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Electrical Load Forecasting Using Ant Algorithm With Short Forecast Time

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Abstract−The characteristics of the demand for electrical energy sometimes make the effort difficult to meet. Forecasting load growth and efforts to satisfactorily meet daily and annual load cycles are two difficulties that must be overcome. The average growth of electricity consumption in Indonesia is increasing every year. Given to build a power plant takes 8 to 10 years, then the system planners should look at the possibilities of the development of Power Systems 10 to 20 years ahead. This is necessary so that there is time to estimate and improve planning in a long-term perspective.The need for electrical energy consumption can also be used as an indicator of the trend in which the development of the sector or area is moving. The increasing need for electric power is certainly to be anticipated by providing a more adequate electrical system both in number and quality in the future. Thus, in electrical a system is needed forecasting (estimate) well to determine the need for electricity within a certain period of time either short-term, medium-term or long-term and the need for peak loads to reduce environmental uncertainty.

Keywords: Load forecasting, Load growth, Electricity consumption

1. INTRODUCTION

Forecasting electrical energy needs is essential for adaptive and sustainable electrical infrastructure planning. By predicting future energy consumption and peak loads, electricity providers can efficiently allocate resources, from the construction of new plants, the upgrading of transmission and distribution networks, to the maintenance of existing facilities. The accuracy of this forecasting has a direct impact on the stability of the electricity supply as well as the efficiency of operating costs that will ultimately be felt by the community and the economic sector as a whole. Without proper forecasting, the risk of shortages or oversupply can occur, leading to costly power outages or suboptimal infrastructure investments.the load quantity approach is chosen to analyze and project the electrical energy requirement. This method allows the identification of economic and social variables that have a strong correlation with electricity consumption. The grouping of customers into four main sectors-household, public and Commercial, hotel and Industrial—is a strategic move to understand the different dynamics of consumption in each segment. For example, population growth and increased per capita income may be the main drivers in the household sector, while business expansion and industrial policy will affect the industrial sector more.

To achieve high accuracy, electricity demand forecasting is performed segmented by customer sector. This approach recognizes that electricity consumption patterns vary significantly across sectors, such as residential, industrial, commercial, and public. By analyzing each sector separately, forecasters can identify specific drivers and unique trends affecting electricity consumption in each segment, resulting in more detailed and relevant projections.Forecasting or forecasting about something that will happen in the future based on data that exists at the present time and the past (historical data). By understanding the meaning of forecasting, then to make a good forecasting, we must first look for factors that can affect the variables to be predicted.

2. RESEARCH METHODOLOGY

Ants are able to sense their complex environment in search of food and then return to the nest by leaving pheromones on the paths they travel.Pheromones are chemical substances that come from the endocrine glands and are used by living beings to recognize sesame species, other individuals, groups, and to help the reproduction process. In contrast to hormones, pheromones spread outside the body and can only affect and be recognized by other similar individuals (one species), This process of pheromone inheritance is known as staggery, a process of modifying the environment that not only aims to remember the way home to the nest, but also allows the ants to communicate with their colony.Over time, in any case traces of pheromones will evaporate and will reduce the strength of their attraction. The longer an ant travels back and forth through the pathway, the longer the pheromones evaporate.When an ant finds a source of food, it does not immediately return to the nest without a trace. Instead, it leaves pheromones along its way home, marking the path it traveled. Other ants that later find traces of this pheromone tend no longer to move randomly, but rather to follow the trail. If these ants also manage to find food, they will return and reinforce the same pheromone trail, creating a positive feedback loop in which the successful path continues to be thickened.An interesting phenomenon occurs when an ant by Chance finds a more optimal (for example, shorter) path to a food source. This Ant will travel the path faster than its counterparts on other paths, and will automatically leave a trail of pheromones more in the same time. As a result, a high concentration of

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pheromones on this optimal path will attract other ants to switch and follow it. Over time, the less efficient pathways will be abandoned as the pheromones evaporate, while the most optimal pathways will dominate and become the only pathways used by ants from the nest to the food site as Figure 1.

