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Decomposition as a Complex-Skill Acquisition Strategy in Management Education: A Case Study in Business Forecasting

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ABSTRACT

Graduate business education has been criticized for utilizing simplistic teaching strategies that compromise the presentation of real-world complex skills in the classroom. In this article, we propose that complex management functions can be effectively taught using decomposition strategies. We demonstrate the usefulness of this strategy in the domain of business forecasting by comparing the forecast accuracy of students instructed in decomposition (*RBF-Instructed*) with that of students not exposed to such instruction (*Uninstructed*), as well as

with an expert system called Rule-Based Forecasting (RBF). *RBF-Instructed* students demonstrated significant improvements over *Uninstructed* students and were at least as accurate as the RBF system. Our findings suggest that academics engaged in teaching complex domains can benefit from building their teaching environment on a decomposition framework. We further suggest strategies for measuring the effectiveness and endurance of classroom knowledge thus imparted. Implications for academia and practice are discussed and a research framework is proposed.

INTRODUCTION

Higher education has been criticized for inadequate representation of real-world complexities and for using unrealistically structured educational settings in complex domains (**Spiro, Feltovich, Jacobson, & Coulsen, 1992**). Management education tends to be mechanistic and linear, assuming a simple cause–effect relationship that creates an impractical learning environment compared to the realities of dynamic, interacting complexities (**Ackoff, 1979**; **Axley & McMahon, 2006**). Such reductive linear teaching strategies, often a consequence of logistical and cognitive simplification, result in limited and impracticable extrapolation of learning to real-world, complex settings. Furthermore, these strategies result in a learning environment that becomes more *subject focused* and less *practice focused*, deferring the application of knowledge to such an extent that it falls into disuse (**Forrest & O'Peterson, 2006**).

For academic knowledge to transcend from pure scientific concerns to informed practice and, in the process, create actionable knowledge, educators must design learning environments that measure knowledge acquisition and create a classroom environment wherein students apply knowledge through practical simulations (**Blood, 2006**). While this is challenging because of the difficulty of determining appropriate mechanisms for ill-structured and dynamic situations, educators can draw upon several theories of simple skill acquisition from the field of cognitive psychology (see, e.g., **Anderson, 1982**; **Delany, Reder, Straszweski, & Ritter, 1998**; **Rickard, 1997**). Underlying many of these theories that have effectively been extrapolated to complex skill acquisition (**Lee & Anderson, 2001**) is the hypothesis that complex tasks can be decomposed into simple, executable segments to which the theories can be applied.

Simplified teaching strategies have been deployed in management education for many decades to ameliorate complex task domains. Such simplification often occurs through course modularization wherein a larger domain is reduced to simpler procedural components. For instance, when teaching information technology (IT) students how to design and manage effective IT solutions, the systems cycle is reduced to feasibility assessment, requirements gathering, design, development, testing, implementation, and support. Such modules, however, run the risk of insularity from one another.

Decomposition, on the other hand, follows a two-step approach—reducing the complex domain into simpler steps and subsequently reintegrating these components to reformulate the whole (**MacGregor, 2001**). Each decomposed unit will then contribute to the whole solution rather than being insulated from others. For instance, in showing students how to create and interpret balance sheets, one must first teach the concepts of assets and liabilities, which must then be recombined to form a complete balance sheet. Decomposition may appear to be a corollary to the systems-thinking perspective (**Senge, 1990**), which emphasizes a holistic view of systems rather than the seemingly reductive perspective implied by decomposition. On the contrary, the reintegration of these components provides greater alignment with systems thinking, which has demonstrated effectiveness in complex situations marked by significant interactions (**Senge, 1990**).

In this article we suggest that, by using decomposition techniques in the classroom, abstruse areas of management education can be effectively coached without compromising the complexity of the application domain. More importantly, we believe that, as a teaching strategy, decomposition can effectively balance the presentation of real-world complexity without leading to the cognitive overload that most educators have been concerned about. We exemplify this proposition with an application to a graduate-level Business Forecasting course. As we elaborate in later sections, we consider the process of forecasting to be a demanding and complex task. Consequently, most managers do not follow a system that incorporates all knowledge components and instead apply forecasting knowledge in an incomplete and ad hoc manner. By imparting such knowledge using a structured, decomposed environment, the tendency to jeopardize its real-world applicability may perhaps be minimized.

In the next section, we: (1) review existing theories and applications that highlight the value of decomposition in developing adequate decision strategies; (2) present a discussion of decomposition strategies used in forecasting literature and practice; (3) describe our learning environment, student characteristics, outcome measures, and results from classroom experiments; and (4) discuss implications of our study and propose initiatives with regard to the use of decomposition in management education and education-related research.

LEARNING VIA DECOMPOSITION

Perhaps the theory most fundamentally at the core of decomposition has been the cognitive load theory (CLT; **Sweller, 1988**), which has been the mainstay of several teaching initiatives over the past few decades. The underlying proposition of CLT is that individuals' working memory is limited (**Baddeley, 1992**) and consequently, complex tasks broken into simple chunks can be more effectively executed as compared to tasks not simplified thus. When extended into the educational environment, CLT suggests that cognitive overload may be avoided through the effective and efficient design of instructional materials (**Kester, Kirschner, & van Merrienboer, 2005**). These improved materials can range from better information presentation (e.g., **Kester et al., 2005**) to providing greater structure to the learning environment (e.g., **Lee & Anderson, 2001**).

One approach to improving the structure of the learning environment is the use of decomposition strategies to simplify the subject domain. Although we could not locate any direct evidence of the use of decomposition strategies in management education, over four decades of research in human judgment and decision making have demonstrated that decomposition improves performance over unaided and intuitive judgment (**MacGregor, 2001**; **Plous, 1993**). While there are neurological explanations for why decomposition is effective (see, e.g., **Ghahramani & Wolpert, 1997**; **Jordan & Jacobs, 1994**), from a psychological perspective decomposition allows the decision maker to optimize the problem-solving domain into manageable chunks so that information processing for each chunk can be minimal and relevant while cognitive overload is minimized (**Card, Moran, & Newell, 1983**; **Lee & Anderson, 2001**; **Newell & Rosenbloom, 1981**).

