Decision Making for Complex Ecosystems: A Technique for Establishing Causality in Dynamic Systems

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Abstract. Understanding naturalistic human use of technology requires accounting for people, processes, and technologies. Modern decision support system strive to facilitate decision making in such ecosystems. However, modeling interaction between people and technology as constrained by explicit or implicit processes quickly becomes a complex spiral of relationships. In order to determine cause and effect in these complex ecosystems we need a form of causal inference that can overcome the limitations of linear cause-effect analysis.

Complex systems are the result of feedback that takes place inside a dynamic systems. In dynamic systems the future values for outcome variables are due to the interactions of causal variables as modified by a shared, often hidden, function. Taken's theorem states that time series variables are causally linked if they are from the same dynamic system. This paper presents the development and application of an approach that examines time-offset relations between variables in order to determine their causal relations. This research examines the effectiveness of this technique through its application to a microwave heating problem.

Keywords: Causality · Decision-making · Decision support systems · DSS · Simulation · Complex systems · Causal inference · Microwave heating

1 Introduction

1.1 Linear Causality

A common form of causal inference examines the effects of changing an independent variable (A) upon the variability in a dependent variable (B). This linear causal inferences requires the change in A to precede the change in B. Statistically significant differences in the distribution of variances signifies to the researcher that the variables are causally related. However, this approach has several drawbacks. First, it is not always practical or ethical to change one variable. Second, this framework only allows the researcher to examine direct, antecedent causal relations. Third, the scientific

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community has recently challenged the use of null hypothesis significance testing (NHST) as a tool for determining causal relations [1].

1.2 Complex Systems

Complex systems are the result of feedback that takes place inside dynamic systems. In dynamic systems the future values for outcome variables are due to the interactions of causal variables as modified by a shared, often hidden, function. Granger causality empowers causal inference by examining if historic information in a variable strongly relates to the present information in another. Taken's theorem extends this type of inference to complex systems through examining the time embedded offsets of variables.

Attractors refer to regions within a hyperspace defined by a set of variables from a complex system. The future values of the variables are drawn towards these regions. The force of the attractor depends upon the proximity of the nearby points. Phase shifts are stable states within a complex system where the force of the attractor is similar to the force of the noise within the surrounding system.

1.3 Decision Support Systems

Modern decision-making support systems often makes use of semi or fully automated algorithms [2]. These algorithms outsource some or all of the mental processing required to create an informed decision. As these systems become increasingly advanced and as the underlying systems they strive to model continue to increase in complexity, it will become increasingly difficult to assess causality in coupled systems.

2 Method

2.1 Microwave Heating

Microwave ovens are a popular technology for preparing food. Microwave heating represents an applied environment that includes people, technology, and processes. It is difficult for practitioners to design proper protocols for people to follow when using a microwave to heat a new product that will result in a uniformly heated product. Every product reacts slightly differently to microwave ovens due to factors such as water or fat content, salinity, starting temperature, etc. Microwave ovens add to this complexity by contributing a set of factors such as shape, size, power, turntable rotation rate, etc. For these reasons it is challenging for practitioners to design products or ovens which consistently yield uniform heating results.

Microwave researchers also find it challenging to create a laboratory environment that yields controlled, granular data. For this reason this research makes use of the QWED QuickWave-3D software to simulate electromagnetic wave propagation within the microwave oven and product, the resulting heating of a product, and for data within simulation output files. This study simulated thawing of a $100 \times 75 \times 13.5$ mm block of frozen beef in a microwave oven operating at 2.45 GHz. The output data set contains values of the electromagnetic fields in and near the waveguide that feeds microwave power to the oven cavity, the fields within the cavity, and the product, and the temperature. The sample interval was 0.5 s time steps within a 3D grid of either 15 or 20 cells per wavelength in and around the product. The initial position of the product was either centered on the turntable (X0Y0), moved 5 mm to the right and 5 mm to the rear of the oven (X5Y5), or moved 10 mm (X10Y10). The turntable rotated at 3 rpm.

2.2 Convergent Cross Mapping

Convergent cross-mapping refers to approaches that utilize time embedded relationships between variables to determine their causal influence [3, 4]. CCM tests for causation through examining the extent to which the historic record for one variable can reliably estimate the sates of another. It does this by examining the correlation between predicted and observed variables across time-embedded delayed versions of the original variables. All of these offset dimensions for a variable collectively forms a manifold. CCM uses the points from the manifold for one variable to predict the points on another. It repeats this process several times. Each iteration considers slightly more historic data. The correlation between these predictions and the actual values across sets of various length yields the final CCM result.

