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RESEARCH ARTICLE

Markov Chain: A Novel Tool for Electronic Ripple Analysis

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Abstract

Objective: To delineate a novel surrogate approach to analyse the ripple component by constructing a complex network using the Markov model. **Methods**: Adjacency matrices (A) are constructed from the digital storage oscilloscope output signal of the Full-Wave (FWR) and Half-Wave Rectifiers (HWR) without and with a filter. The centrality measures - indegree, outdegree, in closeness, out closeness, Weighted Network Clustering Coefficient (WNCC) – are also computed for the Markov chain. **Findings**: With the increase of filter capacitance, more elements in the adjacency matrix become zero. Finally, only one matrix element corresponding to $A_{10,10}$ remains nonzero for FWR and $A_{20,20}$ for HWR, indicating the total rectification of the signal at 10 volts. The Markov chain analysis shows that as the ripple component decreases, the number of unconnected nodes increases and the self-loop of the last node increases. For the rectifier output without filtering, it is found that all the nodes are interconnected through edges. The greater the filtering efficiency, the greater the indegree and outdegree, and the lesser the incloseness, outcloseness and WNCC measures.

Keywords: Complex network; Markov chain; Rectifier; Time series; Ripple

1 Introduction

The design and construction of electronic circuits necessitate the development of novel techniques for analysing the signals that introduced the field of signal processing, dealing with the synthesis and analysis of electrical, electronic, sound, image, and video signals[1,2].The popular signalprocessing techniques include fast Fourier transform, wavelet, nonlinear time series, complex network, and functional analyses[3]. The nature of the signal and the intended result decide the technique to be employed. Among the various techniques for signal analysis, the graph-theoretical approach seems to be the least explored, though graph-based electronic circuit analysis can be seen in the literature[4,5]. The modelling of real-world systems as networks or graphs gave birth to an emerging field of research known as Complex network analysis or Graph theory. Today graph theory has emerged as a potential tool in science, social science, communications, engineering, and technology [6].

Different types of signal models can be used to describe the properties of a signal. In a broad sense, signal models can be split into deterministic and statistical models. The statistical models are a set of the signal's statistical properties. Gaussian, Poisson, Markov, and hidden Markov processes are all examples of these kinds of statistical models [7]. The statistical models are based on the idea that the signal can be well described as a parametric random process and that the random process's parameters can be found precisely and well-defined [8]. The Markov chain model can be used to study systems with randomness. By changing the adjacency matrix of a network into a Markov transition probability matrix [9], it is possible to learn more about the system being looked into. The Markov chain model, representing a system where transitions occur between two states through a finite number of alternative states, is used to study systems of unpredictable nature. A process is termed 'Markov' if the probabilities of transition for shifting from one state to the next depend on the present state and not on any of the previous experiences undergone by the process while arriving at the present state. Even though many complex networks are directed and have weights, the way two nodes interact can be described not only by the presence of a link but also by a link with a direction and a different weight. By converting the directed and weighted network part of a complex system's adjacency matrix into a Markov transition probability matrix, it may be possible to get a deep understanding of the process at work.

Markov chain model is widely used in different fields of science, technology and social science. It finds several biomedical applications like the estimation of event detection and localization of biomedical signals like EEG and lung sounds [10,11]. It is also employed in laser-based applications to understand the system entropy in thermal lens signals and beam quality analysis [12,13]. Andrea et al employed Markov and semi-Markov models in Pharmacoeconomics [14]. The Markov transition probability matrix is made used by Silver and Silva et al. to study the socio-spatial neighbourhood evolution in cities [15]. This model also finds use in material science and electronics, where we can see many reports like building Markov chain algorithms for device construction based on oxide multilayers [16] and also for analyzing voltage profiles for solving energy demands [17]. Electronic signal processing is an area where the potential Markov chain model is the least explored. Hence, the present paper attempts to unwrap the potential of the Markov chain model, taking the most fundamental rectifier circuit as an example.

Rectifiers are unavoidable in several electronic circuits where alternating current (ac) conversion into direct current (dc) is required. The presence of ac components after rectification is known as ripple. Hence, the amount of ac component (V_{rms}) appearing along with the dc component (V_{DC}) at the output of the rectifier circuits is expressed using the parameter ripple factor ($\gamma = V_{rms} / V_{DC}$). When the value γ for a full-wave rectifier is 0.48, that for the half-wave rectifier is 1.21. For removing the ripple content, various types of active and passive filters are used to remove the ripple content, of which the passive capacitor filter is the simplest and most widely used. Passive filters include the shunt capacitor (C), the series inductor (L), the chock input (LC), the section or CLC filter, and the capacitor input filter [18]. Knowledge of the ripple factor is highly desirable in systems working in dc. The paper intends to manifest the potential of complex network analysis in electronic systems where the transformation from an oscillating to a steady state occurs. The reason for such a thought is that the network exhibits clusters with edges in an oscillating system. This study is a new way to look at half-wave (HWR) and full-wave (FWR) rectifier circuits using complex network analysis based on the Markov chain model.

