and fixing $R_1 = 330 \Omega$. The elapsed time for the execution of the simulation is 0.2 s.

2.2. KNIME AI Modeling

The open-source Konstanz Information Miner (KNIME) [36,37] workflow is adopted for output signal prediction. The executed optimized workflow layout is illustrated in Appendix A. The implemented algorithms are the supervised random forest (RF) [38–43] and the unsupervised clustering K-Means algorithms, typically adopted in the literature to analyze manufacturing processes [44–46]. The processed dataset is the total voltage output (Vout) signal achieved by the LTSpice simulator by fixing the electrical resistance $R1 = 330 \, \Omega$ and $RN1 = 300 \, \Omega$. A total of 65,440 records are processed by the KNIME workflow (processed input dataset). The considered attributes are the time step and the output voltage signal (target class of the RF algorithm). The performance of the RF algorithm is estimated by means of the Bland–Altman plot [47], indicating the performance between two different calculus methods, which consider the simulated and the predicted signals: the Bland–Altman plot indicates the relationship between the mean of two signals and their difference and the matching between both signal trends. Other estimated error rates are the coefficient of determination R^2 , the mean absolute error (MAE), the mean squared error (MSE), and the root mean squared error (RMSE) [48]. The optimized RF algorithm is obtained by fixing the following hyperparameters: 100—number of models, 5—minimum node size (minimum number of records in child nodes), 10—limit number of levels and tree depth (number of tree levels to be learned; for instance, a value of ‘1’ only splits a single root node). The heat map is a further tool that is able to compare the matching between the simulated and predicted results. The cluster number fixed for the K-Means calculations is $K = 4$, representing a compromise between good accuracy and reduced analytical complexity (a large number of clusters increases the difficulty in interpreting the results).

3. Results

The results are subdivided into two main parts: the first part is related the simulations of the circuit in Figure 2 by means of the LTSpice tool, and the second part considers the AI data processing executed by the KNIME tool. The results of the proposed model are summarized as follows:

- A parametric analysis of the sensitivity response of the circuit in Figure 2 by considering only the interference effect (time-domain and frequency-domain analysis) to study the single effect;
- An analysis of the possible corrective actions acting on a potentiometer (change in resistance, correcting the signal amplitude to overcome the threshold value);
- An analysis of the full response when integrating interference and white noise, analyzing the amplitude of the output signal having a near-threshold value (limit condition defining a risk map);
- The FR prediction of the signal influenced by interference and noise for the dynamic correction of the signal (correction following the real trend of the highly variable signal);
- A K-Means clustering analysis, defining risk maps for preventive or corrective action by processing the simulated and predicted data.

3.1. LTSpice Circuit Simulations

The goal of the first simulation of the circuit in Figure 2 is to define the principle by which we can correctly detect the input voltage signal in Figure 3a at the output port. Correct detection is equivalent to having efficient optical coupling, enabling the BJT transistor to correctly transmit the signal to a PLC. The pulse trend in Figure 3a could assume different configurations according to the command to transmit (combination of low ‘0’ and high ‘1’ signals representing a coded command). In order to establish a minimum condition to correctly detect an input signal, we hypothesize a threshold of 2 Volts (the maximum input signal amplitude is 5 Volts). The parametric analysis is performed by varying the $Rn1$ values, simulating different amplitude effects of an interference signal

modeled by another pulse generator having half of the pulse duration if compared with the input pulse (see Figure 3b). As shown in Figure 3b, the main effect of the interference is to reduce the amplitude of the pulse and, in particular, of the second half of it. In order to analyze the case before the sensitivity response versus only the interference signal, the parametric simulations in Figure 3c do not consider the effect of a white noise signal. We observe that, fixing the threshold value at 2 Volts, the simulation performed for $R_{n1} = 300 \Omega$ (blue plot in Figure 3c) is a limit case because part of the amplitude is very close to the threshold value. On the other hand, the case simulated for $R_{n1} = 3 \text{ k}\Omega$ is the best one because the amplitude is always above the threshold for the whole pulse duration. The signal obtained for $R_{n1} = 3 \text{ k}\Omega$ does not require a further gain because the entire pulse is above the threshold. The worst effect is for $R_{n1} = 3 \Omega$ because, for half of the duration of the pulse, there is no signal transmission.

The worst effect achieved for $R_{n1} = 3 \Omega$ is observed also by the FFT frequency behavior in Figure 4, showing accentuated ripple behavior at high frequencies if compared with the cases simulated for $R_{n1} = 300 \Omega$ and $R_{n1} = 3 \text{ k}\Omega$. The performed analysis indicates that a decrease in the R_{n1} resistance corresponds to an increase in signal distortion.

