Dynamic Routing Programming for Power Communication Networks by Recurrent Neural Networks based Reliability Prediction and Particle Swarm Optimization

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***Abstract*—The coupling Power Communication Network (PCN) has been proven as an effective supplement to modern power grid for carrying various auxiliary services. Conventional fault processing methods for PCN implement short term recovery of services from interruption caused by external risks. However, such methods normally optimize topological structure of routing according to direct communication states. In this paper, we propose a machine learning based method to predict the reliability of nodes as well as links on PCN and dynamically program routing strategy alongside with the variation of external environment. The method comprehensively takes various factors into account as input to a Recurrent Neural Network to predict the reliability of hardware in incoming days. Based on the predicted reliability, a Particle Swarm Optimization method is exploited to optimize the routing to prompt the robustness of services by avoiding path with potential risk. Our experimental analysis on both simulation cases as well as realistic records demonstrates that the proposed dynamic routing programming method can be applied as a medium and long term supplement to existing fault processing methods.**

Keywords—Recurrent Neural Network, Particle Swarm Optimization, Smart Grid, Routing Programming

I. INTRODUCTION

Smart grid and integrated Power Communication Networks (PCN) carries both power infrastructure as well as corresponding communication functions such as information transmission, status surveillance and management. Services on PCN play a key role on ensure the quality of power system and reliability of related equipments. Furthermore, by communication between nodes, it implements diagnosis and recovery mechanism of congestion and interruption of links to ensure robustness of PCN itself [1].

Current PCN in China normally shares topological structures with corresponding power system. As typical backbone communication networks, nodes connected by optical fibers to implement fundamental functions such as routing and Quality of Service (QoS). Devices constructing PCN are inevitably affected by various factors which can finally lead to information delay and congestion. Such influence could be urgent because of external emergency conditions, e.g., disastrous weather such as storms lead to wide range communication interruption. Power grid over provinces are severely affected into isolated parts [2]. Conversely, the effect could be chronic, such as aging of devices results into instability of specific links as well as services on the paths [3].

Existing works achieved some results in fault tolerance and recovery of PCN from emergency interruption [4]. For instance, a decentralized method is proposed in [5] to detect and recover the link fault. A failure recovery method based on genetic cluster algorithm is also proposed in [6] to detect fault in cluster members and heads. In our previous works, we proposed to automatically perceive the congestion status of the node as well as links between neighboring nodes, and realize fault recovery by reinforcement learning methods [7]. Such works mainly detect the abnormal queueing delay on nodes as the essential feature of networks interruption, which means algorithms can only function after emergency occurs. Thus the whole system still faces the risk of service broke off directly.

On the other hand, from the perspective of service routing optimization, [8] proposed a Dijkstra algorithms based method to prompt the reliability of networks when system undergoes the risk of topological attack. Although the method is effective to prevent services from being interrupted, it still relies on the accurate prediction of incoming risk over PCN and adjust routing according to pre-calculated weights. For practical power system and coupling PCN scenarios, potential interruption is normally unpredictable. It is costly to intervene the whole entirety of system at each time emergency occurs. Moreover, the reliabilities of links and nodes on PCN are time varying parameters, which makes it inappropriate to decide routing strategies according to constant configuration. To address this problem, in this paper we propose a dynamic routing optimization method, which can autonomously learn typical characteristics and resulting effects from historical records, and exploit the knowledge to optimize service routing over PCN, finally prompt the reliability of service and load balance under various risk factors as outside constraints.

Our proposed approach exploits Recurrent Neural Networks (RNNs) [9] to predict key parameters in routing optimization by learning historical data including congestion states of nodes and links, weather forecast data and device states. The routing programming of services is based on Particle Swarm Optimization (PSO) method. The proposed method mainly focuses on medium and long term routing programming based on knowledge learned from historical records. Complemented by short term fault processing method, it can provide more effective management to possible risks on PCN. Meanwhile, we found PSO method shows higher efficiency for such dynamic routing problems with variant weights, especially for networks with larger scale. It can converge to an acceptable solution with higher speed, and resulting in explicit reduction of service risks.

