Surface Wave Antenna Metallic Cell Pattern Design Using Neural Network Method

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***Abstract*—This work presents a surface wave antenna metallic cell pattern prediction method which can be generated based on the required far-field radiation pattern by the mean of applying Wasserstein generative adversarial network (WGAN) and bi-directional gated recurrent unit (Bi-GRU) neural network models. The predicted metallic cell pattern has been 3D-modelled in CST and the radiation pattern shows less than 1 dBi variation level from the desired input radiation pattern.**

Keywords—Neural network, millimetre-wave (mmWave), surface wave antenna.

I. INTRODUCTION

In the FMCW vertical-looking radar (VLR) system design [1], the antenna utilised for upward-looking is a scalar feed horn antenna. The beam is pointing upward with an offset of 0.18º. The angle adjustment needs to be very accurate and is complicated to perform. Such antenna only provides a limited circular observation area with a diameter of 1.2m. Such narrow observation areas can only detect a limited number of insects. Cosecant-squared radiation pattern antennas could offer considerable improvements to the VLR system due to the fact that they enable an adapted distribution in the radiation pattern, which results in better space scanning. Conventionally, the cosecant-squared radiation pattern can be achieved by curve shaped reflectors [2] and phased array antennas [3]. However, these techniques are costly and large in size, which is incompatible with the compact VLR system. Therefore, a low fabrication cost and low profile surface wave antenna, designed by a neural network-based method, is proposed to have the cosecant-squared radiation pattern.

Trapped surface wave (TSW) is a type of surface wave and it travels along the inductive boundaries and keeps being trapped between the two mediums. The TSW plane can be formed by inductive boundaries, such as dielectric-coated plane conductors and corrugated surfaces [4]. The TSW can be disrupted and scattered out to free space by introducing metallic cells on the substrate surface. Different distributions of the metallic cells have different near zone *E*-field and thus have different far-field radiation patterns. The relationships between the metallic cells and the near zone *E*-field and the relationships between near zone *E*-field and far-field radiation pattern can be studied by neural network models. Once the relationships are confirmed, the metallic cell distribution can be obtained by using desired radiation pattern as input.

WGAN is a type of generative adversarial network that uses Wasserstein distance as the loss function. It leads to more stable training than the original GAN with less evidence of mode collapse [5]. WGAN is a data augmentation technique that produces new data samples, in this work, WGAN is used to produce near-zone *E*-field. GRU is a sequence processing model and is suitable for designing an effective sequence learning system to address sequence-in-sequence-out. Bi-GRU combines a forward and a backward GRU and enables the neural network model to improve the classification accuracy [6]. Bi-GRU is used to learn the relationship between near zone *E*-field and far-field radiation patterns and the relationship between near zone *E*-field and metallic cell patterns.

In this paper, a 30º dual-sided cosecant squared radiation pattern will be served as input to the neural network models to design the surface wave antenna. The full 3D electromagnetic (EM) simulation will be performed to verify the performance of the neural network models.

II. ANTENNA GEOMETRY

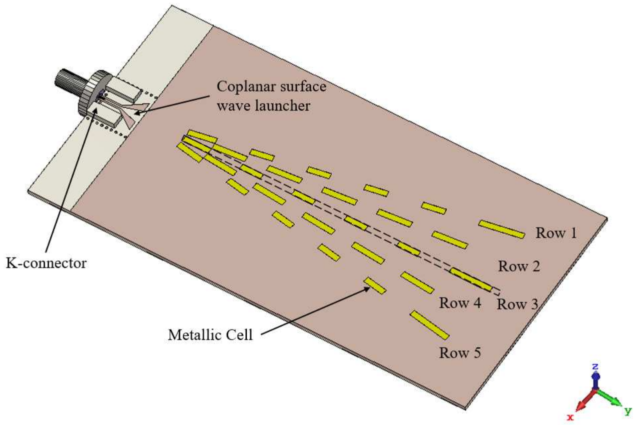

Fig. 1. The proposed surface wave antenna with coplanar SWL.

In this neural network-based method, a planar mmWave surface wave antenna is proposed to provide the training data to the neural networks. Fig. 1 shows the geometry of the proposed antenna operating at 34.5 GHz. The antenna comprises a coplanar surface wave launcher (SWL), five radial rows of metallic rectangular shape cells and a piece of conductor-backed microwave dielectric substrate. The five radial rows of metallic cells are separated by 5º in ϕ direction. The Rows 1, 3 and 5 are the same and consist of six metallic cells, while the Rows 2 and 4 are the same and have five metallic cells. The position of the metallic cells in Row 2 is determined by the position of gaps in Row 3, such that metallic cells in Row 2 fit precisely where the gaps are in Row 3. In the electromagnetic (EM) simulations, a K-connector (Amphenol SV Microwave 1621-60050) is implemented at the feed of this surface wave antenna for including its potential effect in the radiation pattern. In this research, a cosecant-squared radiation pattern in the *yz*-plane is to be determined. Therefore, the metallic cells are located symmetrically along the *y*-axis. The thickness of the metallic cells is 0.0175 mm. The metallic cells are printed on a piece of 0.787 mm thick microwave substrate Rogers RT5880 (ε_r = 2.2, tanδ = 0.009 at 10 GHz), which will provide the surface impedance of *j*117Ω with the appropriate excitation efficiency of 94.2% of the SWL. The substrate is 77.56 mm in length and 40 mm in width.