2 Methodology

The analysis based on the graph's characteristics may be able to portray the transition in the system more attractively, particularly when the system is transitioning from a state of fluctuation to a steady state. One example of this kind of circuit is a rectifier. Depending on the effectiveness of the circuit's filtering, a rectifier may eventually reach a steady state with a constant DC output once the fluctuation is reduced by filtering [19,20]. To demonstrate the usefulness of graph theory in the field of circuit analysis, a half-wave rectifier (HWR), shown in Figure 1 (a), is built, and the alternating current (ac) component and direct current (dc) component at the output of the rectifier circuit is measured with a digital storage oscilloscope (DSO - 5050 A, 50 Hz). The equation used to determine the ripple factor (γ) is as follows:

$\gamma = V_{ac} / V_{dc}$ (1)

In addition to this, the HWR with capacitor filter, shown in Figure 1 (b), is built, and the ripple factor is computed using equation (1) before being confirmed with equation (2).

$$\gamma = \frac{1}{2\sqrt{3} f R_L C} \qquad (2)$$

The complex network of the full-wave rectifier with and without filter is constructed from the output waveform in the Digital storage oscilloscope (DSO). In this work, we analyse half-wave and full-wave rectifiers, without and with filter circuits, using a Markov transition probability-based network. First, the rectifier circuit is constructed, and the output voltage from DSO is recorded in CSV format. In this analysis, we choose the capacitance value as 0.22, 1, 10, 100 and 1000 μF.

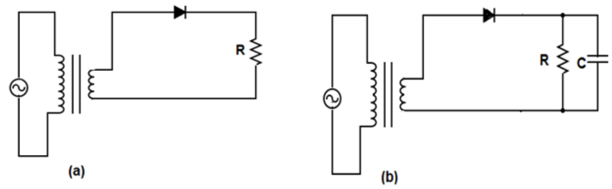

Fig 1. Half-wave rectifier circuit (a) without filter (b) with capacitor filter.

The voltage range of the rectifier signal is split into ten equal-width intervals with equal probability. Since the difference between the maximum and minimum voltage values is 10, the interval width is taken as 1. Then, for each data point, an integer equal to the ordinal status of the interval it falls is assigned consecutively. This ordinal state of the intervals is used as the network's nodes, with node '1' representing the segment's initial interval and node '10' representing the segment's final interval. Finding the co-occurrence of the mapped numbers such that each element delivers the number of transitions from the i^{th} node to the j^{th} node yields the adjacency matrix (A_{ij}), which is used to build the network. The weight of the corresponding transition is represented by the thickness of the edges in the complex network. The adjacency matrix, which gives the number of co-occurrence between two nodes of a fluctuating time series, has diagonal elements representing the self-loops in a multigraph.

By transforming a time series into a complex network, we can investigate the inherent structure and dynamical characteristics of a time series in terms of knowledge from complex network theory. The measures of the network- degree centrality (indegree and outdegree), closeness centrality (in closeness and out closeness), and weighted network clustering coefficient – can be used for analysing the signals. Degree (D) is a simple centrality measure of the node's number of edges and is calculated using equation 3. When the number of incoming edges to a node is referred to as indegree, the number of outgoing edges is called outdegree. A self-loop is considered an incoming and outgoing edge[(21)].

$$D = \frac{2E}{N(N-1)} \qquad (3)$$

Closeness centrality (CC) measures the average shortest distance between each vertex and every other vertex. More specifically, it is the inverse of the average shortest distance between the vertex and each and every other vertex in the network[(22)].

$$CC = \frac{N-1}{\sum_j w(i,\ j)} \qquad (4)$$

where N is the number of nodes and w_{ij} is the shortest path length between node i and node j in the network. For incloseness, the distance measure is from all nodes to node i. For out closeness, the distance measure is from node i to all nodes.