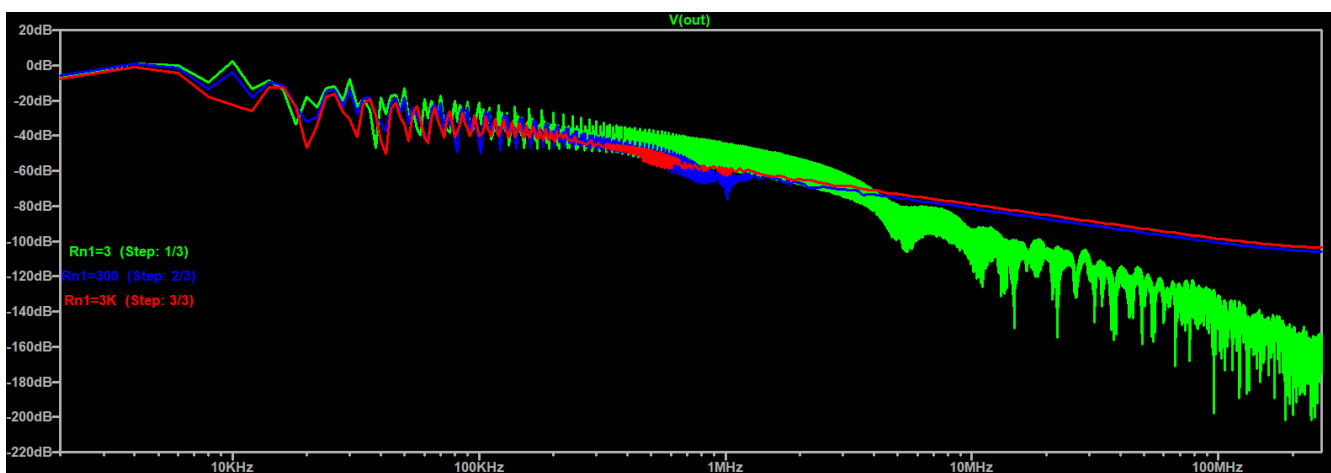


Figure 4. LTSpice parametric simulation of the circuit sensitivity versus the interference: FFT output voltage signal (V_{out}) when varying the electrical resistance R_{n1} , modulating the interference effects ($R_{n1} = 3 \Omega$, 300Ω , $3 \text{ k}\Omega$) and fixing $R_1 = 330 \Omega$.

The corrective actions are simulated by decreasing the resistance value R_1 in Figure 2, with the effect of increasing the amplitude of the whole pulse to overcome the threshold value. Specifically, by decreasing the R_1 value from 330Ω to 180Ω , it is possible to overcome the signal calculated for $R_{n1} = 300 \Omega$, while the signal with $R_{n1} = 3 \Omega$ remains the most critical (see Figure 5). This aspect highlights that it is important to predict the voltage output behavior, especially when considering highly variable signals, thus preventing the possible setting of the potentiometer (signal correction). This is more evident when there is also noise superimposed with the interference.

The circuit simulation is successively executed by superimposing white noise characterized by the random time trend in Figure 6a. The output voltage signal obtained for $R_{n1} = 300 \Omega$ (limit case) and $R_1 = 330 \Omega$ (allowing a significant amplitude ripple in the output voltage) is illustrated in Figure 6b, characterized by the noisy spectra of Figure 6c. This last simulated case represents a reference case to be further analyzed by AI approaches due to the observed high variability around the threshold value: many ripples are noted around the threshold value, thus generating many ambiguous reading conditions (the ‘high’ signal could be detected as ‘low’ and vice versa).

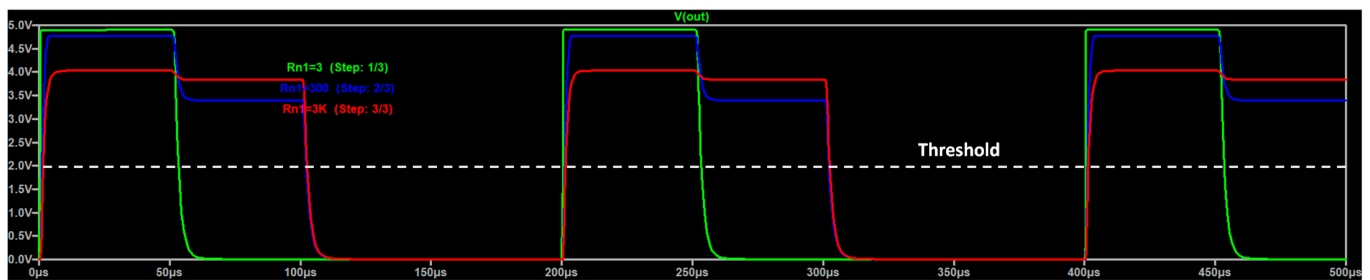


Figure 5. LTSpice parametric simulation of possible corrective actions acting on a potentiometer, compensating for the output signal's distortion: time responses of output voltage signal (V_{out}) when varying the electrical resistance R_{n1} , modulating the interference effects ($R_{n1} = 3\ \Omega$, $300\ \Omega$, $3\text{ k}\Omega$), after the application of a corrective action on the potentiometer ($R_1 = 180\ \Omega$).