Benefits of decomposition and task scalability have been observed in learning with particular emphasis on complex-skill acquisition. **Lee and Anderson (2001)** classify skill acquisition theories into three categories and suggest that task and domain decomposition play a critical role in improved learning in each of these categories

1. ***Skill acquisition by transformation,*** wherein the task domain is transformed into smaller steps that can be more easily executed by the learner. **Card et al. (1983)**, who proposed a method of decomposing a task into three increasingly specific levels: unit, functional, and keystroke, may be the best exemplar of this learning form. Anderson (2002, p. 86) proffered a decomposition thesis that suggests that a task that takes 100 hours (approximating a semesters' worth of work) can be decomposed into learning events involving “small units of knowledge and occupying brief periods of cognition.” Works by **Neaves and Anderson (1981)** and **Newell and Rosenbloom (1981)** must also be recognized in this context. An alternate view of these transformation theories suggests that tasks involving multiple steps can be transformed into macrolevel steps to speed up learning. However, it

is argued that learning opportunities for these decomposed steps are reduced with the magnitude of the steps (**Lee & Anderson, 2001**).

2. ***Skill acquisition by strengthening a procedure*** or methods that underlie a procedure. This approach suggests that learning of decomposed tasks can be improved in the long run via a reduction of the number of steps required to achieve a certain task (see the studies by **Anderson (1982)** and **MacKay (1982)** as illustrations of this technique). Strengthening and transformation can be complementary functions where a complex task is first transformed into manageable steps that are then streamlined to increase efficiency.
3. ***Skill acquisition via procedure selection,*** which suggests that learning improvements can be observed by following a structured approach to selection of a problem-solving procedure. **Logan (1988)** classified these methods into memory retrievals and algorithmic processing. Learners may gain from selecting memory retrieval methods based upon data and its characteristics (**Delany et al., 1998**) or past experience (**Logan, 1988**). To this extent, skill acquisition via procedure selection requires learners to decompose and characterize the task environment and then to determine the best learning mechanism based on these characteristics.

Subsequent to **Newell and Rosenbloom's (1981)** theory of chunking in learning, more recent theories have continued to advocate the value of decomposition. Applications of these theories have demonstrated improvements in complex skill acquisition. For instance, **Lee and Anderson (2001)** decomposed the function of air traffic control into three unit tasks: (a) moving a plane between hold levels, (b) landing a plane on a runway, and (c) getting the plane into a queue from a hold position. Each of these unit tasks were further decomposed into functional tasks. For instance, landing a plane would involve (1) finding a plane to land, (2) moving to the plane, (3) selecting the plane, and so on. Finally, each of these functional tasks was classified further by keystroke. Results indicated that decomposing the task down to the keystroke level improved learning of the overall task.

In a study of expert and novice programmers, **Barry (1988)** found that the most capable programmers emphasized a structured approach to program design and coding, while the least-capable group was overwhelmed with the complexity of the task and attempted to code the program directly without a structured approach. **Vodounon (2006)** extended this into the classroom and trained C++ programmers to modularize and decompose the programming task using reusable code. She found that, while high-performing programmers benefited significantly from decomposition, even those demonstrating poor performance improved their ability to use decomposition as a programming strategy. In forecasting research and practice, decomposition as a simplification strategy has been used for over four decades in various forms, although its use in forecasting education has been nonexistent until this study. We will discuss the use of this practice in greater detail in the next section.

THE PRACTICE OF BUSINESS FORECASTING

Complexity in the Process of Forecasting

Complexity is inherent in the process of forecasting. **Albritton and McMullen (2006)** suggest that this complexity may explain why only 53% of Operations Research/Management Science faculty include forecasting as a topic area in their courses. While one can argue that all one needs is a simple forecasting method and adequate data, a nontrivial view of the forecasting process suggested by **Armstrong (2001)** provides a more realistic perspective (see **Figure 1**). Each stage of the forecasting process presented in **Figure 1** entails coordinated action that requires the use of judgment and analytical skills, inputs from multiple organizational units, and validation and integrity checks. When executed correctly, the forecasting process integrates domain knowledge, historical data, causal forces acting upon the domain, and physical characteristics of the process producing the measured realizations that are to be forecast.

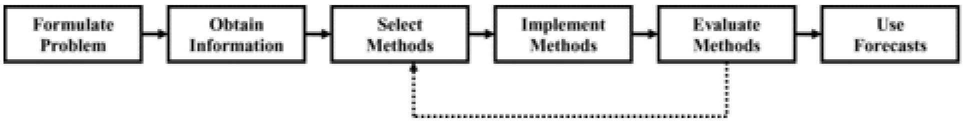

Figure 1 Components of the forecasting process as presented in **Armstrong (1985, 2001)**.

The process of forecasting is also made more complex by the significant reliance on judgmental methods (**Bunn & Wright, 1991**). In examining sales forecasting techniques, **Dalrymple (1987)** found that judgmental methods such as expert opinions and analogies were the most routinely used for sales forecasting, with expert opinions constituting 45%. This preference for qualitative, judgmental results was confirmed in later studies by **Mentzer and Kahn (1995)**, **Frank and McCollough (1992)**, and **Sanders and Mandrodt (1994)**. Judgment in forecasting is often used in three ways: to make pure judgmental forecasts; adjustments to statistical forecasts; and input into the forecasting process, often in the form of domain knowledge. Although judgmental forecasting is criticized for inconsistencies and biases (see **Harvey (2001)** for an overview of judgmental forecasting), there is increasing evidence that, when combined with statistical approaches, judgment improves forecast accuracy (**Armstrong & Collopy, 1998**; **Collopy & Armstrong, 1992**; **Webby, O'Connor, & Lawrence, 2005**). Considering this, educators must embrace not merely the complexity inherent in the forecasting process, but also that present in the use of judgment for forecasting.

The Use of Decomposition for Improving Forecasting

Forecasters not only need to estimate uncertain quantities under uncertain and complex conditions, but often do so with limited time and resources (**MacGregor, 2001**). Decomposition of the forecasting task provides a mechanism for dealing with this complexity and breaking the problem domain down into manageable components. Further, it provides a way of structuring and systematizing various aspects of the forecasting process (**Sanders & Ritzman, 2001**; **Webby et al., 2001**) that may be better than intuition alone (**Dawes, 1979**; **Meehl, 1957**). By breaking down complex forecasting tasks into a set of components that can be estimated and recombined more easily, the target estimate can be more accurate (**MacGregor, 2001**).