II. Reliability Prediction with RNNs

The structure of power grid as well as coupling PCN is illustrated in Fig. 1. Different services can share nodes and links on PCN. Thus, to optimize the services routing requires to comprehensively take into account the reliability of devices on the path as well as importance of services. Since importance of services can be considered as fixed known factors in the model, we propose to predict the reliability of nodes and links, achieving dynamic routing programming both fixed and variant parameters.

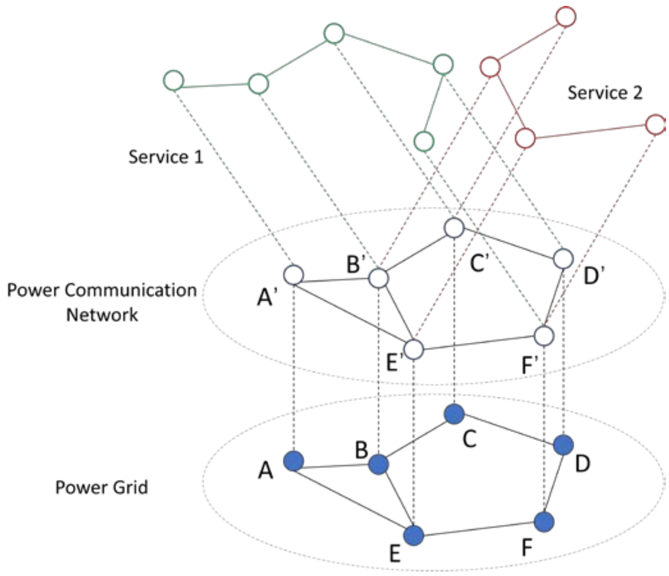

Fig. 1. Power grid shares the same topology with coupling PCN. Services carried on PCN are denoted by different colors.

Conventional service risk analysis methods mainly consider various types of factors as generative models with prior assumptions. Specific risks include nature factors such as earthquakes and storms, equipment factors such as aging and quality defects, human factors such as mis-operation during maintenance. Generative models accounting for these risks normally contain manually fixed hyperparameters without any adjustment alongside with time. It makes PCN tends to pay extra cost to reduce operation risks specifically for those long term unpredictable factors such as human factors. Routing of services could be degraded unnecessarily. Hence, we propose to directly predict the interruption risk of current nodes and links discriminatively by combining various factors from running records.

First, given a PCN model denoted as a graph $G(V,E)$, where V and E are the set of nodes and links respectively, the most explicit feature indicating congestion is the degree of node cache occupancy. During interval Δt at time t, we define the cache occupancy of node v as:

$$o_v(t) = \frac{\sum_{e\in\Delta E} N_{ve}(\Delta t)}{m_v}, \tag{1}$$

where $N_{ve}(\Delta t)$ is the number of packages received from link e, $\Delta E \subseteq E$ is the set consisting of neighboring node to v, and m_v is the maximum number of packages that v can process. We also estimate the congestion state of links by number of packages at its corresponding two nodes.

As an optical communication network, the error rate and optical power also directly reflect the communication quality between nodes on PCN. Besides these direct features, we collect other external factors including Severely Errored Second (SES), Forward Error Correction (FEC) number, Cyclic Redundancy Check (CRC) error, power voltage and age of equipment, temperature of environment and local weather forecast data, etc. All features are concatenated as input vector $\mathbf{o}(t)\in\mathbb{R}^D$ to RNNs, where D is the dimension of input. Common pre-processing methods such as normalization and centralization are deployed on $\mathbf{o}(t)$ to deliver standard input to RNN.