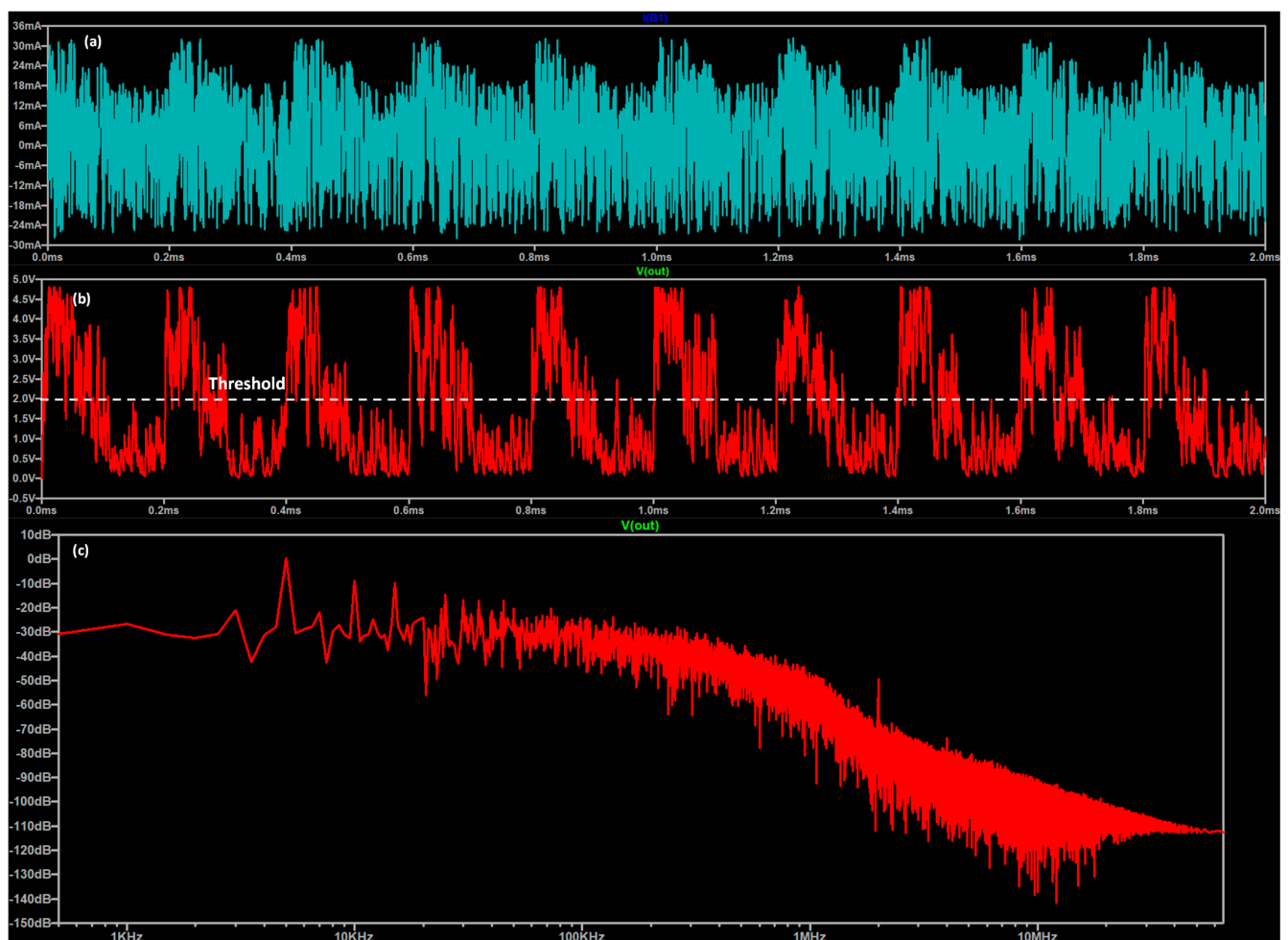


Figure 6. LTSpice results: (a) time responses of the electrical current I_{B1} of the white noise generator; (b) time responses of the output voltage signal (V_{out}) when fixing $R_1 = 330\ \Omega$ and $R_{N1} = 300\ \Omega$; (c) FFT frequency response of the output signal of Figure 6b.

3.2. RF Results

The data from Figure 6b are used to train the RF algorithm, providing the prediction of the noisy output signal. An example of a comparison between the simulated and the predicted trend is illustrated in Figure 7, showing very good matching and proving the good construction of the RF training model (good self-learning using simulated results).

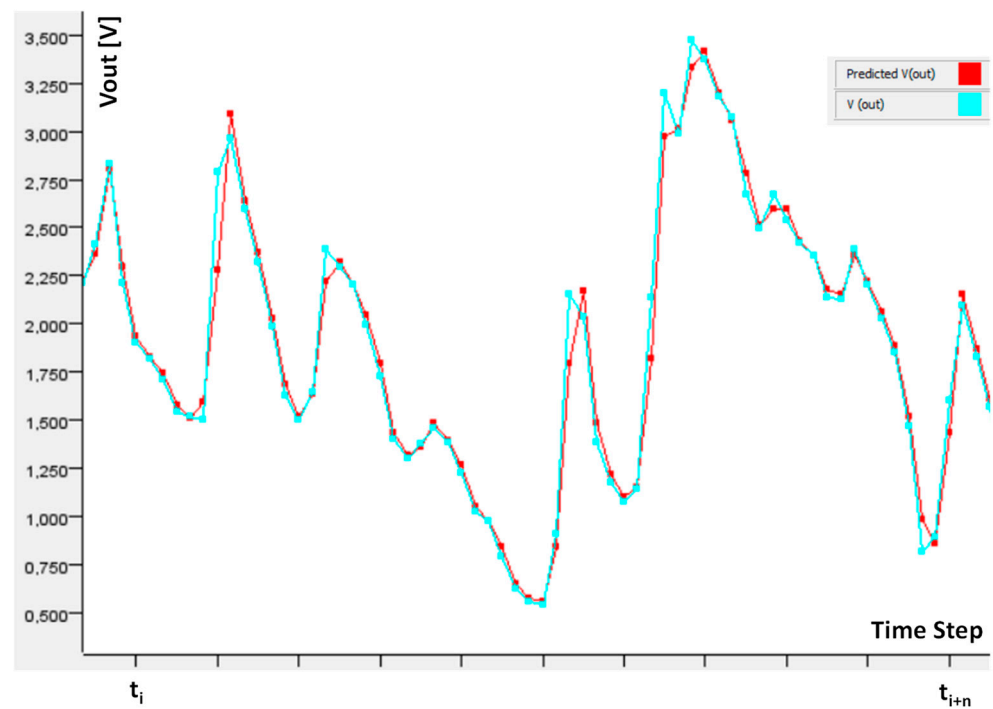


Figure 7. KNIME RF results: superposition of $V(out)$ and predicted $V(out)$ for a specific time window, proving the good signal matching (good training of the RF supervised model).