Although decomposition as a strategy for structuring forecasting problems has been used in practice for several decades, much of the current research lacks an integrated theory of decomposition or a clear direction regarding the form of decomposition (**MacGregor, 2001**). Furthermore, the interdisciplinary nature of the field makes it challenging to provide a cohesive summary of the decomposition literature. Nevertheless, we compiled key strategies used in current practice and research based upon seminal work in the area. To facilitate this compilation, we adapted the learning-by-decomposition framework proposed by **Lee and Anderson (2001)** and discussed in the earlier sections. Specifically, forecasting studies were classified based upon whether they used decomposition to (1) *transform* the data or domain being forecast; (2) *simplify* the forecasting methods, process, or data; or (3) improve the *selection* of forecasting methods to best fit the task domain. It is worth pointing out that, because Lee and Anderson's classification pertains to learning theories in psychology, it is unrealistic to expect a literal translation of it into the forecasting domain. Nevertheless, their framework has provided us with a useful context within which to assimilate a research area that would otherwise be challenging to contain in a comprehensible manner.

Table 1 provides a summary of key decomposition studies in forecasting, using the framework discussed above. Although we have attempted to segregate decomposition studies into the three categories, many studies could fit into two or more categories due to their interrelated objectives. For instance, studies such as those by **Collopy and Armstrong, (1992)**, **Vokurka, Flores, and Pearce (1996)**, and **Tashman and Kruk**

(2002) transformed the task domain in order to either simplify the forecasting process or improve method selection, thereby using one decomposition strategy to support another. Such interdependencies provide further evidence of the complexity of forecasting.

Table 1. Use of decomposition to improve forecasting accuracy.

	Decomposition Strategy Used	**Study**
Accuracy gains due to transformation	Time series characterized using features of time series	Georgoff and Murdick (1986); Collopy and Armstrong (1992); Vokurka et al. (1996); Adya et al. (2000); Adya et al. (2001)
	Decompose forecast domain based upon causal forces acting on the domain	Collopy and Armstrong (1992); Armstrong et al. (2005)
	Decomposition of time series into components; use of decision aids to support decomposition	Edmundson (1990); Webby et al. (2005); Choi and Wohar (1995); Simmons (1990); Ozaki and Thompson (2002)
	Decompose problem domain into additive components (segmentation)	Armstrong and Andress (1970); Dangerfield and Morris (1992); Dunn et al. (1971)
	Decomposition of the time series into theta lines	Assimakopoulos and Nikolopoulos (2000)
Accuracy gains due to simplification of procedure	Forecasting process divided into stages	Armstrong (1985); MacGregor et al. (1988)
	Forecasting process decomposed into short and long horizons, adjustments, and recombining	Collopy and Armstrong (1992)
	Algorithmic decomposition of forecasting problem into series of estimates	MacGregor et al. (1988); MacGregor and Lichtenstein (1991)
	Structured procedure used to generate forecasts	Lim and O'Connor (1996)
	Decomposition used under conditions of uncertainty	MacGregor and Armstrong (1994); Harvey (2001)
Accuracy gains due to improved selection	Method selection and/or weighting based on data and domain characteristics	Collopy and Armstrong (1992); Adya et al. (2000); Adya et al. (2001); Tashman and Kruk (1996); Vokurka et al. (1996)
	Decompose forecast domain based upon forecast ability of component values	Andradottir and Bier (1997); Armstrong et al. (2005); MacGregor and Armstrong (1994)

Decomposition for transformation of domain being forecast

Domain transformation primarily has been accomplished by transforming the domain and data into physical characteristics that are then used to simplify forecasting procedures or select the most appropriate forecasting methods. Possibly one of the earliest works was by **Georgoff and Murdick (1986)**, who characterize the forecasting environment into 16 dimensions related to temporal needs, input and output constraints, and forecasting requirements. While their classification focused more on organizational factors, later studies such as those by **Collopy and Armstrong (1992)**, **Vokurka et al. (1996)**, **Adya, Armstrong, Collopy, and Kennedy (2000)**, and **Adya, Collopy, Armstrong, and Kennedy (2001)** have focused more deeply on characterizing the data and domain. **Collopy and Armstrong (1992)**, for instance, decompose a time series into 28 characteristics (see **Table 2**) that are then used to weight forecasts from four methods.

Table 2. Decomposition of time series into 28 features as used in Collopy and Armstrong (1992) and Adya et al. (2001).

Feature Categories	**RBF Features**	**Descriptions**
Causal forces	Growth	The net directional effect of the principal factors acting on the series. *Growth* exerts an upward force. *Decay* exerts a downward force. *Supporting* forces push in direction of historical trend. *Opposing* forces work against the trend. *Regressing* forces work toward a mean. When uncertain, forces should be U*nknown*.
	Decay	
	Supporting	
	Opposing	
	Regressing	
	Unknown	
Functional form	Multiplicative	Expected pattern of the trend of the series.
	Additive	
Cycles expected	Cycles expected	Regular movement of the series about the basic trend.
Forecast horizon	Forecast horizon	Horizon for which forecasts are being made.
Subject to events	Subject to events	
Start-up series	Start-up series	Series provides data for a start-up.
Related to other series	Related to other series	
Types of data	Positive values	Only positive values in the time series.
	Bounded	Bounded values such as percentages and asymptotes.
	Missing observations	No missing observations in the series.
Level	Biased	Level is not biased by any other events.
Trend	Direction of basic trend	Direction of trend after fitting linear regression to past data.
	Direction of recent trend	The direction of trend that results from fitting Holt's to past data.
	Significant basic trend (t > 2)	The t-statistic for linear regression is greater than 2.
Length of series	Number of observations	Number of observations in the series.
	Time interval	Time interval represented between the observations.
Seasonality	Seasonality	Whether seasonality is present in the series.
Uncertainty	Irrelevant early data	Early portion of the series results from a substantially different underlying process.