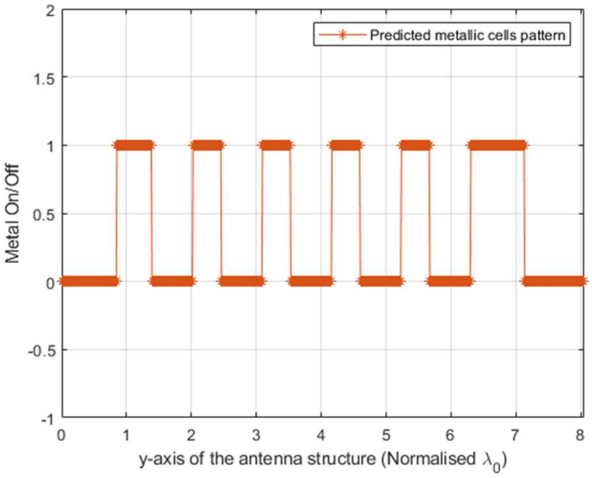

Fig. 2. The predicted metallic cell pattern of the central radial row.

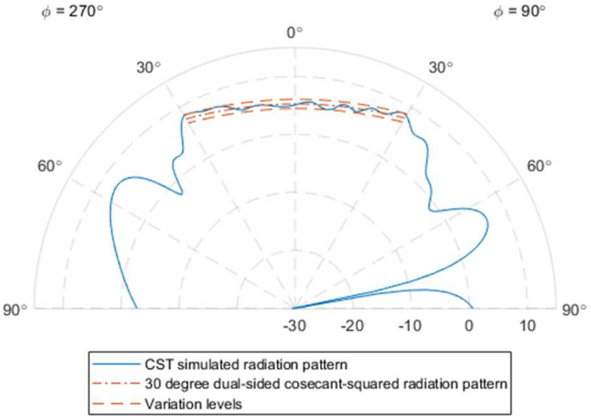

Fig. 3. The far-field radiation pattern (*yz*-plane).

III. METHODOLOGY AND EM SIMULATION RESULTS

In the neural network method, the WGAN and Bi-GRU model need to be trained first before prediction. A user-defined cosecant-squared radiation pattern is input to the neural network models first. The WGAN will generate a random near-zone *E*-field and the Bi-GRU model 1 will produce a corresponding far-field radiation pattern based on the WGAN generated near-zone *E*-field. The produced radiation pattern will be compared with the input radiation pattern to compute the loss (difference). If the loss is unacceptable, this procedure will be iterated until the loss is acceptable. If the loss is acceptable, it means the WGAN generated *E*-field can be used to feed the Bi-GRU neural network model 2 to generate the metallic cell pattern.

The dash-dot line in Fig.3 shows the user-defined 30° cosecant-squared radiation pattern. The input radiation pattern only regulates the dual-sided 30° range, whereas the range beyond the dual-sided 30° does not have any regulation. The 30° dual-sided cosecant-squared radiation pattern is served as the input to the neural network prediction models without considering the radiation pattern outside the range. After input the user-defined radiation pattern to the neural network models, the metallic cell pattern of the central radial row is shown in Fig. 2. The metal on or off denotes the value 1 or 0 in the figure, where 1 means there is metal and 0 indicates no metal at that point. Therefore, the distribution of the metallic cell of the surface wave antenna can be designed according to the value on the *y*-axis. Once the positions of the metallic cells in the central radial row are obtained, the rest of the rows can be defined according to the position relationship between the radial rows.

The ideal 30° dual-sided cosecant-squared radiation pattern is set as the goal to the neural network models. From Fig 3, it can be observed that the CST simulated radiation pattern is within ± 1dBi variation from the ideal cosecant-squared radiation pattern in the range from (ϕ, θ) = (270°, 30°) to (90°, 30°). The maximum gain is 8.49 dBi at (ϕ, θ) = (90°, 29°). This radiation pattern improves the diameter of the circular observation range to 9.8 m.

IV. CONCLUSION

A neural network-based method is proposed to predict the metallic cell pattern of the surface wave antenna. The predicted metallic cell pattern has been 3D-modelled in CST and shows less than 1dBi variation from the ideal input radiation pattern.

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