The weighted network clustering coefficient (WNCC) of a node i measures how densely a node i is connected to its neighbourhood[(23)].

$$C_i = \frac{\sum_{j,k} w_{ij} w_{jk} w_{ki}}{\sum_{j,k} w_{ij} w_{ki}} \qquad (5)$$

Weight for the node i to node j edge is $w_{i,j}$. The average of the weighted clustering coefficients for each node in the network makes up the weighted network clustering coefficient. When analysing a graph, the adjacency matrix can be used to determine how many times a given piece of data jumps from one interval to another. A temporally constant output from an ideal system has only one nonzero diagonal element with a value of one in the weighted probability matrix. Off-diagonal elements of a weighted probability matrix have a higher likelihood of occurring than other elements of the matrix when the perturbation of an ideal system by complicated causes occurs. In order to carry out the network analysis of the data, the software known as Matlab is utilised. The output of the Matlab program gives a weighted adjacency matrix, which is loaded into the open-source Cytoscape software for the graphical visualisation of the created network.

3 Result and discussion

Circuit analysis is unavoidable in electrical engineering for understanding and analysing electrical systems. The present work discovers the possibility of applying graph theory in circuit analysis, considering the most fundamental rectifier circuit as an

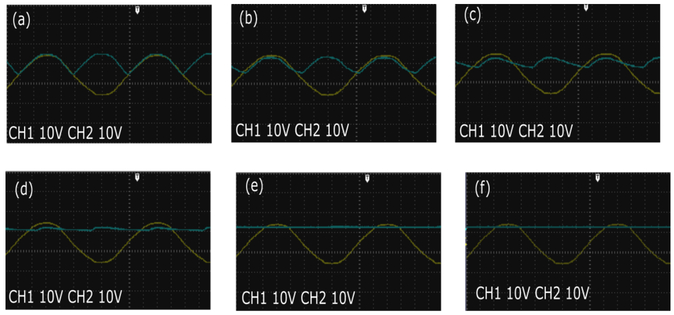

Fig 2. DSO output of the full-wave rectifier with filter capacitance (a) 0, (b) 0.22, (c) 1, (d)10, (e) 100, (f) 1000 μF

example as the methodology can be extended for analysing any signal[24–27]. The output of full-wave and half-wave rectifiers without and with capacitor filters (0.22, 1, 10, 100, 1000 μF) recorded in the digital storage oscilloscope are shown in Figures 2 and 3 , respectively. The outcome of the filter capacitor on the output is analysed by constructing the adjacency matrix A. The representative adjacency matrices for the FWR without and with capacitors (0 μF and 1000 μF) are given in Table S1 and Table S2 of the supplementary file, and the Markov chain constructed is shown in Figure 4. From Table S1, it is understood that there is a significant spread in the transition probability matrix when there is no filter capacitor[27].

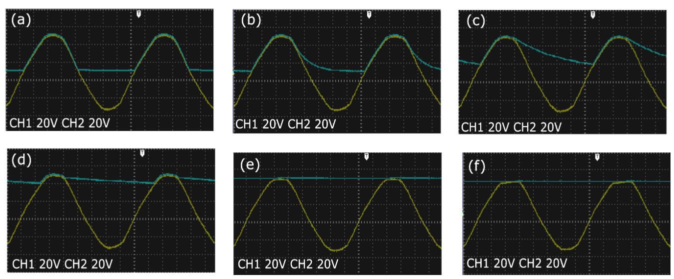

Fig 3. DSO output of the half-wave rectifier with filter capacitance (a) 0, (b) 0.22, (c) 1, (d)10, (e) 100, (f) 1000 μF

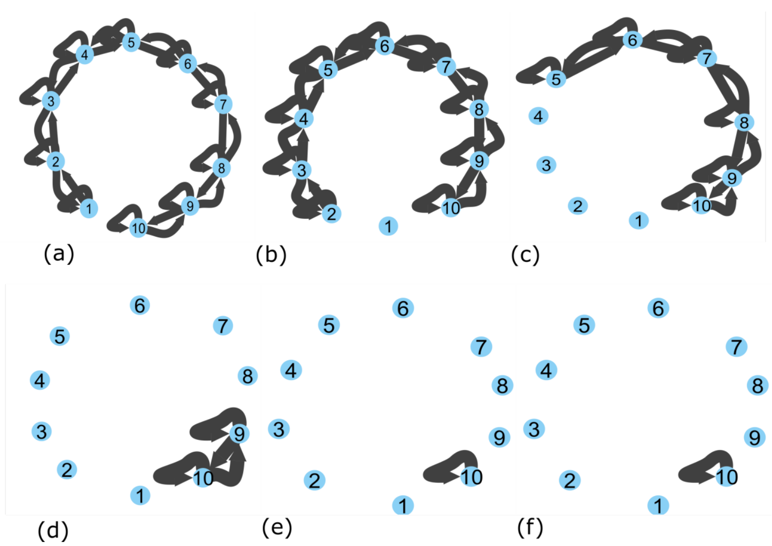

Fig 4. Markov chain constructed from the output of full-wave rectifier with filter capacitance (a) 0, (b) 0.22, (c) 1, (d)10, (e) 100, (f) 1000 μF