	Suspicious pattern	Series that show a substantial change in recent pattern.
	Unstable recent trend	Series that show marked changes in recent trend pattern.
	Outliers present	Isolated observation near a two-standard deviation band of linear regression.
	Recent run not long	The last six period-to-period movements are not in same direction.
	Near a previous extreme	A last observation that is 90% more than the highest or 110% lower than the lowest observation.
	Changing basic trend	Underlying trend is changing over the long run.
	Level discontinuities	Changes in the level of the series (steps).
	Last observation unusual	Last observation deviates substantially from previous data.

RBF = rule-based forecasting.

Edmundson (1990), **Choi and Wohar (1995)**, **Ozarki and Thompson (2002)**, and **Webby, O'Connor, and Edmundson (2005)** found that time-series forecasts can be significantly improved by decomposing the series into its simplest components: trend, cycle, and noise. Decomposition of a forecasting problem has also been implemented by breaking the problem down into independent components that can be additively recombined. This strategy, called segmentation, was successfully deployed in several studies including those by **Armstrong and Andress (1970)**, **Dunn, William, and Spivey (1971)**, and **Dangerfield and Morris (1992)**. See **MacGregor (2001)** for a comprehensive overview. Irrespective of the approach used, transformation of the domain into component characteristics has been beneficial to structuring the forecasting task.

Decomposition for simplification of the forecasting process

Structuring the forecasting process can also yield significant gains in accuracy (**Sanders & Mendrodt, 1994**). **Lim and O'Connor (1996)** demonstrated that forecast accuracy can be improved if the forecaster follows a structured process to generate the forecasts. They asked students to first make an initial forecast. Students were subsequently provided with statistical forecasts and were asked to follow a structured process to review the data and generate revised forecasts. Significant improvements in forecast accuracy were observed as a consequence of structuring.

We located several studies that touted the benefits of process decomposition, some in a generic manner while others using a more domain-specific approach. One of the earliest models was presented by **Armstrong (1985)**, who recommended the division of the forecasting process into several stages, as shown in **Figure 1**. In a later study, **Collopy and Armstrong (1992)** decomposed the time-series forecasting process into subprocesses that generate short-term forecasts and long-term forecasts, which were then blended to provide holistic forecasts (see **Figure 2** for their model). In contrast to these generic models, **MacGregor, Lichtenstein, and Slovic (1988)** successfully used domain-specific algorithmic decomposition to simplify the task of estimating the number of pieces of mail handled by the U.S. postal service in a year.

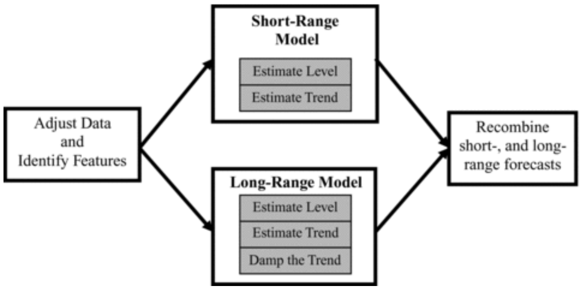

Figure 2 Decomposition of rule-based forecasting process (**Collopy & Armstrong, 1992**).

Decomposition for selection of the appropriate forecasting method

Decomposition efforts aimed at improving method selection for forecasting situations have generally tied in with transformational studies. Illustrative of these efforts are studies by **Collopy and Armstrong (1992)**, **Vokurka et al. (1996)**, and **Tashman and Kruk (2002)** that have relied on features and characteristics of the forecasting problem to enable method selection. For instance, **Vokurka et al. (1996)**, transformed time series into three features that were used to determine the best forecasting method. **Collopy and Armstrong (1992)** demonstrated that similarly decomposed time series can be successfully used to combine forecasts from four component methods. Their strategy, while not explicitly method selection, did yield customized forecasts for each time series. It must be pointed out that research related to neural networks for selecting or weighting forecasting methods has not been discussed here due to the challenges of summarizing this extensive body of research. See **Adya and Collopy (1998)** and **Zhang, Patuwo, and Hu (1998)** for overviews.

In summary, decomposition has been used extensively in forecasting practice for several decades with multiple objectives that range from simplification of the task domain to structuring the method-selection process. The presence of this body of literature serves to reiterate the complexity of the forecasting domain and related pressures to simplify it from the standpoint of improved practice. Use of decomposition strategies in teaching forecasting courses should then be a natural extension.

TEACHING BUSINESS FORECASTING USING DECOMPOSITION

There is a surprising dearth of information on the ways to improve forecasting education. In fact, we found only two studies that provided any direction with regard to management education in forecasting. **Bailey and Gupta (1999)** examined the accuracy of judgmental forecasters at forecasting industrial learning curves. They found that judgmental forecasters are able to outperform statistical methods with just simple classroom instruction. **O'Connor (1989)** concluded that, with well-trained and well-motivated experts, the reliability of judgmental forecasts can be improved. Considering the pervasiveness of decomposition as a forecasting strategy, it is ironic that its use in forecasting education has hitherto remained unexplored.

Rule-Based Forecasting (RBF) as a Decomposition Framework

In their seminal work, **Bunn and Wright (1991)** suggested that significant improvements in forecast accuracy may be achieved by structuring the interactions between judgment and statistical techniques. They further suggested that such structured interactions can be achieved at a single-method level via (a) elicitation of key variables from experts, (b) specification of models based on interactions between these variables, (c) parameter estimation, and (d) data analysis to determine characteristics of the data. Around the same period, research on benefits of combining forecasts from multiple methods attracted significant attention (see **Clemen, 1989** for a detailed overview).

Applying these principles, **Collopy and Armstrong (1992)** developed RBF, a knowledge-based system consisting of 99 "IF…THEN…" rules that integrate judgmental and statistical procedures to combine forecasts from four statistical methods: random walk, linear regression, Holt's exponential smoothing, and Brown's exponential smoothing, based upon specific domain indicators. RBF relies on the identification of up to 28 features of time series (presented in **Table 2**) in order to weight forecasts from these four methods. IF…THEN… rules yield weights that are customized to the forecasting situation based on these features.

In order to capture valid, relevant, and complete forecasting knowledge, RBF rules were elicited using multiple methods—survey of expert opinions of 49 practitioners and educators, examination of empirical forecasting literature, protocol analysis of five leading forecasting experts, and a rigorous process of calibration and refinement. The emergent knowledge was coded as simple IF…THEN… rules in order to present forecasting knowledge in a systematic and structured manner.