The good performance of the RF algorithm is proven by the evaluation of the main statistical parameters of the error rates: R^2 , MAE, MSE, and RMSE (see Table 1).

Table 1. Statistical performance of the RF algorithm.

Parameter	Value
Coefficient of determination (R^2)	0.997
Mean absolute error (MAE)	0.008
Mean squared error (MSE)	0
Root mean squared error (RMSE)	0.014

The good matching between the simulated and predicted results is also proven alternatively by the Bland–Altman plot in Figure 8, observing the high concentration of the values around the ‘0’ value of the ordinate axis $V(out) - Predicted V(out)$.

In order to observe the amplitude variation for each time step, Figure 9 presents a heat map, showing the very small variation between the simulated and predicted results; for each row, we provide a colored band for the $V(out)$ and $Predicted V(out)$ values.

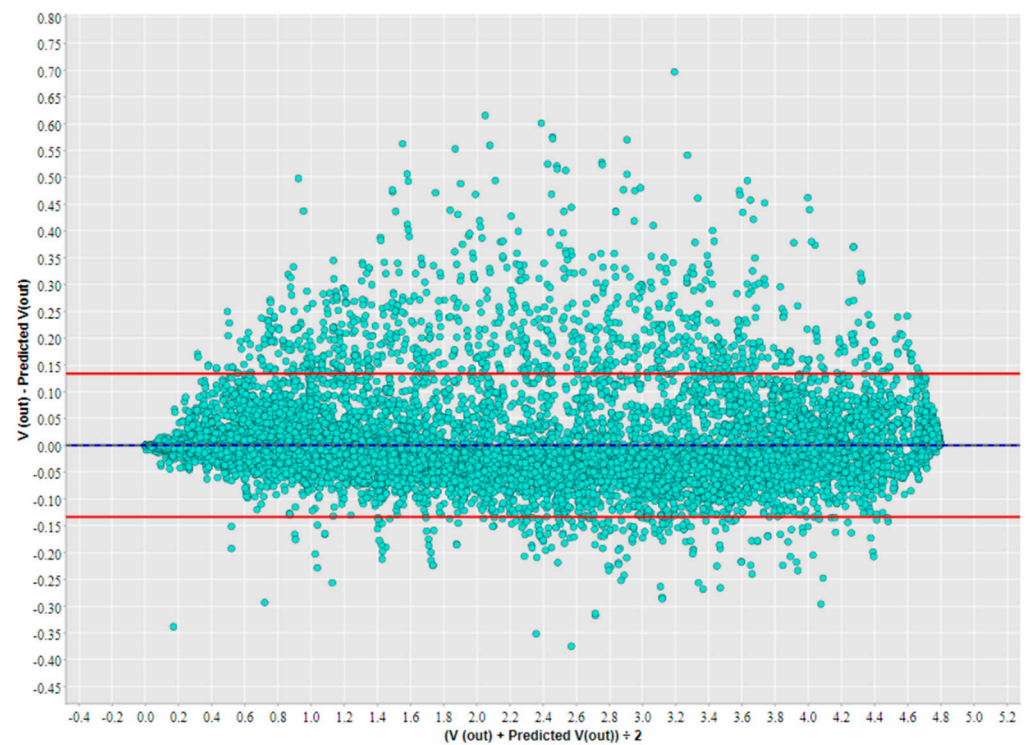


Figure 8. KNIME RF results: Bland–Altman plot.

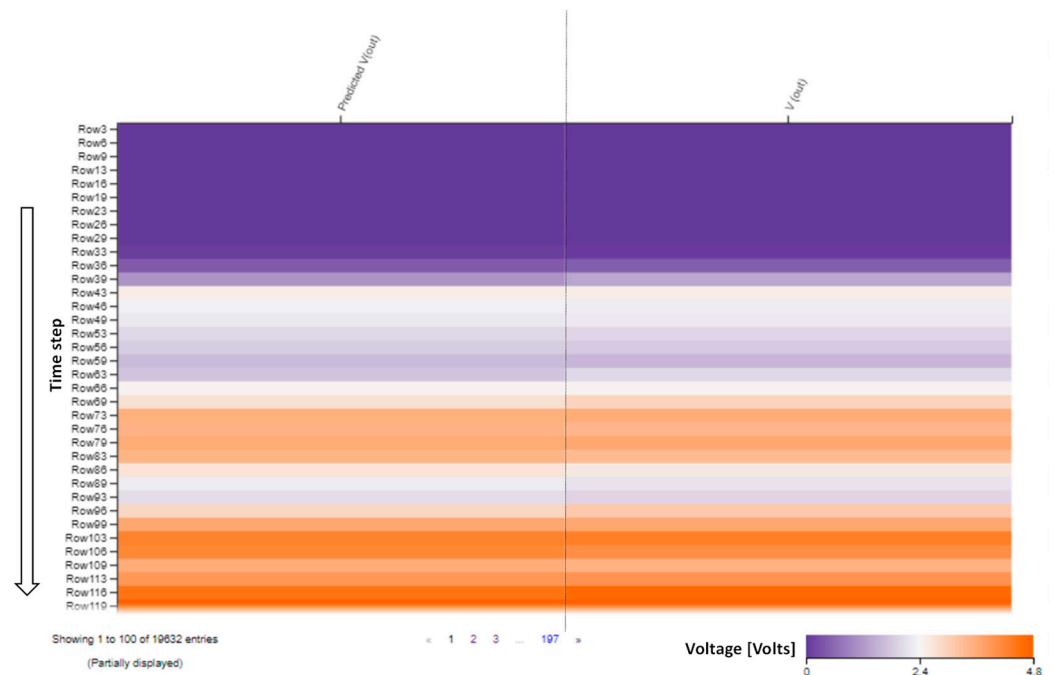


Figure 9. KNIME RF results: example of a part of the heat map plot (left side: Predicted $V(out)$, right side: $V(out)$). Each time step is indicated by a horizontal colored band (rows of the analyzed dataset). Lower right inset: colored scale bar expressing the voltage intensity in Volts.