This research extends CCM to handle larger data sets. The size of the datasets yielded via QWED were far too large to for direct use within the CCM process due to runtimes exponential to the number of input values. To combat this we modified the approach to use the percentile ranks of individual metrics. Percentile-percentile plots are a common, non-parametric technique for analyzing the similarity in the rate of change between two variables. We used CCM to cross map the independent variables across various percentile cohorts within this 3D space.

2.3 CCM Applied to Microwave Heating Uniformity

A common goal in microwave heating is to improve heating uniformity within the product. Poor heating uniformity can result from a multitude of factors [5–8]. Effects such as multiple field reflections and standing waves within the product and preferential heating at edges and corners often contribute to poor heating uniformity. The temperature-dependent complex permittivity of the food influences reflections at interfaces, microwave wavelength within the food, and the dissipative conversion of electromagnetic energy into heat. When the food undergoes phase change (e.g., thawing of ice), the permittivity can change dramatically over a range of 2–3 °C. When increasing temperature leads to increased absorption of microwave power by any of several mechanisms, runaway heating can result. Runaway heating can lead to rapid, local heating, potentially causing burns, charring, and in extreme cases eruptive boiling or fire. In this work we used thermophysical properties (including permittivity) specified for beef in the food.pmo file distributed with QuickWave-3D. We investigate whether the CCM inference approach can assess the causal effect of initial product position (X0Y0, X5Y5, X10Y10) on heating uniformity.

3 Results

To establish the causality of two variables A and B using CCM, examine their resultant cross mapped (xmap) correlation values (ρ). For A xmap to B, if ρ increases as library length (*l*) increases then it implies that B drives A and vice versa. This seems counter-intuitive but it takes place because the information from the driving variable is passing through the passive variable. If both lines increase then both variable drive each other. If neither line increase then neither variable drives the other.

3.1 Cross Map Outputs

Load at X0Y0. Because the median of the temperature (T50) xmap with the median of the electromagnetic field (E50) increases as l increases, this implies that the E50 drives T50 (see Fig. 1). This is consistent with expectations. However, because E xmap T also increases with l this is evidence of weak bidirectional causality. E50 xamps T50 with ρ = 0.96 and E50 xmaps T50 with ρ = 0.50.

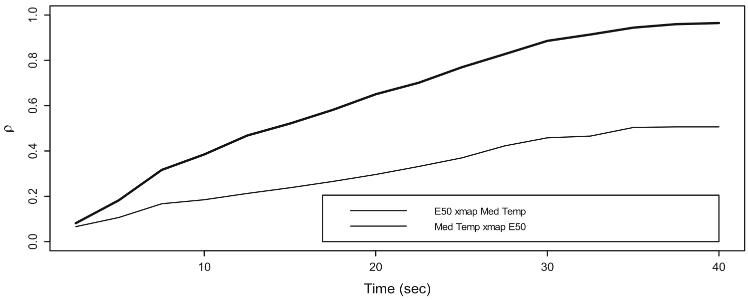

Fig. 1. Load position effects analyzed at X0Y0 using CCM on E50 v. T50

Load at X5Y5. Electromagnetic effect strongly drives temperature. T50 xmaps E50 nearly perfectly with ρ = 1.0 (See Fig. 2). Bidirectional causality is more evident at this location. Here E50 xmaps T50 with ρ = 0.70. Compare this to 0.50 at X0Y0.

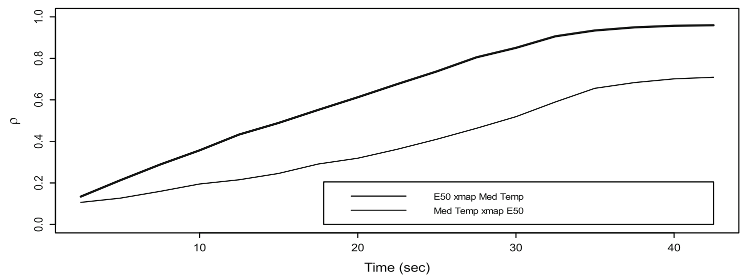

Fig. 2. Load position effects analyzed at X5Y5 using CCM on E50 v. T50

Load at X10Y10. Electromagnetic effect strongly drives temperature. T50 xmaps E50 nearly perfectly with ρ = 1.0 (see Fig. 3). Here bidirectional causality is strongly evident; E50 xmaps T50 with ρ = 0.90. Compare ρ = 0.70 at X5Y5 and to ρ = 0.50 at X0Y0.

