

UNITED STATES PATENT AND TRADEMARK OFFICE

BEFORE THE PATENT TRIAL AND APPEAL BOARD

DIGITAL GLOBAL SYSTEMS, INC.,
Petitioner,

v.

DEEPSIG INC.,
Patent Owner.

Case IPR2024-01358
U.S. Patent No. 11,018,704

PATENT OWNER'S RESPONSE

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Pursuant to 37 C.F.R. § 42.120(a), Patent Owner DeepSig Inc. (“DeepSig” or “Patent Owner”) files this response to the Petition, setting forth reasons why the Petition for *inter partes* review (“IPR”) of claims 1-24 of U.S. Patent No. 11,018,074 (the “’704 Patent”), as requested by petitioner Digital Global Systems, Inc. (“DGS” or “Petitioner”), fails to establish unpatentability of any challenged claim.

I. INTRODUCTION

The ’704 patent is titled, “Machine Learning-Based Nonlinear Pre-Distortion System.” The ’704 patent describes methods, systems, and apparatuses “for correcting distortion of radio signals.” ’704 patent, Abst. In particular, the ’704 patent disclosure “relates to integrating nonlinear pre-distortion machine learning into radio communication systems to correct for radio signal distortion and interference.” *Id.*, 1:17-19.

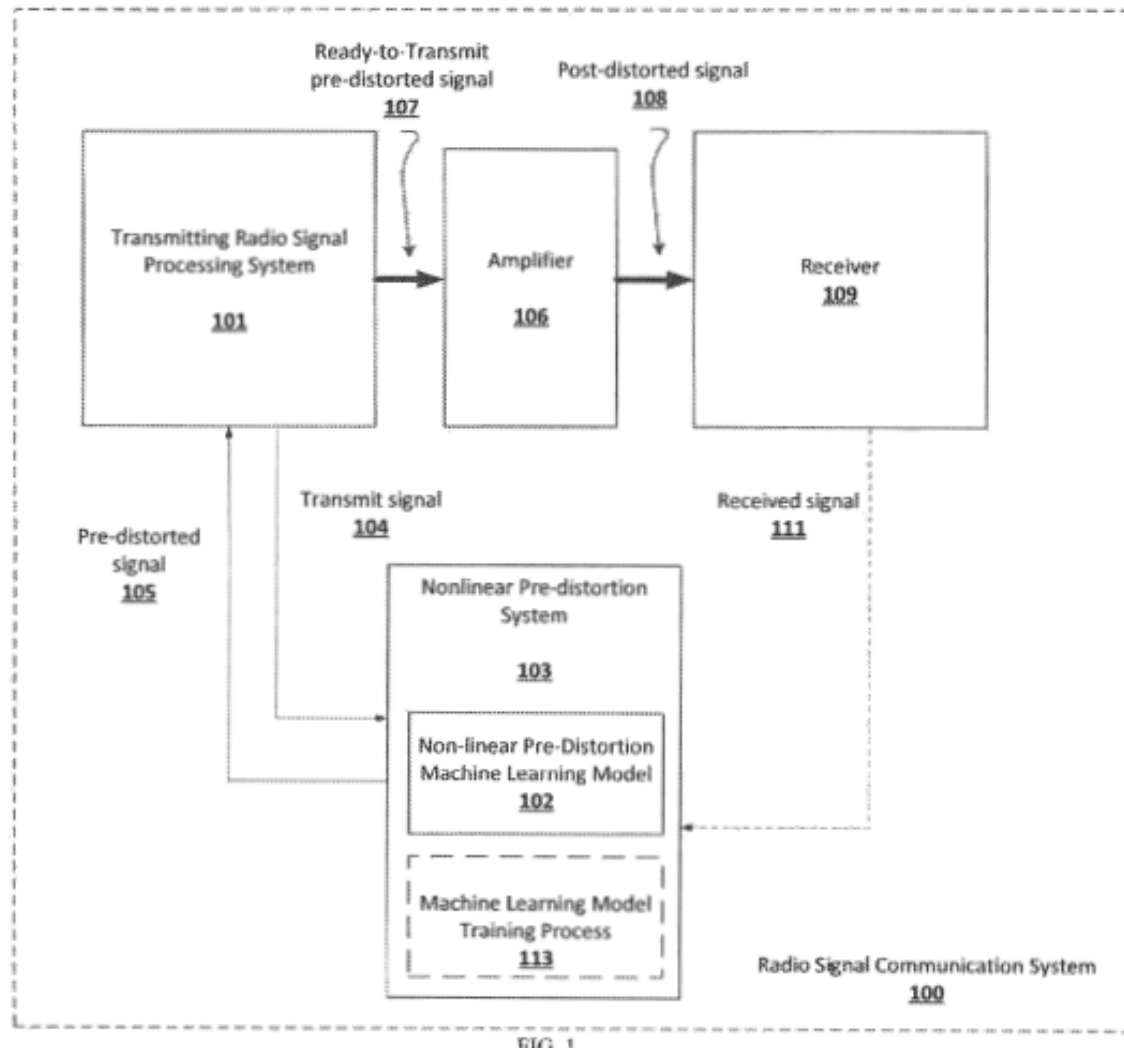
The ’704 patent discloses a nonlinear pre-distortion machine learning model that is associated with a base station, and is designed to correct for distortion that occurs in a radio communication system. The nonlinear pre-distortion machine learning model includes model parameters, tuned for one or more deployment scenarios, and at least one nonlinear function that pre-distorts a radio signal to correct for radio signal distortion and/or interference arising in the components of a deployment scenario. Notably, and unlike the asserted prior art, the ’704 patent

does more than attempt to correct for general distortion that arises in one particular component, such as a transmitter. The '704 patent also can correct for specific distortion that arises from the specific deployment scenario in which the transmitter device is deployed, and can do so because the '704 patent discloses comparing a transmitted signal with a received signal to compute a pre-distortion signal to compensate for deployment conditions including distortion and/or interference at the transmitter, in the signal channel, and at the receiver.

As the '704 patent acknowledges, a “radio communication system 100 may have multiple sources of distortion and/or interference.” '704 patent, 5:29-30. These sources may include “reflectors; bad connectors; imperfections in the digital to analog conversion process; unintended coupling, impedance mismatch or emissions for other electronics; unintended tones, intermodulation products or sidelobes; responses from other analog electronic components such as filters, power supplies, matching networks, junctions, attenuators, and mixers.” '704 patent, 5:43-50. The '704 patent discloses “a nonlinear pre-distortion system 103 to correct the radio signal distortion and interference prior to the radio signals being transmitted to the receiver 109.” '704 patent, 5:50-53.

The '704 patent discloses comparing transmitted and received radio signals, and updating the values of the model parameters for the particular deployment scenario based on this comparison between transmitted and received radio signals.

In an embodiment, the “the nonlinear pre-distortion system 103 uses a nonlinear pre-distortion machine learning model 102 to determine pre-distorted radio signals that *minimize* a distance *between the radio signals that the transmitting radio signal processing system 107 transmits and radio signals the receiver [109] receives 108.*” ’704 patent, 5:54-59 (emphasis added). This concept is illustrated in Figure 1 of the ’704 patent, reproduced below, in which both a received signal 111 and transmit signal 104 are provided to a non-linear pre-distortion machine learning model to generate a pre-distorted signal. ’704 patent, 6:12-20.



As the '704 patent discloses, “the machine learning model training process 113 receives the received signal 111, which includes both the pre-distortion and the distortion effects, from the receiver to determine real time online tuning and *model parameter updates*.” ’704 patent, 6:13-17 (emphasis added). “This process can continue to compensate for changes in the response of a specific amplifier device over its lifetime and through changes in environmental conditions or signal loading conditions.” ’704 patent, 6:17-20.

