

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 PRELIMINARY RESPONSE

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Pursuant to 37 C.F.R. § 42.107, Patent Owner DeepSig Inc. (“DeepSig” or “Patent Owner”) files this preliminary 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”), should be denied.¹

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 Pat., 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 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

¹ By submitting this Preliminary Response, no waiver of any argument is intended by Patent Owner. Patent Owner will have a right to file a complete response to the Petition, should the Board institute *inter partes* review. 37 C.F.R. § 42.120(a).

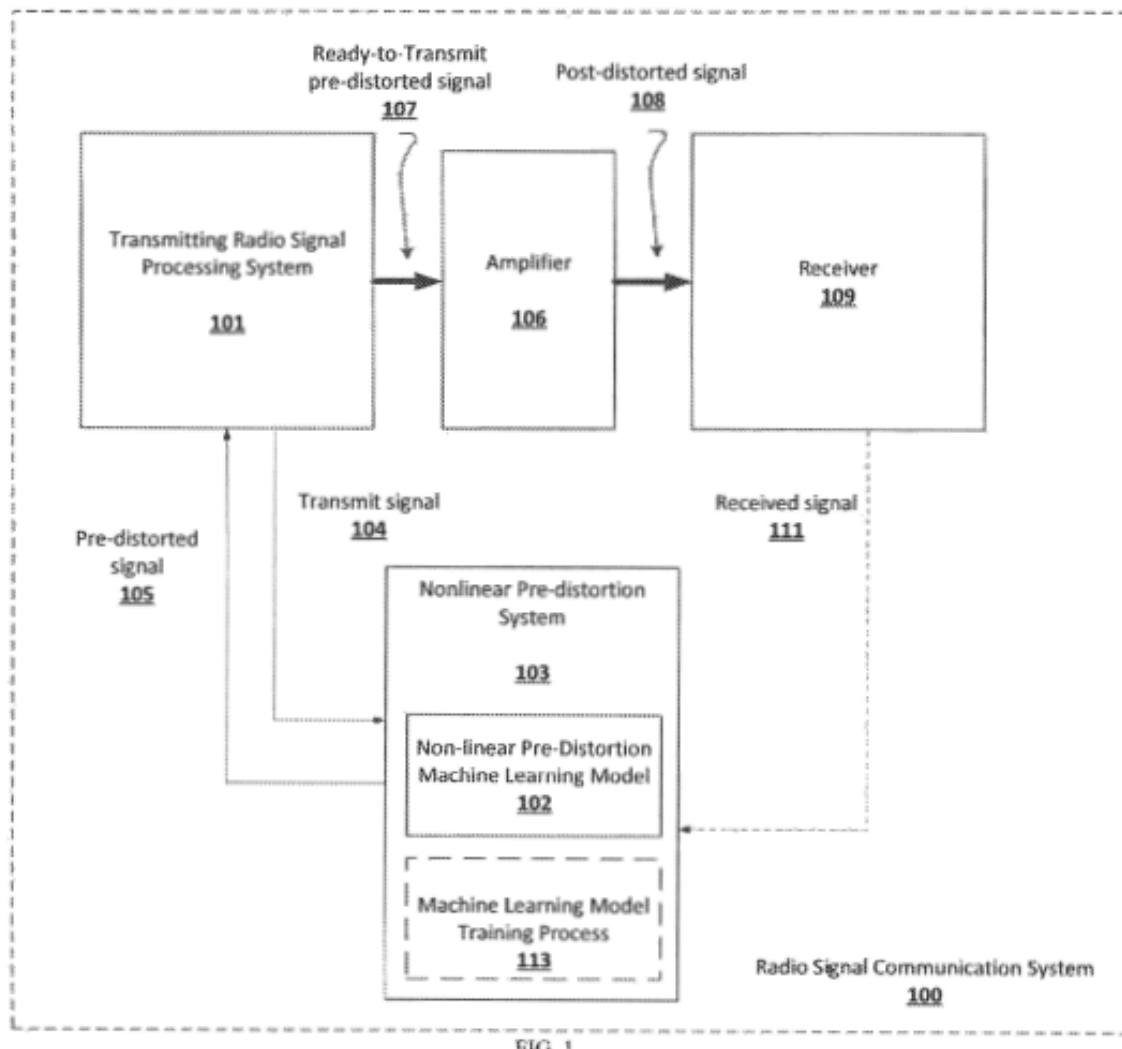
unlike the asserted prior art, the '704 Patent does more than attempt to correct for general distortion that arises in one particular component, such as a transmitter.