RBF was originally validated and tested on 128 annual economic and demographic time series. It was later refined and validated on larger sets of time series (**Adya et al., 2000**; **Adya et al., 2001**). In each of these tests of validation, RBF consistently outperformed comparative benchmarks. Furthermore, in the recent M3-IJF forecasting competition conducted by the *International Journal of Forecasting*, it was one of three leading methods on 3,003 time series (**Makridakis & Hibon, 2000**). This last validation of RBF demonstrated its applicability to a wide range of data, extending well beyond the economic and demographic data that was used to design, calibrate, and test RBF. These studies also enabled us to examine the accuracy of RBF on shorter time period data including quarterly, monthly, weekly, and daily time series.

Why did we choose RBF as our decomposition framework? As may be evident from summary results presented in **Table 1**, the design of RBF represents decomposition at all three levels: transformation, simplification, and method selection. Consequently, RBF provides a well-defined and validated framework within which to design our teaching environment. Furthermore, RBF was "fully disclosed …" (**Collopy & Armstrong, 1992**, p. 1394), which enabled us to obtain all relevant details necessary for execution of this teaching environment and also provided us with a testable benchmark from which to observe student performance.

Figure 2 illustrates the use of decomposition in RBF and outlines the following algorithmic procedure for generating forecasts using RBF.

1. Historical and domain-based features of time series are identified.
2. These features trigger rules that generate multiple sets of weights for short-term and long-term forecasts.
3. Weights are generated for the four methods listed previously and are used to combine forecasts from the four methods.
4. The forecasts for short-term and long-term models are blended or recomposed to generate RBF.

See **Collopy and Armstrong (1992)** for further details on the system and its underlying principles.

Participant Population

Experimental subject characteristics

The students who received RBF training were enrolled in an elective Business Forecasting course in the International Master's Program at Otto-Von-Guericke (OVG) University, Germany for the spring semester of 2004 (*n*= 12) and 2005 (*n*= 14). Of these 26 students, 16 were females. One-way analysis of variance and chi-square tests of key demographics for this group, presented in **Table 3** below, demonstrated no significant differences between the two subsets based on age, grade point average, and work experience. Students in this course were mainly from Europe and China. They all had statistical training, a prerequisite for the course, and spoke and wrote English fluently. The majority had some work experience, mainly with multinational corporations such as Crédit Suisse, Volkswagen, Shanghai Petrochemical Ltd., and Siemens. They were an ideal group for testing the RBF model because of their statistical training, lack of specific forecasting experience, and relatively diverse business experience. These 26 students received RBF training during the semester. We refer to these individuals as *RBF-Instructed*. Two of the students indicated on an initial questionnaire that they each had about 1 year's worth of experience working in a group that was responsible for forecasting. They did not detail their roles in that forecasting group nor were their performances distinguishable from other students in the experiment. The course text was **Hanke, Wichern, and Reitch (2001)**.

Table 3. Basic demographics of RBF-instructed group.

Population	**Age (in Years)**	**Work Experience (Years)**	**GPA**
All RBF-trained	Mean = 23.88	Mean = 2.04	Mean = 2.19
n= 26	Range = 19–32	Range = 0–8	Range = 1.3–2.8
Females = 16	*SD*= 3.01	*SD*= 1.98	*SD*= .47
RBF-Trained–2005 subset	Mean = 23.92	Mean = 1.86	Mean = 2.12
n= 14	Range = 20–31	Range = 0–8	Range = 1.3–2.8
Females = 6	*SD*= 3.00	*SD*= 2.10	*SD*= .52
RBF-Trained–2004 subset	Mean = 24.08	Mean = 2.25	Mean = 2.27
n= 12	Range = 19–32	Range = 0–7	Range = 1.5–2.8
Females = 10	*SD*= 3.15	*SD*= 1.91	*SD*= .42

GPA = grade point average; RBF = rule-based forecasting.

Comparative benchmarks

To determine the effectiveness of RBF training, forecast accuracy of the *RBF-Instructed* group was compared to two benchmarks—the RBF system and an *Uninstructed* student group. For the first benchmark, we used the automated RBF system (**Adya et al., 2001**), referred to as *Auto-RBF*, to produce forecasts based on the model described in **Figure 2**. Participants for the second benchmark, the *Uninstructed* group, were solicited from various courses such as derivatives and options, experimental design, and planning and control that were offered at the OVG in 2004 and 2005. These students had statistical and English-language fluency comparable to the experimental group.

It is important to make a methodological note here regarding treatment of the *Uninstructed* group. This experiment was governed by the rules on *Using Human Subjects for the Ministry of Education: SA, Germany*. Given that the nature of the experiment is to evaluate a teaching protocol, in the control setting we were not permitted to use a technique that is believed to be less effective. Consequently, while an ideal control group would have been students who had taken a traditional forecasting course without the benefit of a decomposed learning environment, protocol regulations did not permit us to create such an experimental setting, thus limiting us to the comparative benchmarks of the *Uninstructed* group and *Auto-RBF*. The evaluation of this experiment is, consequently, consistent with the ethical guidelines under which we were permitted to design the learning environment.

The Learning Environment

The structure of decomposition as modeled in RBF was easily molded to the teaching environment in a manner that students could be taught the forecasting task via simple, procedural steps identified in the previous section. Consequently, our teaching environment mirrored the decomposition strategy used in the design of RBF.

Decomposition via transformation: Identifying characteristics of domain and data

RBF-Instructed students began the semester with an exploration of feature identification where they learned in detail, and with examples, how to identify features of time series evident as patterns in historical data. Specifically, they learned how to identify the following: level changes, suspicious patterns in historical data, outliers, unstable and changing basic trends, extreme observations at the end of a series that can bias forecasts, and trend changes that can affect short- and long-term forecasts. For instruction on feature identification, we found the procedures described in **Collopy and Armstrong (1992)** to be quite effective. These descriptions were complemented with visual illustrations of features. For instance, when explaining that a *changing basic trend* is a change in the underlying trend over the long run, instructors supplemented the description with the plot of a series that illustrated a changing basic trend. This additional support was deemed necessary for students who may not have had prior experience with such feature-identification techniques.