Per the '704 patent, the model's "initial parameters may also be ... based on devices or types of devices expected in a deployment environment in which the machine learning model will be deployed, in this case the parameters may be taken from another model." '704 patent, 8:30-35. Similarly, the '704 patent discloses that "the model parameters are *updated with values for a particular deployment scenario for a radio communication system* upon initial deployment of the nonlinear pre-distortion machine learning model into the radio communication system." *Id.*, 2:17-21 (emphasis added).

Petitioner relies heavily on Jüschke¹ to disclose or suggest the features of the independent claims, but this is incorrect for multiple reasons. First, Jüschke expressly discloses that its neural network processor training is designed to accommodate the distortion resulting from the transmitter device, and therefore is not associated with a base station. Further, Jüschke does not account for any deployment scenarios for that transmitter device. As shown in Jüschke's Figure 4, the training loop exists purely on the transmission side in order to model and accommodate only the transmitter's distortion, and unlike the '704 patent, does not account for the condition of the received signal. Indeed, Jüschke expressly discloses that the goal of Jüschke's training is to generate the inverse of the transmitter's transfer function. Jüschke discloses "[a]s the training of the post

¹ Ex. 1005, EP 2,538,553 A1 to Jüschke *et al.* ("Jüschke").

distortion neural network processor converges, its response or transfer function will approximate the inverse transfer function of the non-ideal *transmitter device's* transfer function.” Jüschke, ¶19 (emphasis added).

Second, Jüschke does not seek to correct for any deployment or use scenarios, and expressly distinguishes its own self-learning algorithm from “use dedicated” algorithms. Jüschke specifically states that by “using embodiments of the [disclosed] self learning/optimizing neural network, the parameters (addressing I/Q-imbalance and PA non-linearity in parallel for different frequency bands) may *commonly be considered and optimized* by embodiments of the present invention in a more advanced manner *compared to use dedicated*, non-self-lea[rn]ing algorithms.” Jüschke, ¶28 (emphasis added). Thus, Jüschke admits that it is attempting to singly correct for a transmitter's common or general distortion, and does so in a manner that differs from techniques that consider the use or deployment scenarios of the transmitter and system.

Therefore, while Jüschke discloses a training algorithm tuned for a transmitter device and that accounts for a non-ideal transmitter device's characteristics, it does so without adopting use-dedicated parameters or values, and does not disclose or suggest a “nonlinear pre-distortion machine learning model associated with the base station, wherein the nonlinear pre-distortion machine learning model includes model parameters associated with values corresponding to

one or more deployment scenarios in the cellular communications system,” as claimed in the '704 patent.

Dependent claims 4-6, 12-14, and 20-22 further recite the use of a distance metric computed between a transmitted radio signal and a received radio signal to update values of the nonlinear pre-distortion machine learning model to correct for distortion in the system. Petitioner relies on Jüschke in view of Holt² to challenge these claims, but even if combined, these references fall short.

Jüschke, on one hand, does not use a received radio signal to correct for system distortion at the transmitter. Instead, Jüschke uses an output of the transmitter in the feedback loop, so there is no distance metric computed between a transmitted radio signal and a received radio signal in Jüschke.

On the other hand, Holt primarily uses encoder models, decoder models, and channel models to emulate a transmitter device or component, a communication channel, and a receiver device or component respectively. Holt, 4:33-39. Holt's “channel coding model can be retrained in order to adapt the channel coding model and corresponding encoding scheme to changing conditions of a communication channel over time” Holt, 4:41-44. Then, the encoder model and decoder model portions of the channel coding model can be retrained, “thereby causing the encoder model and decoder model portions of the channel coding model to learn an

² Ex. 1006, U.S. Patent No. 10,552,738 to Holt et al. (“Holt”).

updated encoding scheme that is appropriate for the new communication channel conditions.” Holt, 4:49-54. Holt’s “encoder model and the decoder model of the channel coding model can automatically devise an appropriate encoding scheme for the communication channel.” Holt, 4:27-30. Holt makes no mention of distortions in a radio signal processing system, or training pre-distortion machine learning models to correct for such distortions.

Further, while Holt does disclose an actual communication channel in limited circumstances, Holt is abundantly clear in its disclosure that the use of an actual communication channel, as appearing in Figures 6 and 11 and described in corresponding portions of the specification, are for used training a *decoder* model only, not an *encoder* model. Thus, Holt does not use received signals from a radio receiver, received via an actual communication channel, to process transmit signals for transmission transmission. Like Jüschke, Holt also fails to disclose using a signal received via an actual communication channel to train an encoder model or to update parameters for a pre-distortion machine learning model to process a transmit signal.

Whether Jüschke and Holt are considered alone or in the Ground 2 combination proposed by the Petitioner, there is no disclosure or suggestion in Petitioner’s asserted art to compute a distance metric between a transmit radio signal and a received radio signal that is then used to update model parameters for

the pre-distortion machine learning model used for processing a transmit radio signal, and generating a pre-distorted radio signal. Thus, these features of dependent claims 4-6, 12-14, and 20-22 are neither disclosed by nor obvious in view of the asserted art in the Petition.

As discussed in more detail below, Petitioner's challenges fail.

II. THE '704 PATENT

A. The '704 Patent Discloses Model Parameters Associated with Values Corresponding to Deployment Scenarios for a Cellular Communications System

As disclosed in the '704 patent, a “pre-distorted radio signal is generated by processing [a] transmit radio signal using a nonlinear pre-distortion machine learning model.” '704 patent, 2:7-9. “The nonlinear pre-distortion machine learning model includes model parameters and at least one nonlinear function to correct radio signal distortion and/or interference.” *Id.*, 2:9-12. “A transmit output radio signal is obtained by processing the pre-distorted radio signal through the transmitting radio signal processing system.” *Id.*, 2:12-14. To account for distortion, noise and interference that results in the communication system, the '704 patent discloses a technique whereby “the model parameters are *updated with values for a particular deployment scenario for a radio communication system* upon initial deployment of the nonlinear pre-distortion machine learning model into the radio communication system.” *Id.*, 2:17-21 (emphasis added).

By updating model parameters with values for a particular deployment scenario, the '704 patent can adjust to complex deployment scenarios having a variety of deployment-specific sources of error in a signal. Distortion or interference during signal propagation, such as that caused by reflection or absorption, bad connections, unintended coupling, or other site-specific features can be detected and corrected. *See* '704 patent, 5:40-53. In addition, environmental conditions for a particular deployment scenario, such as temperature and humidity effects on system components, may be addressed. *Id.*; *see also* '704 patent, 10:24-32, 6:17-20 (“This process can continue to compensate for changes in the response of a specific amplifier device over its lifetime and through changes in environmental conditions or signal loading conditions.”).