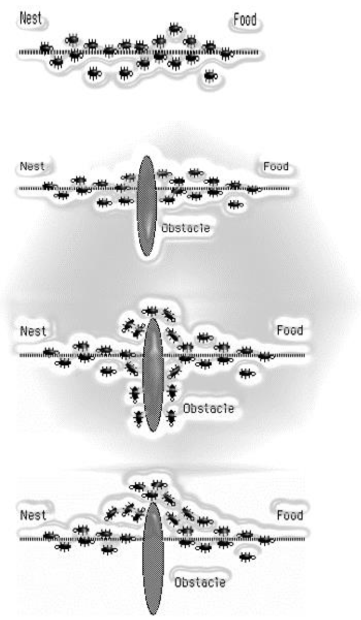

Figure 1: Ant Colony Chooses Shortest Path To Food Source

Adjacency Matrix for a graph with N vertices, the proximity Matrix has size n x n (n rows and n columns). If two vertices are connected then the Matrix element is worth 1, and preferably worth 0 if it is not connected.

	A	B	C	D	E	F	G
A	0	1	1	0	0	0	0
B	1	0	1	1	1	0	0
C	1	1	0	1	0	1	0
D	0	1	1	0	1	1	1
E	0	1	0	1	0	0	1
F	0	0	1	1	0	0	1
G	0	0	0	1	1	1	0

Figure 2. Abcdefg graph proximity Matrix

Adjacency ListIn the end x can be thought of as a list relation separate from the list relation on the graph connected to x. The list representation of contiguity gives an idea of the flexibility with the contiguity Matrix, but this representation is more than neat.The space (memory) used to store and e sides on the graph does not change = n head vertices + 2e list vertices. Performance list for ABCDEFG graph.

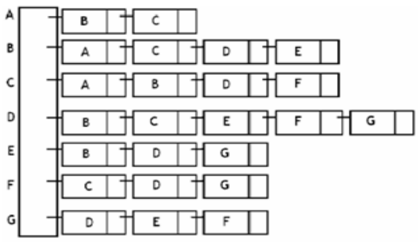

Figure 3. Proximity graph ABCDEFG

3. RESULT AND DISCUSSION

The relationship of forecasting with the Ant algorithm itself is inseparable from the shortest path or route that the Ant finds. Similarly, other algorithms determine the steps logically in order to produce an output that suits the needs. The logical steps are the same as the shortest route found by the ant in the explanation of the Ant algorithm.

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Basically, all existing algorithms have the same purpose, namely to be able to achieve certain goals such as the algorithm of ants in getting their food by the shortest route or other algorithms that aim to solve a problem.

In nature the ant colony is able to find the shortest route on the way from the nest to the places of food sources. Ant colonies can find the shortest route between the nest and the food source based on the footprints on the traverses. The more ants that pass through a path, the more obvious the footprints will be. This will cause the path traversed by ants in small numbers, the longer the density of ants that pass through it will decrease, or even not passed at all. On the contrary, the path traveled by ants in large numbers, the longer it will increase the density of ants that pass through it, or even all the ants will go through the path