Students were also taught to identify causal forces representing domain knowledge about future events that impact the forecast domain. For instance, when forecasting IT workforce needs, the trend toward outsourcing to other countries can be viewed as a force that will result in a downward trend for programmers in that country's labor market, but in an upward trend in demand for project managers and business analysts. In addition, two other features of domain knowledge, functional form of the time series and irrelevant early data, were discussed and demonstrated to the students. These features are described in **Table 2**.

Decomposition by simplification: Understanding components of the process

Subsequent to familiarization with feature identification, students learned higher-level components of the forecasting process as illustrated in **Figure 2**. During this phase they also learned the four component forecasting methods: random walk, linear regression, and two exponential smoothing methods. Additionally, they were taught two-parameter methods, linear regression, moving-average models, the Census II model, exponential smoothing, and Holt–Winters models. This instruction on component methods was executed over a 6-week period. Within this phase, the feature-identification techniques and principles were intensively reiterated.

Decomposition by method selection: Learning to apply forecasting rules

A large number of forecasting studies have focused on tailoring the selection of a single forecasting method for each forecasting situation. While this has resulted in increased accuracy, there is greater compelling evidence regarding benefits of combining forecasts from multiple methods (**Clemen, 1989**). As discussed earlier, knowledge of how to assign weights to the four component methods based on features of the data is encoded in the 99 production (IF…THEN…) rules of RBF. As an illustration, we provide the following rule: *IF the trend of the series is changing, THEN add 15% to the weight on the random walk and subtract it from that on the other three methods.*[1] Such decomposition of forecasting knowledge lends a structure to the task that enables easier assimilation as compared to a larger, more complex structure.

As a final phase in our learning environment, students were introduced to the production rules and their contribution to the forecasting process. While students were not expected to regurgitate the rules at the end of this process, they were expected to understand the application of these rules to the forecasting process. To support this process, several articles were provided to students: **Armstrong and Collopy (1992a)**, **Collopy and Armstrong (1992)**, **Adya et al. (2000)**, and **Adya et al. (2001)**. To enrich the students' understanding of these rules, a detailed example was generated and distributed to them as a 16-page Word document and was discussed over the following 2 weeks. (This teaching plan is available from the second author.) Finally, *RBF-Instructed* students were given a practice series to work on. Their solutions to these exercises were discussed during class before the data for this experiment were distributed.

Underlying Hypotheses and Outcome Measures

We highlighted above the constraints imposed by protocol requirements on the controlled aspect of this experiment. Consequently, we were limited to benchmarking *RBF-Instructed* students with those who had not received instruction in any forecasting technique. It could then be assumed that the performance of *RBF-Instructed* students would improve as a result of this instruction. To this end we formed the following a priori expectations

- *Hypothesis 1:* Forecasts generated by *RBF-Instructed* students will be more accurate than those generated by the *Uninstructed* students.

Our true test of the benefit of decomposition was, however, expected to emerge from a comparison with the automated RBF system itself. While students were expected to gain from the use of structure provided by the RBF model, as the literature documents, we also anticipated that a full and complete replication of its vast knowledge base by students would not be possible. This led to the following hypothesis

- *Hypothesis 2:* Forecasts generated by the *auto-RBF* system will be more accurate than the *RBF-Instructed* students.

The Protocols

Students in the *RBF-Instructed* and the *Uninstructed* groups were asked to generate forecasts for three time series each. These series were selected from 35 time series representing a randomly selected subset of the 126 series from the M-competition used in **Collopy and Armstrong (1992)**.[2] The series pertained to a range of industrial, macroeconomic, and demographic sources. Specific examples include annual female births in England (series 174), iron ore tonnage produced in England (series 77), net sales of GM in the United States (series 5), pulpwood production in the United States (series 64), and car chassis manufactured in France (series 4). While the *RBF-Instructed* group provided forecasts upon completion of the educational instruction, *Uninstructed* students were asked to generate forecasts for three randomly selected series from our subset during the first class meeting. They were given 45 minutes to complete the task; about 30% used calculators. *Uninstructed* students were not given any suggestions as to how to generate the forecasts. They were told to omit those series for which it appeared too complicated to develop useful forecasts and move on to another series. Although extra time was available, only three students requested it. Both student groups were asked to provide one- to six-period yearly forecasts by whatever means they deemed appropriate.

In the 2004 course, the 12 *RBF-Instructed* participants were asked to provide forecasts for three series each. One student produced forecasts that were not reported in the proper scale and two students decided not to provide forecasts for one of their series. This gave 198 forecasts in total over the six forecasting horizons. The *Uninstructed* group in 2004 was composed of 47 students who contributed 840 forecasts over the six forecasting horizons. For 2005, the 14 *RBF-Instructed* students turned in usable forecasts, giving a total of 252. In that year, there were 72 students in the *Uninstructed* group, contributing 1,248 forecasts. This yielded a total of 2,088 *Uninstructed* and 450 *Instructed* forecasts across the 2 years. All students from both groups, *Instructed* and *Uninstructed*, were provided the following information to guide their forecasting task

1. The Cartesian coordinate plot of the time series,
2. The data points in the time series, and
3. The series description taken directly from M-competition data.

To provide comparison with our second benchmark, the *Auto-RBF* system, one- to six-period ahead forecasts were generated for the 35 series discussed earlier. Due to programming issues, the *Auto-RBF* produced forecasts for all of the series except those ending in 0, 1, or 9. We tested to see if there was a bias in the series eliminated and none was found. Consequently, *Auto-RBF* generated one- to six-period forecasts for 27 of the 35 series, resulting in 162 forecasts.

DID DECOMPOSITION-BASED EDUCATION HELP?

Findings from the Benchmark Comparisons

To provide comparability with the works cited above, forecasts were compared using Absolute Percentage Error (APE) and the Relative Absolute Error (RAE) terms after Winsorizing.[3] **Armstrong and Collopy (1992b)** recommend use of median values of error measures when the number of series being evaluated is small to moderate and outliers are present in these series. Following this advice, in addition to the APEs and RAEs, we report median APEs (MdAPEs) and median RAEs (MdRAEs). First, the overall results using averaged APEs and RAEs over all of the six forecasting horizons are presented in **Table 4**.