B. The '704 Patent Discloses Techniques to Correct for Widespread Distortion in the Transmitter, Channel, and Receiver at the Transmitter Side Using a Received Signal

As noted above, the '704 patent discloses comparing transmitted and received radio signals, and updating the values of the model parameters for the particular deployment scenario based on this comparison. In an exemplary embodiment, the “the nonlinear pre-distortion system 103 uses a nonlinear pre-distortion machine learning model 102 to determine pre-distorted radio signals that *minimize* a distance *between the radio signals that the transmitting radio signal processing system 107 transmits and radio signals the receiver [109] receives*

108.” ’704 patent, 5:54-59 (emphasis added). As illustrated in Figure 1 of the ’704 patent (reproduced in Section I above), both a received signal 111 and transmit signal 104 are provided to a non-linear pre-distortion machine learning model to generate a pre-distorted signal. ’704 patent, 6:12-20. The received signal “includes both the pre-distortion and the distortion effects,” and the non-linear pre-distortion machine learning model can therefore “determine real time online tuning and *model parameter updates*.” ’704 patent, 6:13-17 (emphasis added). Through this feedback loop and update of model parameters, the “nonlinear pre-distortion machine learning model 102 [can] determine pre-distorted radio signals that *minimize a distance between the radio signals that the transmitting radio signal processing system 107 transmits and radio signals the receiver [109] receives* **108.**” ’704 patent, 5:54-59 (emphasis added).

C. The Independent Claims

Consistent with the ’704 patent’s disclosure, independent claim 1 recites:

1. A method for correcting distortion of radio signals in a cellular communications system, the method comprising:
 - obtaining, at a base station in the cellular communications system, a transmit radio signal that is prepared for transmitting to one or more radio receivers associated with the cellular communications system;
 - accessing a *nonlinear pre-distortion machine learning model associated with the base station*, wherein the nonlinear pre-

distortion machine learning model includes *model parameters associated with values corresponding to one or more deployment scenarios in the cellular communications system*, and at least one nonlinear function to correct radio signal distortion;

generating a pre-distorted radio signal by processing the transmit radio signal using the nonlinear pre-distortion machine learning model;

obtaining a transmit output radio signal by processing the pre-distorted radio signal through a transmitting radio signal processing stage of the base station; and

transmitting the transmit output radio signal to the one or more radio receivers.

'704 patent, 14:15-35 (claim 1) (emphasis added).³

Similar to claim 1, independent claims 9 and 17 of the '704 patent each recite, in relevant part, “accessing a *nonlinear pre-distortion machine learning model associated with the base station*, wherein the nonlinear pre-distortion machine learning model includes *model parameters associated with values corresponding to one or more deployment scenarios in the cellular communications system*, and at least one nonlinear function to

³ The '704 patent claims require the claimed “nonlinear pre-distortion machine learning model” to be “associated with the base station.” These claims are narrower than the disclaimed claims of U.S. Patent No. 11,777,540, at issue in IPR2025-00194, and this claimed requirement is absent from Petitioner's challenges for at least the reasons set forth in Section IV.B.iii below.

correct radio signal distortion.” *Id.*, 15:35-42 (claim 9) (emphasis added); 16:48-54 (claim 17).

D. Challenged Dependent Claims 4-6, 12-14, and 20-22 Apply Pre-Distortion at the Transmitter Based on a Distance Metric Computed Between a Transmitted Radio Signal and a Received Radio Signal

Consistent with the '704 patent's disclosure, dependent claims 4-6, 12-14, and 20-22 also recite the method step of “updating the values of the model parameters for the particular deployment scenario based at least on the distance metric,” where the distance metric is determined “between the transmit radio signal and the received radio signal.” In full, claim 4 recites:

4. The method of claim 2, further comprising:
 - obtaining a received radio signal that corresponds to a representation of the transmit output radio signal received at the one or more radio receivers;
 - determining a distance metric between the transmit radio signal and the received radio signal; and
 - updating the values of the model parameters for the particular deployment scenario based at least on the distance metric.

'704 patent, 14:62-15:3. In order to minimize that distance metric, updated values for the set of model parameters are determined or updated in the nonlinear pre-distortion machine learning model. Further, these model parameters are applied via a nonlinear pre-distortion machine learning model, which is used *to process the transmit radio signal* to generate a pre-distorted radio signal. Thus, a received

radio signal is used to update model parameter values used for processing the transmit radio signal. These claimed features are found nowhere in the asserted art.

Petitioner challenged similar claimed features in both IPR2025-00049 and IPR2025-00194 based on Jüschke in view of Holt, and those petitions were denied institution for the reasons presented below regarding dependent claims 4-6, 12-14, and 20-22. At minimum, these claims survive Petitioner's challenges. As discussed below, these features are neither disclosed nor suggested by Petitioner's asserted art.

III. THE BOARD NEED NOT REACH ANY CLAIM CONSTRUCTION ISSUES

The Petitioner identifies no terms as requiring constructions. Pet., 15 (Petitioner submits that “[n]o claim term requires construction to resolve the patentability challenges here.”). For the substantive reasons presented below, Petitioner's grounds include fundamental flaws and fail to establish the disclosure of every claimed element in each independent claim. These findings do not require the Board to conduct any claim construction.

IV. PETITIONER'S CHALLENGES FAIL ON THE MERITS

Petitioner asserts three grounds in its Petition, but only two of those grounds, Grounds 1 and 2, apply to the independent claims (claims 1, 9, and 17).

Ground 1 contends that claims 1-3, 7-8, 9-11, 15-16, 17-19, and 23-24 are obvious over Jüschke. Pet., 15-56. Ground 2 contends that claims 1-24 are obvious over Jüschke in view of Holt. Pet., 57-80. Ground 3 is only asserted against dependent claims, and contends that claims 2-6, 10-14, and 18-22 are obvious over Jüschke in view of Holt and Dzierwa.⁴ Pet., 81-86.

However, Petitioner's challenges suffer from extensive flaws. As introduced above, Jüschke fails to disclose the claimed features relied upon by Petitioner. For example, Jüschke discloses that its training of the neural network processor is designed to accommodate the distortion resulting from the transmitter device, but does not disclose that its training is associated with a base station. Jüschke discloses that "[a]s the training of the post distortion neural network processor converges, its response or transfer function will approximate the inverse transfer function of the non-ideal *transmitter device's* transfer function." Jüschke, ¶19 (emphasis added). Similarly, Jüschke does not account for any deployment scenarios, and does not update values based on a distance metric computed between a transmit radio signal and received radio signal.

Moreover, Jüschke does not seek to correct for any deployment scenarios, and instead expressly distinguishes its own self-learning algorithm from techniques that do account for the "use" of the system. Jüschke specifically states that by

⁴ Ex. 1007, U.S. Patent No. 10,122,479 to Dzierwa ("Dzierwa").

“using embodiments of the [disclosed] self learning/optimizing neural network, the parameters (addressing I/Q-imbalance and PA non-linearity in parallel for different frequency bands) may *commonly be considered and optimized* by embodiments of the present invention in a more advanced manner *compared to use dedicated*, non-self-lea[er]ning algorithms.” Jüschke, ¶28 (emphasis added).

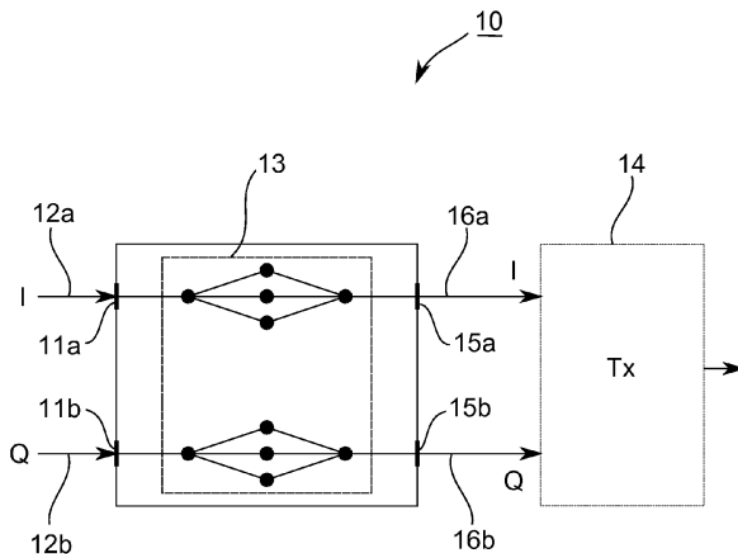
Therefore, while Jüschke discloses a transmitter-based training algorithm that accounts for a non-ideal transmitter device's characteristics, it does so without adopting use-dedicated parameters or values, and does not disclose or suggest a “nonlinear pre-distortion machine learning model [that] includes model parameters associated with values corresponding to one or more deployment scenarios in the cellular communications system,” as claimed in the '704 patent.