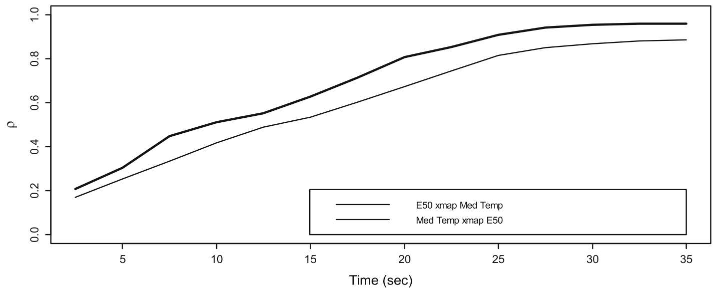

Fig. 3. Load position effects analyzed at X10Y10 using CCM on E50 v. T50

3.2 Analysis

We suspect the bidirectional coupling reflects interactions between the microwave electromagnetic field and product load. Power absorbed from an electromagnetic field is converted to heat (thus, a temperature increase). If the product load is capable of absorbing more power with increasing temperature—as occurs when ice in food thaws—the electromagnetic field in the oven cavity may decrease. Controlling for oven and load type for the range of displacements studied here, moving the product further away from the oven center appears to increase the degree of bidirectional causality.

This method appears to provide a technique to rank the relative strength of two causal relationships within a complex system. Location of a load is a simple but significant variable capable of influencing microwave heating effects and causality relationships across load locations.

4 Discussion

4.1 Implications for Causal Inference in Complex Systems

While [1] has illustrated the usefulness of CCM for establishing causality in complex system, the extended CCM method mentioned in this paper will allow the use of CCM on larger data sets.

4.2 Implications for Microwave Heating Processes

Practitioners creating microwave heating processes will benefit from understanding how differences in product or oven characteristics effect heating uniformity. The results so far suggest that incorporating this technique within microwave simulations would be a step towards transforming such simulations into decision support systems.

4.3 Implications for Decision Support Systems

The need to understand causal relationships between different variables will increase. Decision support systems are increasingly adopting machine-assisted decision-making approaches. These approaches continue to encompass an increasing share of the decision-making responsibilities. Techniques such as those mentioned in this paper will allow researchers to build systems capable of automatically discovering the direction of relationships between variables.

5 Future Work

As mentioned, this is currently a work in progress. We plan to further improve the efficiency of the CCM method. This will allow future work to examine additional design variables such as load geometry, dielectric properties, oven design, rotation or translation rate, packaging design, and packaging materials. Further understanding of the use of these methods to guide system input variables will inform the incorporation of this technique into decision support systems.

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References

1. Trafimow, D., Marks, M.: Editorial. Basic Appl. Soc. Psychol. **37**, 1–2 (2015)
2. Kirk, R.A.: Evaluating a cognitive tool built to aid decision making using decision making approach as a theoretical framework and using unobtrusive, behavior-based measures for analysis. Doctoral Dissertation, Retrieved from ProQuest (3684297) (2015)
3. Sugihara, G., May, R., Ye, H., Hsieh, C., Deyle, E., Fogarty, M., Munch, S.: Science **338**, 496–500 (2012)
4. Ye, H., et al.: Distinguishing time-delayed causal interactions using convergent cross mapping. Sci. Rep. **5**, 14750 (2015)
5. Risman, P.O.: In: Lorence, M.W., Pesheck, P.S. (eds.) Development of Packaging and Products for Use in Microwave Ovens, pp. 66–105. Woodhead, Cambridge (2009)
6. Wapping-Raaholt, B., Ohlsson, T.: In: Lorence, M.W., Pesheck, P.S. (eds.) Development of Packaging and Products for Use in Microwave Ovens, pp. 38–65. Woodhead, Cambridge (2009)
7. Vadivambal, R., Jayas, D.S.: Non-uniform temperature distribution during microwave heating of food materials—a review. Food Bioprocess Technol. **3**, 161–171 (2010)
8. Murphy, E.K., Yakovlev, V.V.: RBF network optimization of complex microwave systems represented by small FDTD data sets. IEEE Trans. Microw. Theory Tech. **54**(1), 245–256 (2006)