3.3. K-Means Results

The goal of the proposed DT model is to define risk maps indicating correct and incorrect conditions. These maps are constructed by means of K-Means analysis, defining safe and risky clusters. The four clusters in Figure 10 (cluster_0, cluster_1, cluster_2, and cluster_3) are interpreted as follows:

- cluster_0 (green color)—values corresponding the '0' value of the transmission (no transmission corresponds to the 0 Volt amplitude of the input pulse);
- cluster_1 (red color)—a dangerous region related the condition of uncorrected transmission (pulse voltage values under the threshold value of 2 Volts) and requiring preventive or corrective actions;
- cluster_2 (brown color)—safety region near the threshold (no corrective actions are required but an alerting procedure is enabled);
- cluster_3—safest region of correct signal transmission (no corrective actions are required).

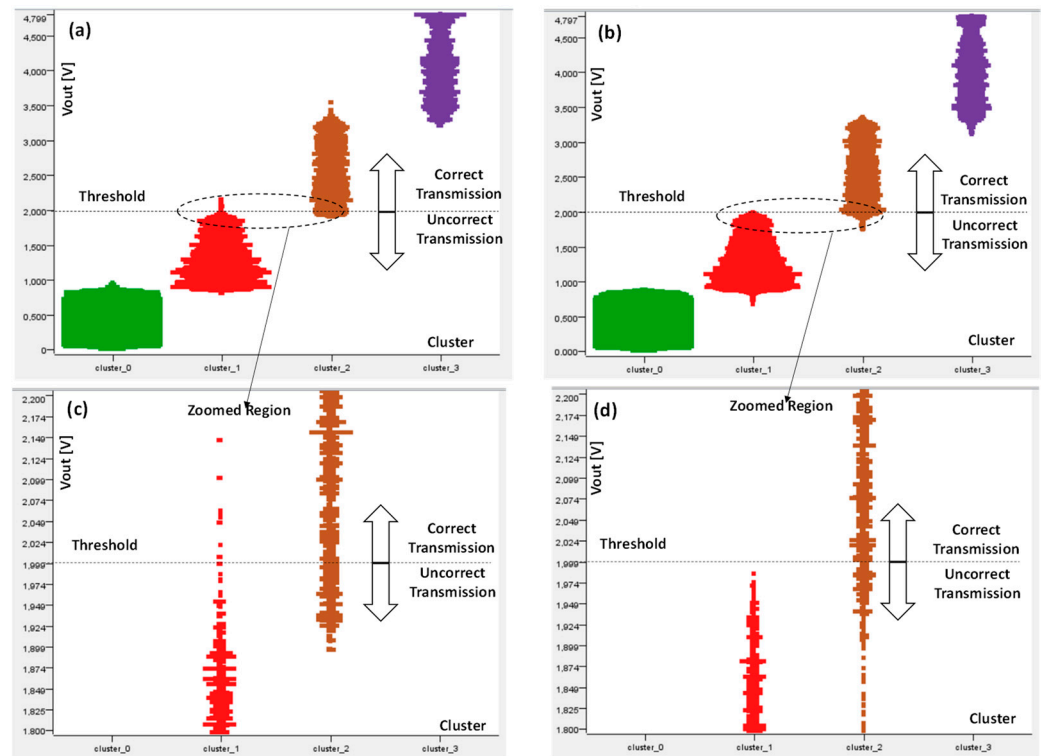


Figure 10. KNIME K-Means risk maps results obtained for $K = 4$: clusters indicating correct and incorrect signal transmission. (a) K-Means applied to the simulated $V(\text{out})$ of Figure 6b; (b) K-Means applied to the Predicted $V(\text{out})$; (c) zoomed-in region of (a); (d) zoomed-in region of (b). cluster_1 (red samples) indicates a high risk in achieving uncorrected transmission.

Figure 10a,b illustrate the whole clustering analysis for the simulated and predicted voltage signals, respectively. Figure 10c,d are the zoomed-in parts (see parts enclosed by the dashed line) of the previous figures around the threshold value. The risk analysis is performed on both the simulated and predicted results by providing further information about the setting of the potentiometer: if both the simulated and the predicted values are in cluster_2, preventive action, i.e., tuning the R1 value, should be executed according to the deviation from the threshold line.

4. Discussion

The proposed DT model is the integration of different tools simulating the electrical variables of an optocoupler system. Many advantages are obtained with the use of these tools, such as the possibility to estimate the DT sensitivity versus all of the electrical parameters, the modeling of modulated interferences and noise, and the combined use of supervised and unsupervised AI algorithms to prevent corrective actions. On the other hand, the circuit model used for simulation could be complex: a large number of interferences or noise could increase drastically the computational cost and necessitate advanced calculation technologies, such as graphics processing units (GPUs) or quantum

computers. In Table 2, we detail the main advantages and disadvantages of the proposed model.

Table 2. Advantages and disadvantages of the approaches proposed in the DT.