Additionally, whether considered alone or in combination, Jüschke and Holt fail to disclose using a signal received via an actual communication channel to train an encoder model or to update parameters for a pre-distortion machine learning model to process a transmit signal. Dependent claims 4-6, 12-14, and 20-12 survive Petitioner's Ground 2 challenge.

A. Jüschke Does Not Disclose Deployment Scenarios, or the Claimed Associations of Deployment Scenarios with Model Parameters or Model Parameter Values

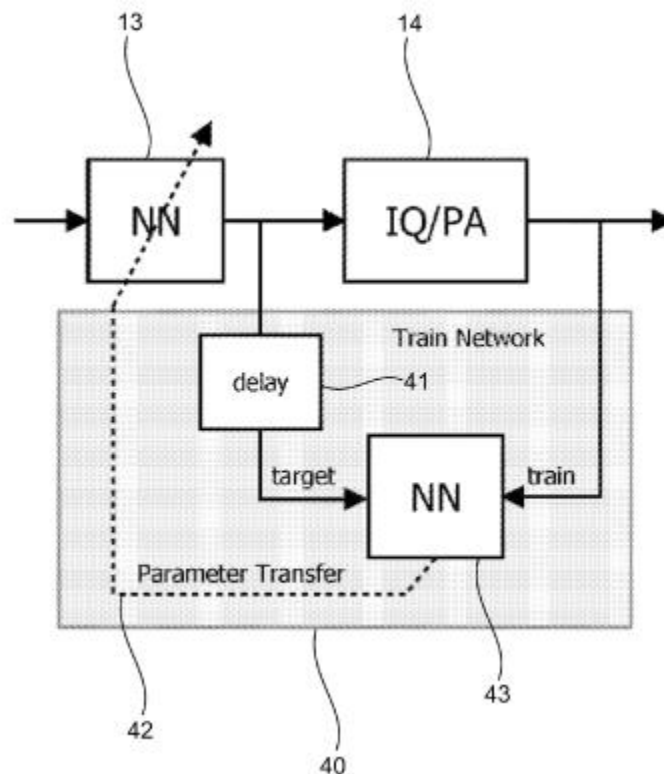
In Jüschke's FIG. 1, reproduced below, Jüschke discloses an apparatus (10) having an input (11a, 11b) for I and Q components of a signal (12a, 12b), a pre-

distortion neural network processor (13) to obtain a pre-distorted digital baseband signal (16a, 16b), and a transmitter device (14). Jüschke, FIG. 1; Abst.



According to Jüschke, the neural network processor 13 is used “to mitigate the IQ imbalance, which may lead to undesired RF signal images.” Jüschke, ¶13. Jüschke explains that the “neuron is an information-processing unit,” and “the basic elements of the neuronal model are a set of synapses or collecting links, each of which is characterized by a weight was drawings of its own [*sic*].” Jüschke, ¶14. A “signal x_j at an input of synapse j connected to neuron k is multiplied by the synaptic weight w_{kj} .” *Id.* “An adder sums up the input signals, weighted by the respective synaptic weights.” *Id.* “An activation function” is then applied to the “the weighted sum of the inputs ... plus a bias term b_k .” *Id.*

Per Jüschke, the training of this neural network processor is designed to accommodate the distortion resulting from the transmitter device 14 only. Jüschke explains that the “post-distortion neural network processor may be used to identify the inverse transfer function of the nonideal transmitter device’s transfer function using supervised learning.” Jüschke, ¶18. “As the training of the post distortion neural network processor converges, its response or transfer function will approximate the inverse transfer function of *the non-ideal transmitter device’s transfer function.*” Jüschke, ¶19 (emphasis added). Indeed, Jüschke’s training loop exists purely on the transmission side, as shown in Jüschke’s Fig. 4:



See Jüschke, Fig. 4. As illustrated, Jüschke's training loop begins at the output of the non-ideal analog transmitter device 14. Jüschke, ¶48. This training loop passes to the "input layer of the post distortion neural network." *Id.* "Undistorted, and, hence, ideal digital baseband IQ samples 12a, 12b may [also] be provided to the post distortion neural network 43 as target output values." *Id.* The neural network 43 therefore approximates the inverse of the transfer or distortion function of the analog transmitter device 14 only, to compensate for the analog transmitter device 14's distortion. As Jüschke again explains and confirms, "As the response of the post distortion neural network 43 converges, its response will essentially be the inverse of the transfer or distortion function of the analog transmitter device 14." *Id.* Further, "[a]fter convergence of the post distortion neural network 43, the trained weight (w_{kj}) and/or bias parameters (b_k) of the post distortion neural network 43 may be transferred to the pre-distortion neural network processor 13, as is indicated by the dashed line 42." *Id.*, ¶49.

Thus, Jüschke does not disclose any association of the weight or bias parameters, which are used to approximate the transmitter device's inverse transfer function, to any deployment scenario, and does not associate its training to a base station. Instead, Jüschke simply trains the weight and bias parameters using a training algorithm based on the output of the non-ideal analog transmitter device 14 to offset the distortion resulting from that non-ideal analog transmitter device.

Notably, Jüschke also distinguishes its self-learning algorithm from “use dedicated” algorithms. Jüschke states that by “using embodiments of the self learning/optimizing neural network, the parameters (addressing I/Q-imbalance and PA non-linearity in parallel for different frequency bands) may *commonly be considered and optimized* by embodiments of the present invention in a more advanced manner *compared to use dedicated*, non-self-lea[rn]ing algorithms.” Jüschke, ¶28 (emphasis added). As such, Jüschke does not disclose any initial values of the synaptic weights or bias values corresponding to the use or deployment scenario of the transmitter. Instead, Jüschke is focused solely on correcting for the transmitter 14. As Jüschke explains: “[i]n order to fit the feed-forward pre-distortion neural network *to a specific downstream hardware component*, the apparatus may further comprise a training processor for training weight and/or bias parameters (w_{kj} , b_k) of neurons of the pre-distortion neural network processor.” Jüschke, ¶17 (emphasis added). Jüschke confirms that this *downstream hardware component* being accounted for is the “analog transmitter device arranged downstream to the pre-distortion neural network,” and not any deployment scenario in which the transmitter associated with the pre-distortion neural network is being used, or even any base station in which the transmitter may be arranged. Jüschke, ¶29.

Similarly, Jüschke explains that “[t]he training processor may be adapted to train the weight and/or bias parameters of the post distortion neural network processor using the Levenberg-Marquardt training algorithm and to transfer the trained weight and/or bias parameters of the post distortion neural network processor to the pre-distortion neural network processor *upstream to the analog transmitter hardware.*” *Id.* (emphasis added).