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.

As the '704 Patent acknowledges, a “radio communication system 100 may have multiple sources of distortion and/or interference.” '704 Pat., 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 Pat., 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 Pat., 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 Pat., 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 Pat., 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 Pat., 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 Pat., 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 Pat., 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 Jüschke² 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***, but Jüschke

² Ex. 1005, EP 2,538,553 A1 to Jüschke *et al.* (“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 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 Jüscke discloses a 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.

As discussed in more detail below, Petitioner's challenges fail, and the Petition should be denied without institution.

II. THE '704 PATENT DISCLOSES AND CLAIMS 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 Pat., 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 Pat., 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.”).

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 Pat., 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 Pat., 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 Pat., 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 Pat., 5:54-59 (emphasis added).

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 Pat., 14:15-35 (claim 1) (emphasis added).

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) (emphasis added); 16:48-54 (claim 17).

Thus, each of the independent claims challenged in the Petition include common features that are neither disclosed nor suggested by the

Jüschke reference, whether considered alone or in combination with
Petitioner’s secondary references.

III. THE BOARD NEED NOT REACH ANY CLAIM CONSTRUCTION ISSUES TO DENY THE PETITION

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.”). Without waiving its right to submit constructions
in a Patent Owner Response, Patent Owner submits that the Board need not engage
in any pre-institution claim construction to deny the Petition. 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 construction of the above-
identified terms.

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.³ Pet., 15-56. Ground 2 contends that claims 1-24 are
obvious over Jüschke in view of Holt.⁴ Pet., 57-80. Ground 3 is only asserted

³ “Jüschke” is defined in fn. 2, *supra*.

⁴ Ex. 1006, U.S. Patent No. 10,552,738 to Holt et al. (“Holt”).

against dependent claims, and contends that claims 2-6, 10-14, and 18-22 are obvious over Jüschke in view of Holt and Dzierwa.⁵ 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 account for any deployment scenarios. 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).

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 “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).

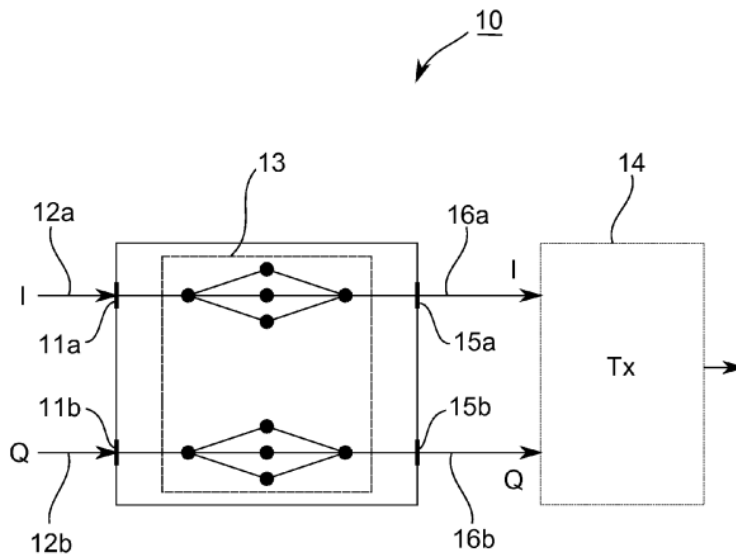
⁵ Ex. 1007, U.S. Patent No. 10,122,479 to Dzierwa (“Dzierwa”).

Therefore, while Jüschke discloses a 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.

For these reasons and as discussed below, Grounds 1 and 2 are facially deficient in establishing the unpatentability of any challenged independent claim, and Ground 3 does not remedy the deficiencies of either Grounds 1 or 2. For these reasons, the Petition should be denied without institution.