Table 4. Overall accuracy comparisons with benchmarks.

Test Groups	APE	RAE
Auto-RBF (n= 162)	9.4	85.7
RBF-Instructed (n= 450)	11.1	88.5
Uninstructed (n= 2,088)	14.3	102.6

APE = absolute percentage error; RAE = relative absolute error; RBF = rule-based forecasting.

Using the Kruskal–Wallis test, we see that overall there are differences in forecasting errors among the three test groups at $p < .001$ for both the APE and the RAE. To identify where those differences lay, we used the **Hettmansperger (1991)** nonparametric test, a multiple-comparison test that uses the Kruskal–Wallis rank-sum information. This test indicated no difference between the APEs and the RAEs of the *Auto-RBF* and the *RBF-Instructed* groups. Furthermore, both of these groups had lower forecast errors compared to the *Uninstructed* group. Based on these outcomes, we find support for Hypothesis 1. On the contrary, we do not find support for Hypothesis 2, because forecasting accuracy of the automated RBF system did not appear to be statistically different from the forecasting performance of the *RBF-Instructed* students. In other words, forecasts from *RBF-Instructed* students were as accurate as those from the system. Summary results are presented in **Tables 5** and **6**.

Table 5. Median absolute percentage error (MdAPE) of benchmarks.

Group (No. of Forecasts)	***1-Ahead***	***2-Ahead***	***3-Ahead***	***4-Ahead***	***5-Ahead***	***6-Ahead***
Auto-RBF (162)	4.3	7.9	10.7	12.9	14.9	10.7
RBF-instructed (450)	5.3	7.6	10.0	14.5	19.2	17.0
Uninstructed (2,088)	6.3	9.6	14.2	18.3	20.0	23.0

RBF = rule-based forecasting.

Table 6. Median relative absolute error (MdRAE) of benchmarks.

Group (No. of Forecasts)	***1-Ahead***	***2-Ahead***	***3-Ahead***	***4-Ahead***	***5-Ahead***	***6-Ahead***
Auto-RBF (162)	94.3	79.0	92.2	84.4	89.5	78.8
RBF-instructed (450)	93.0	88.7	89.0	86.4	87.7	78.2
Uninstructed (2,088)	103.5	102.6	106.9	107.0	101.6	99.3

RBF = rule-based forecasting.

These disaggregated results are consistent with the information presented above in **Table 4**. In all cases the *Auto-RBF* and *RBF-Instructed* outperform the *Uninstructed* group.

Discussion of Findings

Our results support the proposition that decomposition as a learning strategy improves the acquisition of a complex skill. We utilized decomposition in the learning environment by: (1) transforming the data and domain into useful features; (2) simplifying the forecasting task into a series of simple steps that should be easy to remember; (3) using these simplified steps to weight a set of forecasting methods; and (4) recombining the individual components to produce a final, more robust solution. This enabled the simplification of a seemingly complex task to a well-defined structure that was easier to learn and assimilate. We believe that students demonstrated improved forecasting accuracy because of the structure provided via decomposition. This manner of structuring forecasting knowledge facilitates improved dissemination to forecasters and integration into their forecasting process. Using this approach, forecasters can combine judgmental and statistical approaches in a holistic, objective, and measurable manner.

We expect that the structure enabled by decomposition aided *RBF-Instructed* students in processing relevant information or using the information they processed more effectively given the forecasting tasks that they attempted. We do not believe that we taught students to process less information. Rather, it is more likely that they were able to distinguish between relevant and irrelevant information using the decomposition strategy. This is consistent with **Shanteau (1992)**, who found that experts and novices process the same amount of information but superior expert performance emerges, in part, from the ability to distinguish relevant from irrelevant information. Specifically, the information used by experts is more relevant to the task than that used by novices. The implications are interesting. Practitioners and educators could utilize existing expert knowledge-based systems from their domains to guide novice decision making. Because these systems model relevant expert knowledge while overlooking extraneous decision factors, using them might potentially result in improved novice decision making.

That said, there are several areas of improvement in our implementation of decomposition. The concept of learning focuses on the way in which students acquire new skills and knowledge and the manner in which existing knowledge and skills are modified (**Schuell, 1986**). Nearly all conceptions of learning have addressed three criteria for definition: (1) a change in the individual's behavior or ability to do something, (2) a stipulation that such change must result from some sort of practice or experience, and (3) a stipulation that the change is an enduring one (**Schuell, 1986**). While we were able to observe a clear change in the students' ability to conduct the forecasting task, our course design did not enable us to assess the longevity of this learning. Although this is an inherent limitation in the general teaching environment in management schools, there are creative ways in which faculty can measure the long-term benefit of learning via decomposition. In the next section, we elaborate on these and other guidelines that may enhance future learning initiatives that intend to use decomposition.

IMPLICATIONS AND GUIDELINES FOR EDUCATORS

Decomposition as a strategy for complex-skill acquisition and utilization has been suggested for several decades. We have examined its applicability in the area of management education, where there is a surprising dearth of information on delivering the essential aspect of this pivotal discipline. Below, we provide several simple suggestions for practitioners and educators who might consider using decomposition as a teaching strategy.

Consider a Decomposition Framework Within Which Domain Knowledge Can Be Articulated

In order to design an effective learning environment, educators must first challenge themselves to locate a decomposition framework within which the learning environment may reside. This knowledge source must be validated, representative of the field, and accepted as a standard. For us, this was relatively simple to do. RBF models are based on over four decades of empirical knowledge that has been tested and validated in multiple instances. Other sources of such structured knowledge may exist. For instance, academics may find industry best practices to be good source of decomposition framework. When represented as simple principles and knowledge nuggets (see, e.g., **Armstrong, 2001**), these may be effectively integrated into the class content.

Our practical and theoretical experience with decomposition as a teaching strategy has suggested that certain domains lend themselves better to the use of decomposition strategies in the classroom environment. Domains where steps can be easily expressed as chunks and outcomes can be objectively measured lend themselves well to decomposition. Forecasting represents one such domain. Other such areas could be financial investments, economics, accounting, business process management, and project management. Courses on team building, organizational behavior, and ethics—where the application of concepts is personal and individualistic in nature and where objective outcome measures are not readily available—may be challenging to implement in a decomposition setting. To this extent we offer the following propositions as further research possibilities:

- ***Proposition 1(a)***: Decomposition teaching strategies are more easily designed and tested in environments where knowledge can be structured and expressed as chunks.
- ***Proposition 1(b)***: Decomposition teaching strategies are more easily applied to domains where learning concepts and outcomes can be objectively measured.