B. Petitioner’s Ground 1 Fails to Satisfy the Claimed Model Parameter Values and Associations with Deployment Scenarios

Whether considered alone or in view of Holt, Jüschke fails to disclose every claim requirement of the challenged ’704 patent claims 1, 9, and 17. In particular, claim 1 of the ’704 patent recites, in relevant part, “accessing a *nonlinear pre-distortion machine learning model associated with the base station*, wherein the nonlinear pre-distortion machine learning model *includes model parameters associated with values corresponding to one or more deployment scenarios in the cellular communications system*, and at least one nonlinear function to correct radio signal distortion.” ’704 patent, claim 1 (emphasis added). Petitioner refers to these claimed features of claim 1 as [1B.1], [1B.2], and [1B.3] as indicated below:

[1B.1] – “accessing a nonlinear pre-distortion machine learning model associated with the base station”;

[1B.2] – “wherein the nonlinear pre-distortion machine learning model includes model parameters associated with values corresponding to one or more deployment scenarios in the cellular communications system”; and

[1B.3] – “and at least one nonlinear function to correct radio signal distortion.”

Similar to claim 1, independent claims 9 and 17 of the '704 patent each recite, in relevant part, “accessing a nonlinear pre-distortion machine learning model associated with the base station, wherein the nonlinear pre-distortion machine learning model includes model parameters associated with values corresponding to one or more deployment scenarios in the cellular communications system, and at least one nonlinear function to correct radio signal distortion.” *Id.*, 15:35-42 (claim 9); 16:48-54 (claim 17).

Petitioner relies on Jüschke to disclose the above-recited elements of claims 1, 9, and 17. Pet., 23-32. This is incorrect, and Jüschke's failure to disclose at least elements [1B.1] and [1B.2] is fatal to the Petition.⁵

⁵ Patent Owner addresses both elements below, but begins with element [1B.2] for ease of discussion.

i. Petitioner Fundamentally Misunderstands and Fails to Properly Evaluate Element [1B.2]

Element [1B.2] recites, “wherein the nonlinear pre-distortion machine learning model includes model parameters associated with values corresponding to one or more deployment scenarios in the cellular communications system.”

As disclosed, the '704 patent seeks to develop a use-dependent nonlinear pre-distortion machine learning model for a base station that depends on the deployment scenarios in which it is used. As depicted in Figs. 1 and 3 of the '704 patent, the machine learning model 102 can receive a transmit radio signal 104 as input. *See* '704 patent, 7:19-20. The input signals 305 and input values to other layers are combined using multiplications with weight vectors 312 and accumulates/summations of these products along with bias vectors along with other operations. '704 patent, 7:20-26. The weight vectors can be multiplied with neuron layer inputs, while bias vectors can be added with the products of these summations (e.g., $\text{out} = \text{activation}(\text{in}_0 * w_0 + \text{in}_1 * w_1 + b_0)$). '704 patent, 7:26-29. The weight vectors of all the layers as well as other parameters including bias vectors are referred to as “model parameters.” '704 patent, 7:26-29.

The '704 patent decides what parameters to use for a given deployment scenario and then further refines values used for those deployment-specific parameters based on the deployment scenario. When initializing the model, the

'704 patent uses a model with “a fixed model architecture defining the node types and connections.” '704 patent, 8:23-27. The “fixed model architecture” may be chosen “from among a plurality of model architectures based on multiple training processes and comparison of distance metrics.” '704 patent, 8:28-30. Concerning the parameters in the model, the '704 patent explains the “initial parameters may also be chosen for a specific device or type of devices in a pre-deployment environment or based on devices or types of devices expected in a deployment environment in which the machine learning model will be deployed, in this case the parameters may be taken from another similar model.” '704 patent, 8:30-35. Thus, the initial parameters may be “based on devices or types of devices expected in a deployment environment in which the machine learning model will be deployed.” *Id.*

In addition to selecting the initial parameters, the '704 patent further refines values used for those deployment-specific parameters based on the deployment scenario. The '704 patent next explains how the system “determines updated values for the set of model parameters of that minimize the distance metric computed between the candidate transmit radio signal and the received radio signal.” '704 patent, 8:36-54. That training to update the values of the parameter set in the model is also based on potential deployment scenarios, as “the system iterates over multiple candidate transmit radio signals that correspond to various

potential deployment scenarios of the radio communication system to continually reduce the distance metric computed between the transmitted and received radio signals.” ’704 patent, 9:15-20.

Additionally, the ’704 patent allows for feedback to the initial model selection, providing that the error value or loss value corresponding to a distance metric can be “used to guide model selection (e.g. by training and evaluating a plurality of possible model architectures and selecting those with lower distance metrics for further evaluation or usage).” ’704 patent, 9:32-36; *see also id.*, 7:14-18 (disclosing that “[t]he neural network model may be selected from a plurality of possible model architectures (e.g. connections, layer sizes, hyper-parameter settings) based on an automated search process during the training phase in order to optimize performance”).

Petitioner treats the claimed recitation—“model parameters associated with values corresponding to one or more deployment scenarios in the cellular communications system”—as a single inquiry: whether Jüschke has a learning model with “model parameters” that are used in the cellular communications system. Pet., 26-29.

Indeed, Petitioner points to Jüschke’s generic array of “weight and bias parameters (w_{kj} , b_k)” in its attempt to satisfy this limitation, but without showing that the parameters themselves are selected for the model to correspond to one or

more deployment scenarios. *See, e.g.* Pet., 28, 29. As such, Petitioner fails to satisfy element [1B.2] relying on Jüscke alone.

**ii. Even Under Petitioner's Incorrect View of Element [1B.2],
Petitioner's Analysis Fails**

Further, even under Petitioner's view of element [1B.2], which requires only that the parameter values correspond to “one or deployment scenarios in the cellular communications system,” Jüscke still fails to render these features obvious for the following reasons.

By contrasting its disclosed system from “use dependent” systems, Jüscke confirms that it does not disclose or suggest the claimed features, which contemplate use-dependent “deployment scenarios.” Jüscke expressly discloses that by “using embodiments of the self learning/optimizing neural network, the parameters (addressing I/Q-imbalance and PA non-linearity in parallel for different frequency bands) may *commonly be considered and optimized* by embodiments of the present invention in a more advanced manner *compared to use dedicated*, non-self-lea[rn]ing algorithms.” Jüscke, ¶28 (emphasis added); *see also* Jüscke, ¶59. Simply put, in Jüscke's own words, Jüscke's algorithms are not “use dedicated” algorithms. In the context of element [1B.2], Jüscke's neural network does not “include[] model parameters associated with values corresponding to one or more deployment scenarios.” Thus, Jüscke's comparison distinguishes its “self learning” algorithms from “use dedicated” algorithms. In other words, Jüscke

distinguishes its own solution from “use dedicated” algorithms for setting or implementing its pre-distortion neural network processor, and parameters thereof.

For an additional reason, Jüschke fails to disclose or suggest any “nonlinear pre-distortion machine learning model” that includes “model parameters associated with values corresponding to one or more deployment scenarios in the cellular communications system.” Petitioner argues that Jüschke’s weight and bias parameters (w_{kj} , b_k) disclose the claimed “model parameters” of element [1B.2]. Pet., 26. However, Jüschke fails to disclose that any such parameters are “associated with value corresponding to one or more deployment scenarios in the cellular communications system,” as claimed. Petitioner contends that Jüschke’s “weight and bias parameters are implemented in deployments for GSM and LTE.” Pet., 26. Thus, Petitioner asserts that these “models and parameters apply to configurations mirroring the deployment scenarios explicitly described in the ’704 patent.” *Id.* Petitioner also asserts that “because Jüschke’s weight and bias parameters are implemented and trained for optimizing specific transmission environments (e.g., inline-mode deployment), POSITA would have understood that Jüschke’s *parameters correspond* to the particular configuration they are implemented for.” Pet., 29.