Proposed Approach	Advantages	Disadvantages
Circuit simulation	Possibility to design a multi-port circuit testbed suitable for the implementation of a specific DT model for different application fields (sensing, actuation, automatic systems, etc.). Due to the different input ports, the DT is considered as a multidimensional model, integrating different distortions of interference or noise. A SPICE-based simulator is able to model each interference or noise. The circuit simulation provides the dataset to train the AI supervised algorithm.	The computational cost for an elevated number of input ports (ports coupling interference and noise to the DT model) could be very high. For calculations involving a quasi-infinite number of input ports, a quantum computer may be required.
Parametric analysis of electrical variables	A parametric simulation is fundamental to study the circuit sensitivity versus parameter variation as for the variation in the resistance modulating the distortion amplitude or the variation in the electrical signal profile due to the coupling of other circuit elements.	A parametric analysis could increase the difficulty in interpreting the results, increasing the complexity of the DT model. In this context, it is preferable to fix some parameters to describe the real behavior of the analyzed circuit, making the DT model much closer to reality.
AI supervised algorithms	The use of the output of the LTSpice simulator is useful to obtain an efficient RF training model with a very low error rate. This strategy could be adopted to increase the data input dimension. Other supervised AI algorithms could be adopted for the DT data prediction.	Different important aspects should be considered when using AI supervised algorithms for data pre-processing: the first step to execute correctly the algorithm is to clean the dataset, removing outliers or generally incorrect data (incorrect data could be an output with an apparently low error rate) and adjusting missing values. This phase typically requires a lot of time.
AI unsupervised algorithms	Unsupervised algorithms are further approaches to support data analysis. In the present work, K-Means is used for the clustering of the RF results, thus providing further risk maps to control in order to prevent corrective actions.	A large number of clusters for analysis increases the complexity involved in interpreting the output of the unsupervised algorithm.
DT dashboards	Graphical dashboards are useful to preliminarily test the DT model and to optimize the adopted algorithms.	None

The limitations of the proposed model are mainly associated with the reliability of the AI results; the automation of the data processing, enabling the automation of corrective actions; and the difficulty in identifying the disturbance type for complex noisy circuits. Possible future developments in Industry 5.0 scenarios could include the formulation of guidelines, establishing criteria to select predictive results, and the integration of all tools into a unique platform, enabling the automatic selection of the corrective actions with a low error rate. In Table 3, we detail these aspects.

Table 3. Limitations and perspectives regarding important properties of the DT model.

DT Property	Limits	Perspectives
Reliability of predictive results	The predictive results must replicate the real behavior of a device as truthfully as possible. In this direction, it is therefore necessary to establish criteria to verify the reliability of the results.	The challenge of the Industry 5.0 era is to use predictive results to optimize production. Specific guidelines defining criteria to distinguish reliable predictive results can make models safer and fully integrated into the new production processes.
Automation of the matching of the circuit simulation approach with AI data processing	Circuit simulation is a separate phase from AI analysis. This requires continuous manual matching between the two approaches.	The perspective is to develop a unique code implementing a scalable DT model that automatically interconnects the circuit simulation with the AI data processing, adopting suitable calculus optimizers.
Enabling of corrective actions	The corrective actions are enabled by considering threshold values and risk maps. For signals that vary very rapidly (such as signals with accentuated noise), we require very fast corrective actions, which can be performed by advanced technologies.	An ideal DT model should control automatically the corrective actions by analyzing the risk maps in real time. Moreover, for very rapidly varying signals, the AI-based DT should enable, through suitable compensatory circuits, processes of amplitude amplification by potentiometers [49], filtering, or general signal adjustments (correcting the signal phase or profile).
Black box behavior	The ‘black box’ behavior of the DT model does not allow us to classify all signals, especially when multiple effects are considered.	A universal DT model could simulate each type of circuit as an ‘object’ loaded into a unique simulator engine. A complete DT model could classify each input signal by means of a reverse engineering approach that is able to reconstruct and filter all input signals.

Concerning the desire to fully integrate the circuit simulation and AI tools, we define the following pseudocode in Algorithm 1, determining all of the DT specifications for the specific case study of optocoupler implementation in real scenarios.

Algorithm 1 DT pseudocode (data processing automation and output reading)

1. Loading of the circuit ‘object’ into the DT platform (the objects could be stored as libraries of the DT platform);
 2. Initial setting of the DT: definition of the input ports, output ports, and thresholds;
 3. Initial circuit parametric simulation considering an initial range to vary the parameters;
 4. **If** the results are closer to the threshold, **Then** refine the variation step of the parameter and/or the sampling until the desired accuracy;
 5. **Else** (results are far from the threshold) change the parametric range until the solution is closer to the threshold;
 6. **End if** (end of parametric circuit simulations);
 7. Importing of the simulation dataset into the AI training model;
 8. Execution of the supervised algorithm until the error rate is the minimum (optimization of the algorithm hyperparameters, observing the performance dashboards);
 9. Execution of the unsupervised algorithm;
 10. Formulation of the risk maps (risk of uncorrected transmission);
 11. Actuation of corrective actions according to circuit simulations simulating the corrections;
 12. Monitoring of real data after the application of the corrective action to optimize the DT settings.
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The total elapsed time of the DT model is the sum of the computational cost of each algorithm and tool. As observed in Table 4, only half a minute is required to execute the whole DT model when using a Core i5 2.4 GHz/16 GB RAM processor.

Table 4. DT computational cost.