As the capacitance value of the filter capacitor increases, more and more matrix elements become zero and finally, a single nonzero matrix element corresponding to $A_{10,10}$ remains. This suggests that the signal is completely rectified at a voltage 10, corresponding to row or column number, with no ripple component. The adjacency matrix can be represented pictorially through the complex network- Markov chain, as shown in Figure 4. Here, the thickness of the lines connecting the node indicates the weight of the edges and self-loops. As the level of rectification increases with the increase in capacitance value, the number of unconnected nodes increases, resulting in the high weighted self-loop of the last node. The analysis for the half-wave rectifier circuit, shown in Figure 1, is also carried out. The adjacency matrix constructed from the output of the half-wave rectifier without and with filter is given in Table S3 and Table S4 of the supplementary file and the corresponding Markov chain in Figure 5. The inference drawn from the adjacency matrix and Markov chain of a full-wave rectifier is found to agree well for the half-wave rectifier also.

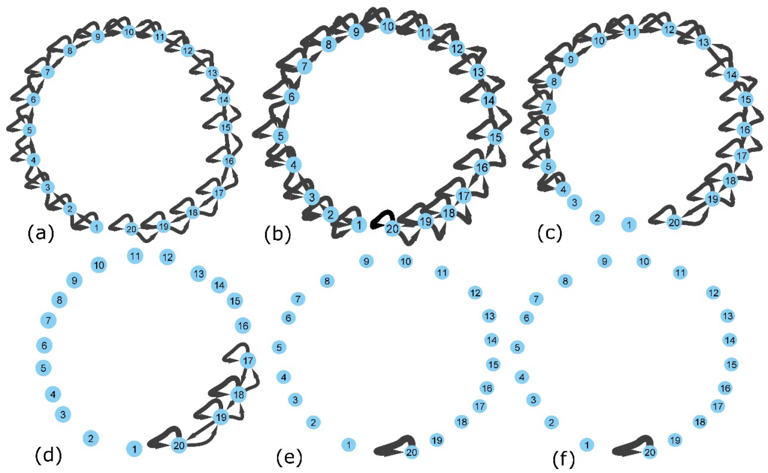

Fig 5. Markov chain constructed from the output of half-wave rectifier with filter capacitance (a) 0, (b) 0.22, (c) 1, (d)10, (e) 100, (f) 1000 μF

The variations of the graph features - indegree, outdegree, incloseness, outcloseness, and WNCC - for the FWR and HWR are shown in Figure 6. Figure 6 (a) and (b) show that as the ripple content decreases, with the capacitance value of the filter capacitor, the number of incoming edges to the nodes increases and saturates once the rectification is complete. This state indicates a zero ripple condition. The variation of 'outdegree', which tells about the number of outgoing edges, shown in Figure 6 (c) and 6(d), reveals that the lesser the ripple content, the lesser the 'outdegree'. These results demonstrate that the graph features 'indegree' and 'outdegree' can be considered a measure of the ripple component present at the output. The same can also be applied to analysing the fluctuations in the output of other circuits.

Figure 4 and Figure 5 show that with the increase of filtering, the number of unconnected nodes increases and the number of interconnected nodes decreases. Also, it is evident from the adjacency matrices and the Markov chain that the number of self-loops increases, lowering the centrality measure. From Figure 6(e) and (f), it can be seen that the incloseness centrality of FWR and HWR decreases with the decrease of ripple content in the signal and finally reaches zero, which is the expected result of the centrality measure. The variation of outcloseness centrality measure, shown in Figure 6 (g) and (h), is also found to decrease with the decrease of ripple component and becomes zero when the signal becomes DC. Thus, the analysis reveals that the centrality measures – incloseness and outcloseness – can be used to reflect the fluctuations arising in the signal.