The flaw in Petitioner’s argument most clearly reveals itself in Petitioner’s conclusion for element [1B.2]. There, Petitioner argues that “a POSITA would

have understood that Jüschke's weight and bias parameters addressing I/Q and PA corrections teach *model parameters associated with values*, and Jüschke's configurations, including in-line configurations, teach *one or more deployment scenarios in the cellular communications system.*" Pet., 29. The problem with this conclusion is that element [1B.2] requires more than model parameters associated with values, ***alongside the existence of a transmitter*** deployed in a cellular communications system. Rather, element [1B.2] requires that the model parameter values must "correspond[] to one or more deployment scenarios in the cellular communications system." Jüschke makes clear that its model parameter values are neither trained nor set in any manner that relates to a deployment scenario of a transmitter device, but rather are tuned to approximate the inverse transfer function of the transmitter device 14.

As introduced above, Jüschke discloses that the training of the neural network processor is designed to accommodate the distortion resulting from the transmitter device, and Jüschke's training loop is isolated on the transmitter side, as shown in Figure 4. Jüschke also explains that the "post-distortion neural network processor may be used to ***identify the inverse transfer function of the nonideal transmitter device's transfer function*** using supervised learning." Jüschke, ¶18 (emphasis added). "As the training of the post distortion neural network processor converges, its response or transfer function will approximate the

inverse transfer function of the non-ideal transmitter device's transfer function.”

Jüschke, ¶19.

Thus, Jüschke does not disclose any correspondence of the weight or bias parameters, or the values thereof, to any deployment scenario disclosed or suggested by Jüschke. Instead, Jüschke simply trains the weight and bias parameters using a training algorithm to offset the distortion resulting from the non-ideal transmitter device, regardless of deployment scenario.

Petitioner suggests a correlation between Jüschke's type of mobile communication system and the parameters of Jüschke's training model, but the alleged correlation is a fiction of Petitioner's creation. Petitioner relies on Jüschke's paragraph 59 to argue that Jüschke *optimizes* its weight and bias parameter values for its particular mobile communication system such as “GSM, WCDMA and/or LTE.” Pet., 26 (quoting and citing to Jüschke, [0059]).

Petitioner misreads Jüschke's actual disclosure in this paragraph. In particular, Petitioner alleges that Jüschke's parameters “are ‘optimized’ *for the same.*” Pet., 26 (allegedly quoting Jüschke, [0059]). Petitioner's implication is that Jüschke somehow discloses that its weight and bias parameters are optimized for a deployment scenario such as GSM, WCDMA, and LTE networks. This is wrong.

Rather, Jüschke once again discloses that its system is “optimized” “in a more advanced manner *compared to use dedicated*, non-self learning algorithms.”

Jüschke, ¶59 (emphasis added). Jüschke does not disclose any correspondence between the parameter values resulting from the neural network training and the particular network in which the transmitter is operating. Rather, as already discussed, Jüschke trains the weight and bias parameters using a training algorithm to offset the distortion resulting from the non-ideal transmitter device, regardless of deployment scenario. Indeed, Jüschke expressly discloses that its technique is superior to a “use dedicated” algorithm for training.

Dr. Ding's supporting declaration does not lend any evidentiary support to Petitioner's assertion as to element [1B.2]. The Petition cites to paragraphs 142 and 146-47 of Dr. Ding's declaration throughout its discussion of this element [1B.2]. But a review of those paragraphs reveals that Dr. Ding does nothing more than restate the arguments advanced in the Petition. *Compare* Pet., 26-29 with Ex. 1003, ¶¶142-47. In the face of such unsupported and conclusory testimony, Petitioner's expert testimony should not be relied upon. *Consolidated Trial Practice Guide* at 36 (Nov. 2019) (“expert testimony cannot take the place of disclosure from patents or printed publications”); 37 C.F.R. § 42.65(a).

For these reasons, the Petition fails with regard to Ground 1 and independent claims 1, 9, and 17. Grounds 2 and 3 do not remedy the failures of Ground 1's challenges to the independent claims, particularly as Petitioner does not rely on Holt or Dzierwa to remedy the deficiencies of Jüschke with regard to element [1B].

iii. Jüschke Also Fails to Render [1B.1] Obvious

Addressing element [1B.1], Petitioner argues that “Jüschke’s teachings, including its flexible radio transmitter, can be implemented within a base station.” Pet., 25. Based on the arrangement of the radio transmitter implemented in a base station, Petitioner follows that a “POSITA would have understood that Jüschke teaches that neural network 13 ... can be associated with the base station by being implemented in a flexible transmitter that itself is implemented in a base station.” Pet., 25. Recall that Petitioner bases its Petition on the notion that “Petitioner ... interprets all claim terms in accordance with their plain and ordinary meaning.” Pet., 15. Thus, Petitioner does not seek to redefine “associated with the base station” to be “implemented within” the base station.

Moreover, Petitioner’s logic for suggesting “implement within” satisfies “associated with” is wrong, and nothing in Jüschke supports an association between a base station and neural network 13. For example, Jüschke fails to disclose whether the existence (or non-existence) of a base station supporting a transmitter would have any effect on the neural network 13 designed to approximate the transmitter’s inverse transfer function, and Petitioner fails to present any evidence of such an effect or association. Petitioner’s assertion of some association between a base station and a neural network 13 is purely conclusory.

As already introduced above, Element [1B.1] requires that a “nonlinear pre-distortion machine learning model” is “associated with the base station.” For all the reasons explained above, Jüschke’s makes clear that the self learning/optimizing neural network implemented in Jüschke approximates the inverse transfer function for the transmitter device. Petitioner plainly fails to identify any association between a base station in which a transmitter is located and Jüschke’s neural network, and lacks any evidence of such association. Indeed, Jüschke’s disclosures indicate that the existence or non-existence of a base station would have no bearing on Jüschke’s neural network since the goal of the training is simply to approximate the inverse transfer function of only the transmitter. Under these circumstances and disclosures, Petitioner provides no basis by which a POSITA would view Jüschke’s neural network as somehow associated with a base station.

For at least these reasons, Jüschke fails to disclose any association between a base station in which a transmitter device is located and the self learning/optimizing neural network implemented by Jüschke, or the weight and bias parameters achieved to account for the transmitter distortion.

For these reasons, Jüschke also fails to disclose or suggest Element [1B.1].

iv. Claims 9 and 17 Also Survive Petitioner's Challenges

For each of the reasons provided above, the Petition's challenge of independent claims 9 and 17 is also deficient. Petitioner states that "Claim limitations [9C]-[9G] are nearly identical to [1A]-[1E] and rendered obvious by Jüschke for the reasons discussed in Sections VI.B.2-8, *supra*" (Pet., 54) and "Claim limitations [17A]-[17E] are nearly identical to [1A]-[1E] and rendered obvious by Jüschke for the reasons discussed in Sections VI.B.2-8, *supra*." Pet., 56.

As explained below, the addition of Holt and Dzierwa is not provided to shore up the Petition's failures as to element [1B]. As such, Patent Owner respectfully submits that claims 1, 9, and 17 survive these proceedings.

C. Petitioner's Reliance on Holt for Independent Claims 1, 9, and 17 Does Not Remedy the Shortcomings of Jüschke

The Petition proposes to combine Holt with Jüschke in Ground 2. However, the Petition does not rely on Holt to remedy the shortcomings of Jüschke as addressed in Section IV.A-B above. Instead, Petitioner relies upon Holt to disclose a loss function, and proposes to modify Juschke's training with Holt's loss function for elements [1E], [9G], and [17E]. Pet., 64-67.