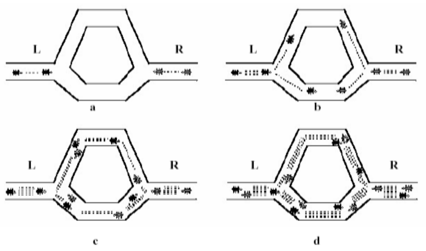

Figure 4. Methods of ants finding food sour

Shows there are two groups of ants that will travel. One group named L is a group that departs from the left direction which is an anthill and another group named R group that departs from the right which is a source of food. The two groups of ants from the departing point were in a decision-making position as to which path to take. Group L ants split two more groups. Part of the way up and part of the way down. This also applies to the group of ants R. that groups of ants walk at the same speed by leaving pheromones or footprints on the path traveled. The pheromones left by the group of ants that passed through the upper path have experienced a lot of evaporation because the ants that passed through the upper path are fewer in number than the ones below. While the pheromones that are on the way down, their evaporation tends to be longer. Because the ants that go through the bottom path are more numerous than the ants that go through the top path. the other ants finally decided to go down the path because there were still a lot of pheromones left. While the pheromones on the upper path have evaporated so much that the ants do not choose the upper path. The more ants that go down the path, the more ants that follow it. analyzing each sector separately, consumption patterns and driving factors in each segment can be obtained, resulting in a more accurate and relevant projection of electrical energy needs on daily, weekly and monthly predictions Figure 5.

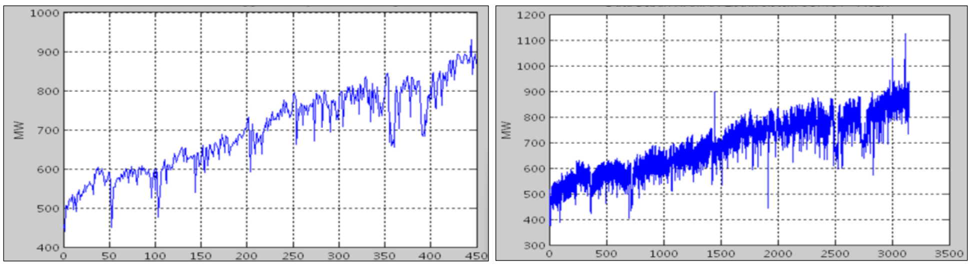

Figure 5. Daily and weekly load prediction

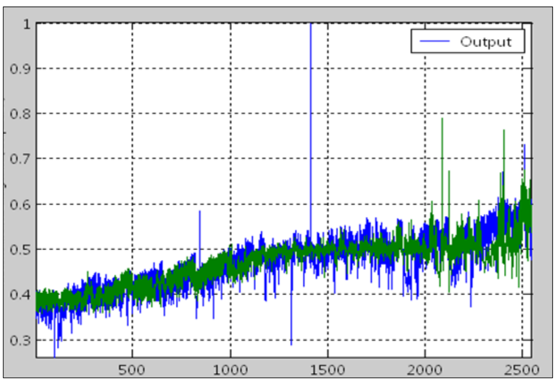

Figure 6. Load forecasting graph

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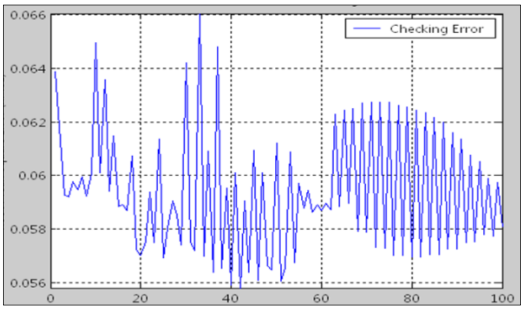

Figure 7. Checking Error

4. CONCLUSION

The application of Ant algorithms in short-term electrical load forecasting allows system operators to make faster and more informed decisions, from generation scheduling, resource allocation, to response to unexpected disruptions. By predicting electricity loads over a short span of time (for example, hourly or daily), electricity providers can optimize fuel usage, minimize operational costs, and ensure a stable supply of electricity. The relatively efficient computational speed of this algorithm, although it sometimes requires careful adjustment of parameters, makes it a promising tool for implementation in operational environments that require quick response.the successful implementation of the Ant algorithm for forecasting short-term electrical loads largely depends on the quality of historical data and the optimal adjustment of the algorithm parameters. Artificial pheromones and probability transition rules must be arranged in such a way as to balance exploration and exploitation. With continuous refinements to the model and input data, the Ant algorithm can be a highly effective solution to address the growing challenges of electrical load forecasting, contributing to more intelligent and adaptive electrical systems in the future.

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