Algorithm/Tool	Computational Cost (Seconds)
Optocoupler circuit simulation (LTSpice)	0.208
Parametric circuit simulation (LTSpice)	0.841
RF (KNIME)	26
K-Means (KNIME)	2

The significant novelties of this work are in the modeling of the DT. The main characteristics of the proposed DT model are summarized in Table 5.

Table 5. DT model novelties.

Innovative Feature of the DT	Description
High level of complexity by introducing additional forms of noise and interference	The proposed model is able to include in the simulation as input ports different disturbing additive effects, such as interference, noise, and hardware attacks (inclusion of cybersecurity elements). Furthermore, the model is spatially multidimensional, able to couple disturbances coming from different directions of the spatial 3D domain.
Modeling and simulation of the whole machine's communication channel, including the PLC and related optoelectronic components	The model is structured to include, in the same 'black box' object, both the PLC communication channel and the related optocoupler switching circuits.
Combined analysis of machine learning unsupervised and supervised algorithms	The risk maps (see Figure 10) are furthermore constructed by applying the unsupervised K-Means algorithm to the supervised RF results (predicted results of the whole output voltage signal, including all disturbance effects).
DT scalability	The DT model is scalable to include a large number of input ports and to be implemented in big data systems (a large number of input signals provides a large dataset to be adopted for the training of the AI supervised algorithms).
DT modularity	The use of input and output ports allows the integration of the DT model with other 'objects' or DT 'black box' models composing the whole production line.

Focusing our attention on the possibility to simulate the whole machine's PLC communication system, in Figure 11, we illustrate a circuital scheme for the PLC line, including the optocoupler device and the 'coupling point' (green input ports in Figure 1) of possible noise or interference.

The disturbances acting in the PLC model in Figure 11 can be impulsive [50–52] (in agreement with the pulses used in the proposed DT model) or Gaussian [53] or exhibit other long-term statistical characteristics [54]. The proposed model is suitable for each type of disturbance.

The computational complexity will increase with the number of input ports. An increase in the input ports will increase the computational cost and the number of records that must be processed by the AI algorithms. On the other hand, an increase in the records could be useful to increase the AI training performance. This work demonstrates that, for a reasonable level of complexity in the disturbed system, excellent values regarding

the AI performance and computational cost can be obtained (see Tables 1 and 4). Furthermore, when considering a very large number of input ports to process, we would require an increase in the computational energy. In this direction, a quantum computing tool could be a good solution to drastically decrease the computational cost by adopting a reasonable amount of computational energy. The choice of the RF and the K-Means algorithms is mainly due to the suitability of these algorithms in industrial electronics applications [48]. Other algorithms could be used and optimized to achieve similar performance. The prospects of the DT model include the possibility to classify and to distinguish the origin of the noise or interference throughout the whole PLC line in order to apply one or more corrective filtering circuits acting on different stages. Furthermore, the simulation and prediction of disturbed output signals are fundamental for the design of each PLC transmission line component to provide stable and robust solutions. The proposed DT model is universal and can be applied to compare the results of other, simpler DT models. In this direction, the DT should simulate a single type of noise in the time domain and frequency domain by adding ‘step by step’ the effects of other additive or multiplicative noise, which is classified as stationary noise (colored background noise, narrow-band noise), and impulsive noise (asynchronous periodic impulsive noise, synchronous periodic impulsive noise, asynchronous impulsive noise).