The complex network – Markov chain – constructed from the adjacency matrix for FWR and HWR shows the increase of self-loop on rectification and confining the self-loop to a single node corresponding to the rectified DC output. This lowers the number density of edges. From Figure 6 (i) and (j), the variation of WNCC with the filtering capacitance value for the FWR and HWR, respectively, it can be seen that WNCC decreases. The observed variation of WNCC agrees well with the theory that the number density of connection between a node i to its neighbourhood decreases as the WNCC decreases. The study also suggests the potential of WNCC as the measure of rectification similar to the centrality measures -indegree, outdegree, incloseness and outcloseness. Such an analysis based on the features of the network is novel. In contrast to the existing methods [26,27], the method proposed in the paper requires no formulae depending on the circuit elements for understanding the ripple component. Here, though the ripple content is not quantified, it appears as edges and self-loops. For this reason, we propose Markov chain analysis as a surrogate method for ripple or fluctuation analysis.

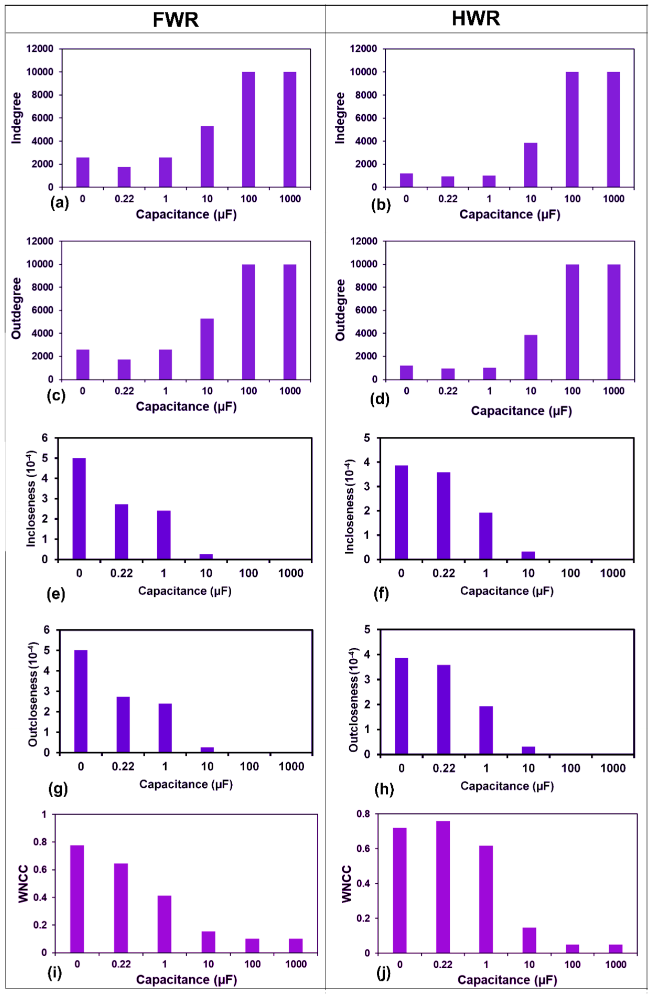

Fig 6. Variation of (a) and (b) indegree, (c) and (d) outdegree, (e) and (f) incloseness, (g) and (h) out closeness, (i) and (j) WNCC of FWR and HWR.

4 Conclusion

Developing novel techniques for analysing and understanding the system performance has always been challenging in electrical and electronic engineering. The present work elucidates the potential of a complex network-based Markov chain model in analysing fluctuations in an electronic system, taking the most fundamental rectifier circuit as an example. FWR and HWR circuits are constructed, and the output signals without and with capacitor filter circuits are recorded in the DSO, from which adjacency matrices are constructed. It is found that the spread of adjacency matrix element is more when there is no filter capacitor. With the increase of capacitance value of the filter capacitor, the component decreases, which appears as the transformation of the adjacency matrix to diagonal. As the ripple component decreases, it is found that only one matrix element corresponding to $A_{10,10}$ remain nonzero for FWR and $A_{20,20}$ for HWR, indicating the total rectification of the signal at 10 volts. The lesser the ripple component, the more the number of unconnected nodes or the self-loop. When the graph features, indegree and outdegree, increases with the increasing value of filter capacitance, the measures incloseness, outcloseness and WNCC are found to decrease. This suggests the possibility of employing the complex network features of the Markov chain model as a measure of ripple component. Though the methodology has been demonstrated through FWR and HWR, it can be extended to analyse any electrical/electronic systems transitioning from an unsteady state to a steady state. Another merit of the present method is that it requires no formulae depending on the circuit elements for understanding the ripple component. The presence of ripple appears as edges and self-loops. Hence the complex network-based Markov chain analysis can be regarded as a surrogate method for ripple/fluctuation analysis.

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