Because the addition of Holt is not provided to shore up the Petition's failures as to element [1B], claims 1, 9, and 17 survive this second ground as well.

D. Ground 3 Does Not Remedy the Shortcomings of Jüschke

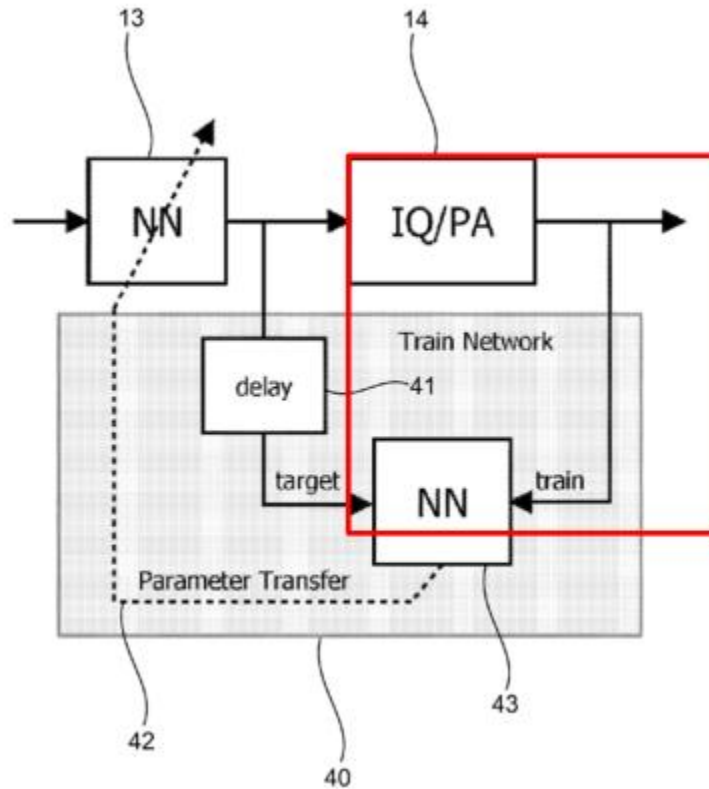
Once again, the Petition does not rely on Dzierwa to remedy the shortcomings of Jüschke as addressed in Section IV.A-B above. Instead, Petitioner relies upon Dzierwa for features of dependent claims 2, 10, and 18. Pet., 83-87. Therefore, Ground 3 does not establish any likelihood of success as to independent claims 1, 9, and 17.

E. Ground 2 Also Fails Against Dependent Claims 4-6, 12-14, and 20-22 Because Neither Jüschke Nor Holt Trains an Encoder Model or Transmitter Using a Received Radio Signal as Required by These Claims

Dependent Claims 4-6, 12-14, and 20-22 are challenged only in Ground 2, based on Jüschke in view of Holt. As introduced above, exemplary dependent claim 4 includes the following method steps: [4A] “obtaining a received radio signal that corresponds to a representation of the transmit output radio signal received at the one or more radio receivers;” [4B] “determining a distance metric between the transmit radio signal and the received radio signal;” and [4C] “updating the values of the model parameters for the particular deployment scenario based at least on the distance metric.”

Initially addressing element [4A], Petitioner concedes that Juschke's training loop exists purely on the transmission side, as Petitioner describes the feedback loop initiating from the “analog transmitter output” rather than from any signal received at one or more radio receivers. Pet., 63; *see also* Pet., 67. Petitioner also

annotates Juschke's Figure 4 as showing the output of the analog transmitter device 14, rather than any received signal from a receiver, being fed back.



Pet., 68. Petitioner then alleges that a “POSITA would have understood that a transmit output radio signal being from transmitter device 14 would be the same signal received by a radio receiver.” Pet., 68. This faulty allegation ignores all the distortion, noise, and interference that would disturb the signal between the output from the transmitter device 14 and the radio receiver. Notably, this is a distinction that the ’704 patent recognizes and corrects for, while Juschke does not.

As already introduced, Juschke also expressly discloses that “[a]s the training of the post distortion neural network processor converges, its response or

transfer function will approximate the inverse transfer function of the non-ideal *transmitter device's* transfer function.” Jüschke, ¶19 (emphasis added). Thus, Jüschke is focused on using the output of the transmitter device 14 to correct for distortion that results at the transmitter device. Jüschke does not train the post distortion neural network processor based on any received radio signal from one or more radio receivers, or on a distance metric computed between Jüschke's “transmit radio signal” and a “received radio signal.”

Shifting from Jüschke's failure to determine a distance metric between Jüschke's “transmit radio signal” and a “received radio signal” to train a transmitter device, Petitioner next looks to Holt. Pet., 72-74. But Petitioner fails to realize that Holt is equally unsuccessful in disclosing or suggesting these claimed features.

Petitioner relies upon Holt to disclose “adaptive training of a channel coding model including an encoder model, a channel model..., and a decoder model.” Pet., 11 (quoting Holt, Abst.). As Holt explains, Holt discloses a “computing device 100” that can perform the “creation and/or use of a channel coding model 110 that includes an encoder model 112, a channel model 114 and a decoder model 116.” Holt, 9:27-33.

Holt confirms that the channel model 114 is not a communication channel, but rather a model of a communication channel.⁶ Holt's "channel model 114 can be trained to emulate a communication channel according to the techniques described by the present disclosure." Holt, 10:2-4. The "role of the channel model 114 is to faithfully emulate the communication channel." Holt, 10:47-49. The "model trainer 118 can train channel model 114 using a loss function that describes a difference between an output of channel model 114 and an output of a communication channel, when a same set of input data is provided to both the communication channel and the channel model 114." Holt, 10:56-60.

Describing the encoder model, Holt discloses that the "encoder model 112 can be trained to encode input data for transmission over a communication channel according to the techniques described by the present disclosure." Holt, 9:58-61. Holt also discloses that the "decoder model 116 can be trained to learn how to decode data coming out of a communication channel back into the original input

⁶ Without discussion or explanation, the Petition alleges that an "actual communication channel' can also be used." Pet., 12 (quoting Holt, 18:1-2); *see also* Pet., 59. This is not accurate. Holt's disclosure explains that the decoder model 212 can "decode data coming out of the channel model 208" and also be "trained ... to learn how to decode data coming out of the communication channel 302 (e.g., the actual communication channel 302 used to train the channel model 208, as depicted in FIG. 5)." Holt, 17:62-18:3. Holt does not disclose or suggest a wholesale substitution of an actual communication channel with the communication model throughout Holt's disclosure, and Petitioner makes no attempt to explain why such a wholesale substitution would be obvious or why it would reasonably be expected to be successful.

data provided to the encoder model 112 and/or to the communication channel”

Holt, 10:17-20. On one hand, Holt notes that “FIGS. 3-4, 6-7, and 10-11 variously include some aspects associated with *training a decoder* model 116.” Holt, 10:22-23 (emphasis added). On the other hand, Holt discloses that “FIGS. 3, 4 and 7 variously include some aspects associated with *training an encoder* model 112.” Holt, 9:61-63 (emphasis added). Therefore, a POSITA faced with Holt *would not* have had reason to look to Holt’s Figures 6 or 11 for teachings on training an encoder model.