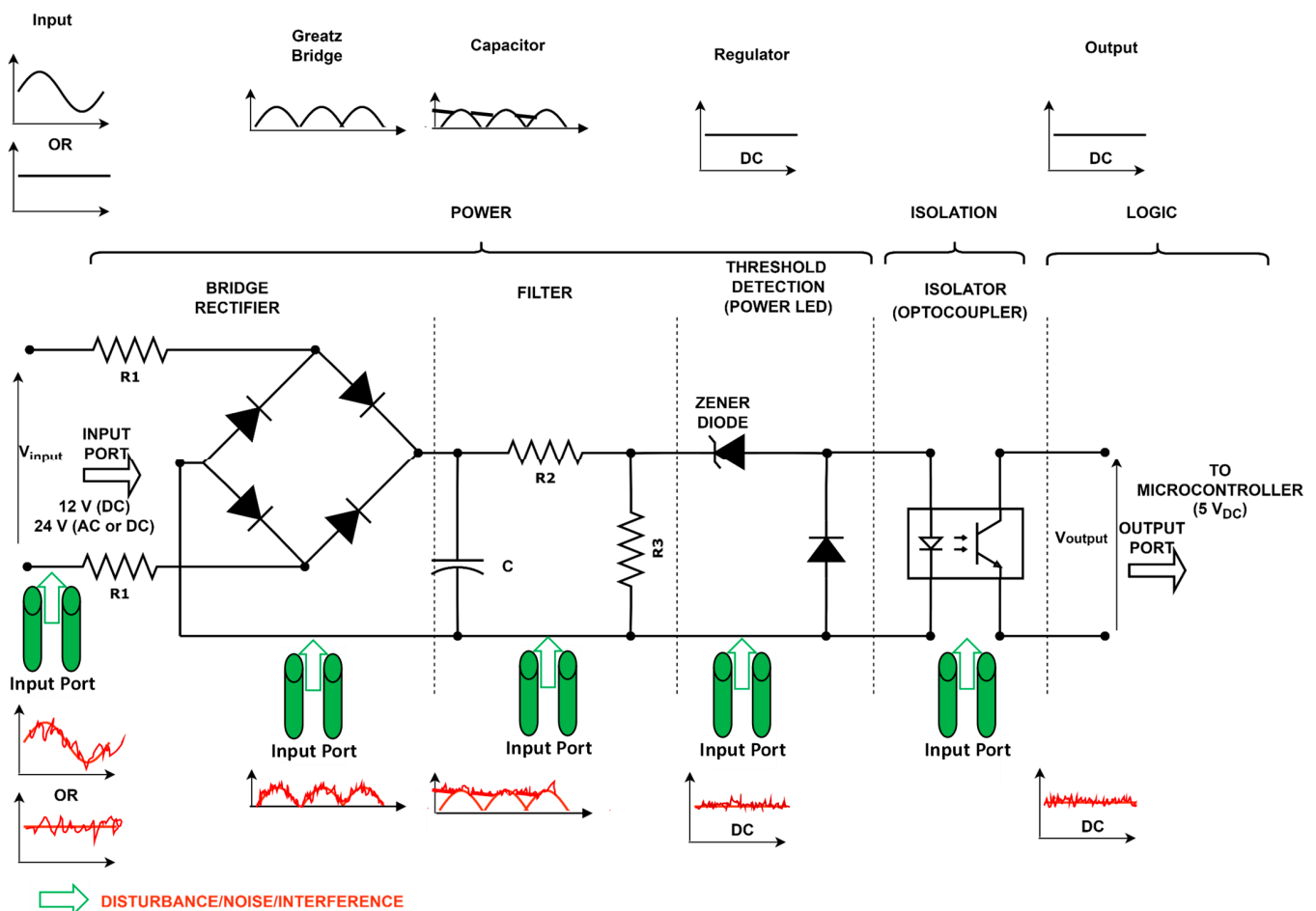


Figure 11. DT model applied to the whole PLC line including the optocoupler. Possible interferences or noise could be coupled at the input port or in other parts of the PLC line, such as the circuit rectifier stage, filter stage, threshold detection device, or isolation optocoupler.

5. Conclusions

This work introduces a DT model with innovative features that is applicable to an entire PLC transmission line, showing scalability, modularity, and spatial multidimension-

ality. Specifically, the DT model is able to couple the effects of different undesired signals simultaneously disturbing the PLC system. The AI-DT multidimensional model is based on the concept of the coupling of multiple ports. The DT model is applied to an optocoupler circuit encompassing all of the data processing steps, including circuit simulations and RF and K-Means data processing. The performance results of the RF algorithm prove that the output of the circuitual simulations is a dataset that can be used to efficiently train AI supervised algorithms. Furthermore, this paper provides an approach to constructing risk maps, which are useful for the selection of corrective actions. The AI-based DT behaves as a universal ‘black box’ model, adaptable to different types of circuits and applicable in different Industry 5.0 scenarios requiring the processing of a large number of variables. The discussion mainly focuses on the definition of the main aspects of DT implementation in complex Industry 5.0 production processes.

Funding: This research received no external funding.

Data Availability Statement: The data are included in the paper.

Acknowledgments: This work was developed within the framework of the Laboratory of the Dept. of Engineering of LUM University.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

The KNIME workflow in Figure A1 is applied to predict the output voltage (Vout) and to classify the risk of signal deterioration through clustering K-Means analysis. The workflow is constituted by the following nodes.

- Data pre-processing nodes: The first nodes able to manipulate the input dataset such as row filtering, string-to-number conversion (creation of the time step attribute), missing value elimination, data normalization to decrease the error rate of the algorithm (data normalized to the range of 0 to 1), and data partitioning, enabling the creation of the training and testing datasets.
- Data processing nodes: Nodes related the processing of the RF (learner and predictor nodes) and of the K-Means algorithm; data de-normalization nodes to return the processed data back to the original scale.
- Algorithm performance nodes: Statistical results of R2, MAE, MSE, and RMSE (numeric scorer).
- Data visualization nodes: Data manipulation nodes that are able to prepare data to visualize (column filters and column appender); graphical dashboard plotting results (scatter plot, line plot, Bland–Altman plot, heat map).

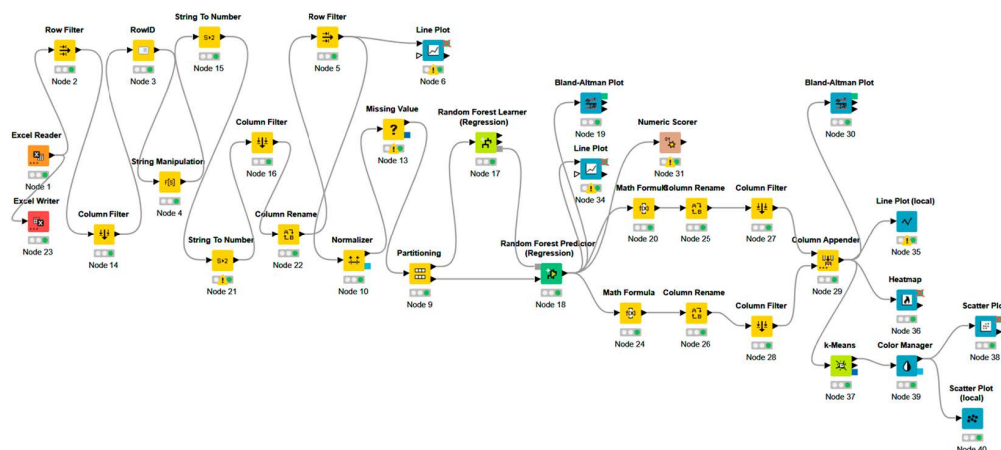


Figure A1. KNIME workflow applied to the RF prediction and K-Means clustering results. The workflow is the AI engine of the DT model in Figure 1.

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