We adopt Long Short Term Memory (LSTM) [9]–[11] unit as our implementation of RNN. It consists of four gate functions and a memory cell c. Given input vector $\mathbf{o}(t)$ at time t, LSTM outputs $\mathbf{z}(t)$ as resulting inference. Simultaneously, information in c is recursively passed to next LSTM at time $t+1$, hence historical states can be retained within RNN continuously. The model is trained to predict the reliability of node or link in consequent week from aforementioned features. Our supervision information of reliability comes from the manual intervention records. The reliability $r(t)$ is negative correlated to times that the link is substituted by and recovered from backup link as

$$r(t) = \frac{2e^{-\sum_{i=1}^{7}\alpha_i C_i(t)}}{1+e^{-\sum_{i=1}^{7}\alpha_i C_i(t)}}, \tag{2}$$

where $C_i(t)$ is the change times occurring to target at the i -th day after time t. We use bias weights $\alpha_1 > \alpha_2 >,\ldots,> \alpha_7 > 0$ to emphasize the influence of observations from more neighboring days since we believe these observations are more relevant and urgent. The format of $r(t)$ is similar to sigmoid function to ensure a probability in the case that $C_i(t)\in[0,+\infty)$.

III. Routing Programming by Particle Swarm Optimization Method

Given predicted reliability risk for every node and link, we attempt to dynamically optimize service routing with PSO method. Note that the importance of different services should also be considered during optimization. We obtain these priorities information from QoS directly. The reason we choose PSO method to optimize routing strategy is because our proposed routing programming serves as a supplement for short term routing fault processing method. Instead of searching for global optimal routing paths at each programming time, an acceptable solution as better initialization to fault recovery is sufficient here. Conventional routing methods such as Dijkstra algorithm focuses on searching a global optimum by calculating multiple services risks at all nodes and links. In contrast, PSO method tends to converge to an acceptable local optimum with much higher efficiency. As a result, the routing strategy can vary alongside with external factors with very low cost at each time.

The particle $\mathbf{x}_i^k$ in the swarm here corresponds to a routing solution and its aggregated reliability calculated from all nodes and links. Here i is the index of the particle at the k -th iteration. Without mutual information from other particles, particle $\mathbf{x}_i^k$ adjusts routing paths at every nodes towards the best substitution with highest reliability $\mathbf{p}_i^k$. On top of that, mutual information $\mathbf{p}_g^k$ is delivered in the format of current best solution to impact the behavior of $\mathbf{x}_i^k$. We list the whole routing optimization procedure in Algorithm 1.

Algorithm 1 Routing optimization based on PSO method.

Require: Current routing solution $\mathbf{x}$ as well as reliability prediction $\mathbf{r}$ at time t .

Initialize N_p particles $\{\mathbf{x}_i^0\}_{i=1}^{N_p}$ by Gaussian distribution with $\mathbf{x}$ as expectation and a small variance.

for k iterations **do**

1. Calculate the $\mathbf{p}_g^k$ from current particles.
2. Calculate $\mathbf{p}_i^k$ s for every particle $\mathbf{x}_i^k$ s.
3. Update each particle by standard PSO method as (3).
4. Validate and rectify the resulting particle $\mathbf{x}_i^{k+1}$ under the constraints of QoS.

end for

return The resulting $\mathbf{p}_g^k$ at the last iteration.

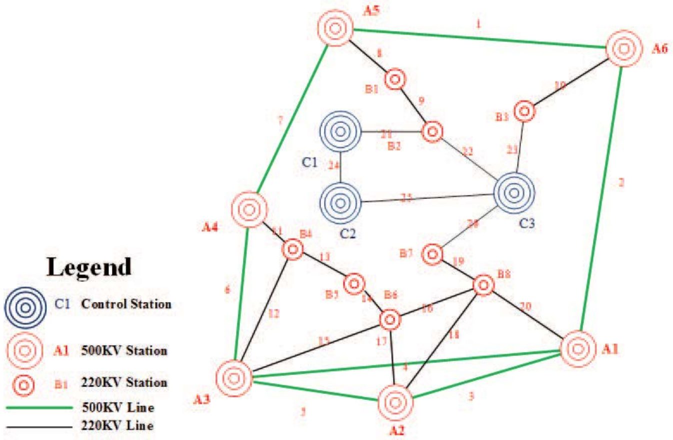

Fig. 2. The topological diagram of part of a power grid adopted as simulation scenario.