Petitioner specifically looks to Holt’s disclosure of the loss functions, and proposes to incorporate Holt’s loss function features into Jüschke. Pet., 58-60, 72-73. Petitioner points to Holt’s Figure 3 to exemplify “a first loss function 216 from an encoder model input 204 and decoder model output 214 with channel model 208 in between.” Pet., 58-59. However, Petitioner acknowledges that Holt’s Figure 3 is directed to computing a first loss function based on a channel model 208, not an actual channel, and does not involve any “received signal.” Pet., 58-59 (annotating Holt’s Figure 3). Therefore, this first loss function is based on a modeled channel, and is not computed between a “transmit radio signal” and a “received radio signal” that is obtained from a radio receiver.

Moreover, Holt’s first loss function is first “backpropagated through the decoder model while modifying the decoder model to train the decoder model, for

example, by modifying at least one weight associated with the decoder model.”

Holt, 5:67-6:3. Any error remaining in the first loss function is then

“backpropagated through the encoder model while modifying the encoder model to train the encoder model, for example, by modifying at least one weight associated with the encoder model.” Holt, 6:8-12. Thus, the backpropagation of the first loss function through the decoder model means that Holt adjusts for the difference between the output from the channel model (Holt’s second set of outputs 210) and the output from the decoder model (Holt’s third set of outputs 214) at the decoder model. Only the remaining error, *after the decoder model is trained*, would be backpropagated through the encoder model. Contrary to Petitioner’s suggestion otherwise, Holt’s Figure 3 does not disclose a process whereby the encoder model is adjusted based on a difference between Holt’s inputs 204 and outputs 214.

Apparently realizing this defect of Holt’s Figure 3, Petitioner next looks to Holt’s Figure 6, which unlike Figure 3, describes an “Actual Channel” 302 as it relates to Holt’s “Fourth Loss Function.” Pet., 59-60. Petitioner’s annotation of Holt’s Figure 6 is reproduced below:

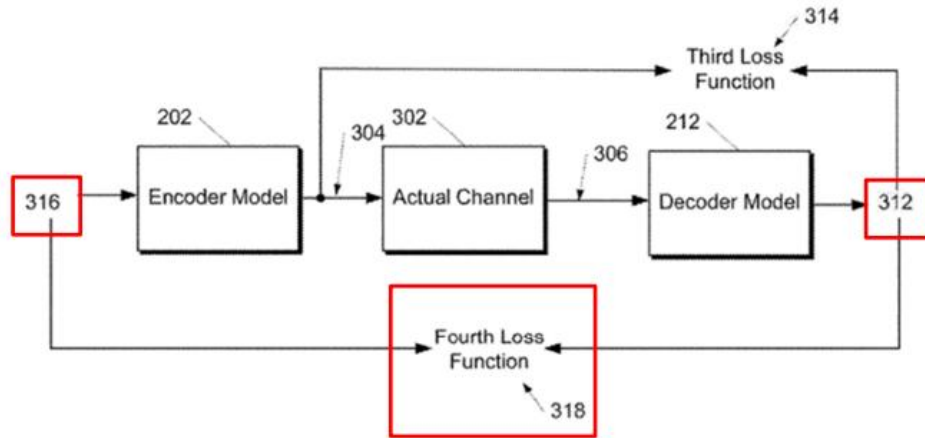


Figure 6

Pet., 60 (annotating Holt, Figure 6). Holt's Figure 6 is described also with respect to Holt's Figure 11. *See* Holt, 3:33-35 ("FIG. 6 depicts a block diagram of a fourth aspect of an example model training technique according to example embodiments of the present disclosure"); 3:51-54 ("FIG. 11 depicts a flow chart diagram of a fourth additional aspect of an example method to perform machine learning according to example embodiments of the present disclosure").

As already noted above, however, Holt's Figures 6 and 11 "include some aspects associated with training a *decoder model* 116." Holt, 10:22-23 (emphasis added). Holt expressly discloses that the "fourth loss function 318 can describe a difference between the third set of inputs 316 and the sixth set of outputs 312," and "can be backpropagated through the decoder model 212 while modifying the decoder model 212 *to train the decoder model* (e.g., *by modifying one or more weights associated with the decoder model 212*) to generate outputs that attempt to

reconstruct the data provided to the encoder model 202.” Holt, 18:40-48.

Similarly, describing Figure 11, Holt discloses “training the decoder model at 718 based on the fourth loss function involves backpropagating the fourth loss function through the decoder model *to train the decoder model* by modifying the decoder model (e.g., by modifying at least one weight associated with the decoder model).” Holt, 21:7-12 (emphasis added).

Holt is abundantly clear in its disclosure that the use of an actual communication channel in Figures 6 and 11 is for training a decoder model only, not an encoder model. Just as Jüschke falls short, Holt does not train its encoder model, or modify any transmit signal, based on any received radio signal from a radio receiver, or on a distance metric computed between a “transmit radio signal and a received radio signal” from a radio receiver. Petitioner’s assertions to the contrary are wrong.

Thus, even if combined, Jüschke in view of Holt still fails to disclose or suggest every feature of the challenged dependent claims 4-6, 12-14, and 20-22. This is because whether considered alone or in combination, there is no distance metric computed between a transmit radio signal and a received radio signal that is used to update values of the model parameters for the pre-distortion machine learning model, which is used for processing the transmit radio signal and generating a pre-distorted radio signal. Jüschke uses a feedback loop at the

transmitter only to process a transmission signal, while Holt uses its fourth loss function to train a decoder model only, not an encoder model. Thus, even if combined, the combination of these references therefore fails to disclose these claimed features of dependent claims 4-6, 12-14, and 20-22.

V. CONCLUSION

For the reasons presented above, Patent Owner asks the Board to confirm the patentability of independent claims 1, 9, and 17, and all the claims that depend therefrom, as challenged in Grounds 1 and 2, and also of dependent claims 4-6, 12-14, and 20-22 as challenged in only Ground 2.

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/Wayne M. Helge/

Wayne M. Helge, Reg. No. 56,905

James T. Wilson, Reg. No. 41,439

BUNSOW DE MORY LLP

277 S. Washington St., Suite 210 #1088

Alexandria, VA 22314

T: (571) 208-0186

Email: whelge@bdiplaw.com

Email: jwilson@bdiplaw.com

Amit Singhal, Reg. No. 71,021

ROSSI, KIMMS & MCDOWELL LLP

20609 Gordon Park Square, Suite 150

Ashburn, VA 20147

T: (703) 726-6024

Email: amitsinghal@rkmlp.com

Counsel for Patent Owner DeepSig Inc.

CERTIFICATE OF WORD COUNT

The undersigned certifies that the foregoing PATENT OWNER'S RESPONSE complies with the type-volume limitation in 37 C.F.R. § 42.24(b)(2). According to the word-processing system's word count, the brief contains 8,414 words, excluding the parts of the brief exempted by 37 C.F.R. § 42.24(a).

By: /Wayne M. Helge/
Wayne M. Helge (Reg. No. 56,905)
Counsel for Patent Owner

CERTIFICATE OF SERVICE

Petitioner has consented to e-mail service in this proceeding. Pursuant to 37 C.F.R. §42.6, the undersigned certifies that on this date, a copy of the foregoing document was served by email upon the following counsel at the below email addresses:

KING & SPALDING LLP
Brian Eutermoser – beutermoser@kslaw.com
Chris Campbell – ccampbell@kslaw.com
John Roehrick – jroehrick@kslaw.com

Dated: June 10, 2025

/Wayne M. Helge/
Wayne M. Helge (Reg. No. 56,905)
BUNSOW DE MORY LLP
277 S. Washington St., Suite 210, #1088
Alexandria, VA 22314
Email: whelge@bdiplaw.com
Telephone: 571-208-0186

Counsel for Patent Owner