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

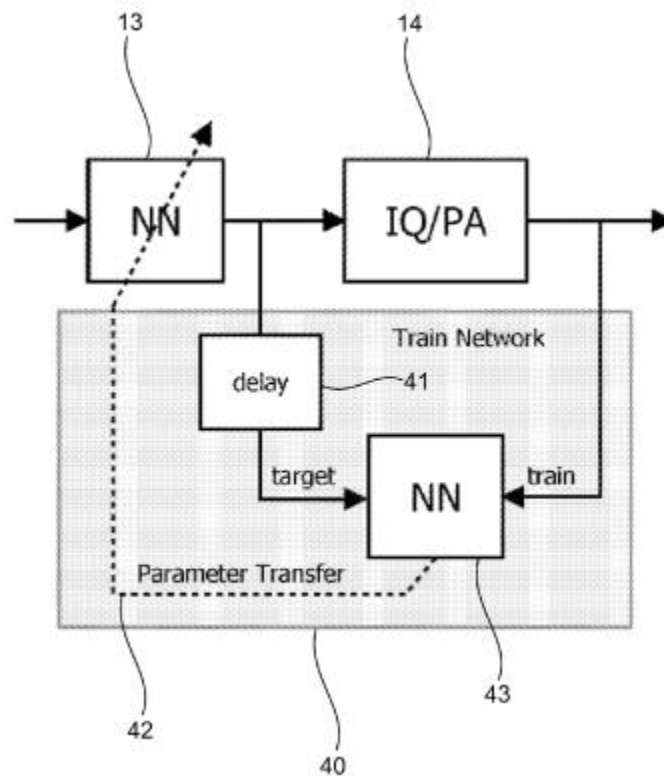
In Jüschke's FIG. 1, reproduced below, Jüschke discloses an apparatus (10) having an input (11a, 11b) for I and Q components of a signal (12a, 12b), a pre-distortion neural network processor (13) to obtain a pre-distorted digital baseband signal (16a, 16b), and a transmitter device (14). Jüschke, FIG. 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. 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. 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**

These technical details confirm that Jüschke, whether considered alone or in view of Holt, fails to disclose every claim requirement of the challenged '704 Patent claims. 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 Pat., 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 clearly incorrect, and Jüschke’s failure to disclose at least elements [1B.1] and [1B.2] is fatal to the Petition.⁶

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 Pat., 7:19-20. The input signals 305 and input values to other layers are combined using multiplications with weight vectors 312 and

⁶ Patent Owner addresses both elements below, but begins with element [1B.2] for ease of discussion.

accumulates/summations of these products along with bias vectors along with other operations. '704 Pat., 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 Pat., 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 Pat., 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 Pat., 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 Pat., 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 Pat., 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 Pat., 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 Pat., 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 Pat., 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”).

In this context, element [1B.2]’s recitation of “model parameters associated with values corresponding to one or more deployment scenarios in the cellular communications system” would be understood such that both the parameters in the model *and* their associated values “correspond[]to one or more deployment scenarios in the cellular communications system.”

Petitioner, on the other hand, 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 Jüschke 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,” Jüschke still fails to render these features obvious for the following reasons.

By contrasting its disclosed system from “use dependent” systems, Jüschke confirms that it does not disclose or suggest the claimed features, which contemplate use-dependent “deployment scenarios.” Jüschke 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.” Jüschke, ¶28 (emphasis added); *see also* Jüschke, ¶59. Simply put, in Jüschke’s own words, Jüschke’s algorithms are not “use dedicated” algorithms. In the context of element [1B.2], Jüschke’s neural network does not “include[] model parameters associated with values corresponding to one or more deployment scenarios.” Thus, Jüschke’s comparison distinguishes its “self learning” algorithms from “use dedicated” algorithms. In other words, Jüschke 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 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, claims 1, 9, and 17 survive these proceedings, and the Petition should be denied without institution.

C. Petitioner's Reliance on Holt 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 Jüschke'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, and the Petition should be denied without institution.

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.

V. CONCLUSION

For the reasons presented above, the Petition should be denied, and no *inter partes* review should be instituted.

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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 PRELIMINARY RESPONSE complies with the type-volume limitation in 37 C.F.R. § 42.24(b)(1). According to the word-processing system's word count, the brief contains 5,902 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: December 20, 2024

/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