We update the particle at each iteration by following standard equation in PSO as:

$$\begin{aligned}\mathbf{x}_i^{k+1} = \mathbf{x}_i^k + c_1 * rand() * (\mathbf{p}i^k - \mathbf{x}_i^k) \\ + c_2 * rand() * (\mathbf{p}_g^k - \mathbf{x}_i^k),\end{aligned} \tag{3}$$

where c_1 and c_2 are combination weights to control the direction of update. The whole procedure of optimization is restrained by QoS, preventing routing solution from invalid. Our experimental results demonstrate that only small number of iterations (≤ 3) can lead to obvious change to routing as well as reduction of system risks. Hence we adopt a fix number of iterations as PSO strategy to achieve a slow dynamic routing programming alongside with time.

IV. Experimental Results

A. Performance Analysis in Simulation Scenarios

In this section, we analyze the performance of our proposed method in a simulation scenario. Here we take a simulation scenario as [8] into consideration as Fig. 2. The power grid architecture consists of several control stations and transformer stations at different levels. In this case, the coupling PCN shares the same topology as Fig. 2. The importance of every node and link are labelled with number. There are ten routes of relay protection services for power grid running on this topology.

Differing from case analysis in [8], where the interruption to network is a known external condition, here we aim to detect the urgency and predict the risk of reliability. We generate the simulation data leaded by variation of external factors with the same generative models described in [8]. We assume that the reliability of PCN is affected by three types of external factors: nature factor, equipment factor and human factor. For nature factor, we add two weather events represented by the resulting influence and corresponding forecast records to simulation. For equipment factor, the malfunction probability $p_i(t)$ of equipment at time t is suggested as:

$$p_i^T(t) = 1 - e^{-t/T_i}, \tag{4}$$

which exponentially correlates to the running period and specific duration constant T_i . For human factors, without any extra assumptions, human intervention can be formulated by Poisson distribution as:

$$p_i^\lambda(t) = 1 - e^{-\lambda_i n_i(t)}, \tag{5}$$

where λ_i average arrival rate constant of human factor.

We train the prediction model with generated operation records over one year. All records consist of aforementioned entries as described in Section II. The learned model is exploited to predict reliabilities on a test set with similar generated patterns. Predictions are combined with PSO method to implement the routing programming. By the optimization of routing, services are re-arranged to bypass links with higher potential risks. In Fig. 3, we demonstrate the risk control by our proposed method against different external influences.

Here we take link 'A4-A3' and a service with route 'A5-A4-A3-A2' as example. We illustrate the performance of proposed method at two different 90 days. The comparison of each period consists of simulated reliability of link (Sim A4-A3), predicted reliability of link (Predict A4-A3) and reliability of the whole service (Service). Here reliability is calculated according to equation 2. The first period ranges from day 50 to day 139, in which we simulate a weather attack as well as a human mis-operation respectively. From Fig. 3, one can see that the proposed method predicted the severe reduction of reliability from weather forecast data. Hence the routing optimization method attempted to avoid the interruption by modifying the topological graph and delivering the service through backup route. However, for unpredictable human factors, the method failed to predict the incoming interruption in advance. The adjustment of routing was only achieved by direct features of interruption. Also note that after external interruption disappeared, our proposed method recovered the default routing autonomously.

For the second period covering day 350 to day 439. We observe another routing switch due to aging factor of equipments. When reliability prediction showed that some link retained higher reliability than current candidate, it optimized the route of service autonomously. Therefore, we believe that our proposed method can serve as a long term dynamic routing programming mechanism.