Conform the Learning Environment to the Decomposition Framework

When designing the learning environment, educators must conform to the decomposition structure facilitated by the decomposition framework deemed relevant to their domain. For educators this would guide the design of the teaching environment, selection of reading materials, provision of examples from existing literature, and mechanisms for validating learning. In our case, we relied on many readings from scholarly journals and existing measures such as forecast accuracy to organize our thinking on the learning process. For students, this might provide the structure and knowledge in an easy-to-use format. Specifically, one could prepare course material as a series of decomposed, yet integrated, modules as we did in our courses.

Assess Improvement in Decomposition Abilities Via Pre- and Postlearning Tests

Long-term benefits of teaching by decomposition can only be assessed completely when educators are able to observe problem-solving strategies *before* and *after* instruction. Here, we suggest that management educators actively engage in assessing student skills, experiences, and maturity about use of decomposition strategies prior to initiation of the educational period, as we did for our experimental situation. It also seems critical to benchmark the process so as to calibrate the effect of the decomposition on the transfer of knowledge. Focus in this assessment should not simply be on accuracy of the final response, but also on efficiency of the problem-solving strategy as well as on evidence regarding the use of decomposition. For this, educators may need to devise evaluative methods that rely on protocol analysis and observation, rather than on traditional examination-based techniques. Class presentations, diagramming techniques that can model the process of decomposition utilized, and descriptive narratives that require students to elucidate their problem-solving strategies pre- and postlearning will provide a good starting point for learning effectiveness.

Determine Whether the Decomposition Strategy is Enduring

We expect that, as a problem-solving strategy applied to forecasting or other domains, decomposition will be enduring. However, in this regard this study has inherent limitations because we were unable to determine the effectiveness of decomposition as a strategy beyond the classroom environment. There is some concern that much of management education is not utilized once students complete their educational programs (**Forrest & O'Peterson, 2006**). Learning environments strive to provide education that informs decision making on a routine basis. Unfortunately, most learning systems fail to deliver an assessment that determines the extent to which knowledge attained at the university is applied once the students enter the real world. At most, a capstone course may attempt to assimilate and retest this prior knowledge. It is up to educators to determine whether knowledge application is long term or not. Possible follow-up research studies soliciting participation of students beyond graduation may be a way of fine tuning future course offerings. We hope that alumni may be willing to participate in follow-up initiatives without necessitating a research study if follow-up assessments are presented as curriculum-revision initiatives.

Do Improvements in Learning Via Decomposition Occur as a Result of Reduced Overload?

What explains improved learning in a decomposition domain? Although chunking has been used to explain such improvements, as educators we may benefit from a deeper understanding of the cognitive contributions of decomposition. Based on experience, we hypothesize that learning via decomposition possibly enables skill acquisition by reducing the overload experienced by the learner. To develop testable propositions in this area, we integrate the skill-acquisition taxonomy proposed by **Lee and Anderson (2001)** and **Sweller's (1988)** CLT theory of information overload.

CLT suggests that cognitive overload can be intrinsic, extrinsic, and germane. *Intrinsic overload* is inherent to the task itself and cannot be directly influenced by instructional designers (**Sweller, van Merrienboer, & Paas, 1998**). *Extraneous overload* is experienced by the learner while interacting with the instructional material and encountering information not beneficial for learning. Finally, *germane overload* is experienced during a learner's interaction with instructional materials that are relevant to learning but are too excessive for the learner to process adequately. We combined the CLT with the skill-acquisition taxonomy discussed throughout this article to propose the following research ideas summarized in **Table 7**.

Table 7. Does decomposition reduce overload? Some research propositions.

	Intrinsic Overload	**Extrinsic Overload**	**Germane Overload**
By transformation	Proposition 2(a)		
	Task domain can be decomposed into simpler tasks thereby simplifying inherent task characteristics.		
By strengthening a procedure		Proposition 2(b)	Proposition 2(c)
		Knowledge environment can be decomposed into hierarchical knowledge structures to eliminate extrinsic factors.	Knowledge environment can be decomposed into hierarchical knowledge structures that can allow the learner to focus on germane factors.

By speedier method selection	Proposition 2(d)		Proposition 2(e)
	Characterization of task domain into features aids memory retrieval by enabling extraction of similar characteristics from past exposure.		Decomposition of knowledge into structured rules enables speedier application of germane forecasting knowledge based on task characterization.

- ***Proposition 2(a): Decomposition*** teaching environments can reduce intrinsic overload by transforming a complex task domain into simpler tasks.
- ***Proposition 2(b):*** Decomposition of the functional domain into knowledge structures can reduce the extrinsic overload caused by the presence of irrelevant factors.
- ***Proposition 2(c):*** Decomposition of functional domain into knowledge structures can reduce germane overload by reducing the number of factors considered relevant to the task.
- ***Proposition 2(d):*** Decomposition of task domain into a small number of characteristics (features) will aid easy retrieval from past experiences based on simplified task structures.
- ***Proposition 2(e):*** Decomposition of task domain into structured rules as opposed to an unstructured environment will facilitate more rapid application of germane forecasting knowledge based upon task characterization.

CONCLUSIONS

While many domains have successfully used decomposition strategies for skill acquisition, an explicit discussion of the use and value of decomposition in management education has been lacking. As a first step, we must clearly distinguish between course modularization and decomposition. Modularization is more an organizing tool to simplify the delivery of the course material. It is not challenging to locate the former because modularization is often used to simplify the teaching environment from the educator's perspective. In the process, however, such simplification compromises the complexity of the functional domain. Decomposition, on the other hand, must be used as a problem-solving strategy wherein the task is first decomposed into manageable modules but later recombined to obtain the final solution. We suggest that, when decomposition is used as a problem-solving strategy in the classroom, a simplification of the teaching environment will follow naturally. In this article, we have provided a preliminary blueprint of how decomposition and recomposition can be integrated into complex management education.

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