We also compare the influence of iteration number k in algorithm 1 in Table I. Here the case of disastrous weather attack as in the first period of Fig. 3 is adopted for comparison. One can see that the prompt brought by PSO method is saturated when $k \geq 3$. This is because our proposed routing optimization is well initialized by existing full functional routing system. Only a few steps of iterations can result in acceptable optimization during interruption.

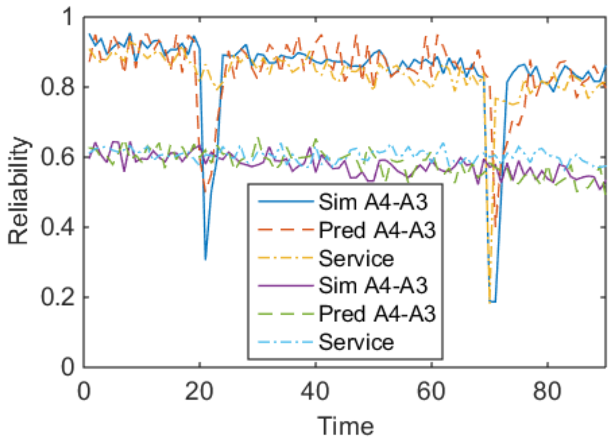

Fig. 3. The performance of dynamic routing programming with reliability prediction at different periods.

B. Performance on Realistic Operation Records

In this section, we experimentally test the performance of our proposed routing programming method on realistic running records. Our data comes from operation and maintenance records of optical transmission equipments in state grid, in which typical entries such as SES, FEC number and CRC errors as described in section II are contained. The weather forecast reports are also supplemented into data at corresponding dates. We train our prediction model with data covering one year from 2016 to 2017. The adjacent data from year 2018 is utilized for validation. With the dynamic routing optimization, we observe an obvious gain of 30% at average reliability of different services. In Fig. 4, we illustrate the number of routing switches at each month during the running of routing optimization method. One can see that most of the routing changes are caused by external factors such as human mis-operation or equipment aging. There also exists obvious increasing of routing changes during summer due to some weather conditions.

TABLE I. PROMPTS BROUGHT BY DIFFERENT ITERATIONS k IN ALGORITHM 1.

Iteration number	Average reliability prompt
1	$0.31 \to 0.31$
2	$0.31 \to 0.62$
3	$0.31 \to 0.79$
4	$0.31 \to 0.79$

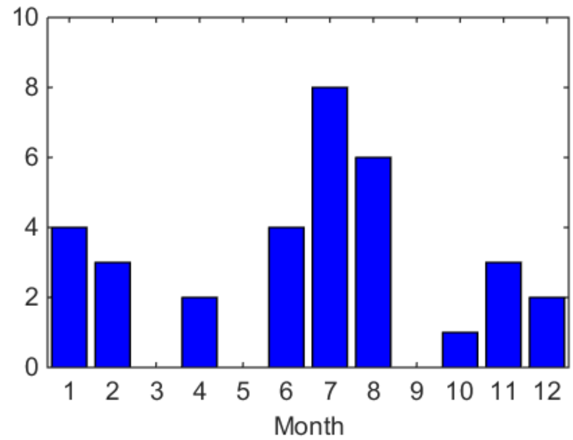

Fig. 4. The number of routing switches caused by dynamic routing programming at each month in our validation set.

V. CONCLUSION

This paper proposes a two stage dynamic programming method for services on PCN. By integrating LSTM units as reliability prediction models and PSO method as routing optimization method, we propose a comprehensive routing programming system to autonomously adjust routing strategy to avoid potential risk to services. Experimental results on both simulated and realistic data show that our proposed method can follow the variation of environment with only trivial extra computation cost. In our future work, we will further study the possibility of jointly learning prediction and optimization method as a whole entirety for dynamic routing programming.

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