# Chapter 30
# Fuzzy System Dynamics of Manpower Systems

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## ABSTRACT

*Manpower recruitment and training in uncertain and turbulent environments is a challenge to decision makers in large organizations. In the absence of numerical precision on market growth and the ensuing manpower demand, designing manpower planning policies is vital. Often times, companies incur losses due to overstaffing and/or understaffing. For instance, organizations lose business when critical human resources leave. As a result, it is essential to develop robust effective dynamic recruitment and training policies, especially in a fuzzy and dynamic environment. In this chapter, a fuzzy systems dynamics modeling approach is developed to simulate and evaluate alternative dynamic policies relating skills recruitment, skills training, and available skills from a systems thinking perspective. Fuzzy system dynamics is implemented based on fuzzy logic and system dynamics concepts in order to arrive at robust strategies for manpower decision makers. It is anticipated that fuzzy system dynamics can help organizations to design effective manpower recruitment strategies in a dynamic and uncertain environment.*

## INTRODUCTION

Over the last three decades, several researchers and practitioners have increasingly focused their attention on developing robust manpower recruitment and training policies, especially for organizations (Mehlmann, 1980; McClean, 1991; Rao, 1991; Anthony & Wilson, 1990; Nilakantan & Raghavendra, 2005; Skulj et al. 2008; Mutingi et al., 2012). In the absence of numerical precision on the likely future market demand, it is often difficult to develop effective manpower recruitment and training strategies, especially in the case of large organizations. As such, future demand for human resources is often fuzzy or uncertain (Guerry, 1999; Mutingi et al., 2012). When future manpower demand is imprecise, uncertain, or vague, managers in large organizations frequently

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face challenges in developing manpower recruitment policies to maintain human resources at the right level over time. In the same token, future supply and demand of goods and services in the marketplace is precise. As a result, researchers and practitioners resort to the use of fuzzy set theoretic methods, dynamic approaches, and related methodologies in order to address problems found in complex ill-structured systems, such as manpower systems, supply chain systems, inventory management systems, production planning systems, manufacturing systems, transportation systems, and other industrial systems (Madronero, Peidro, & Vasant, 2010). In general, soft computing approaches have become the most appropriate and practical solution methods for solving real life problems, as postulated by numerous authors in the literature (Vasant et al., 2007; Vasant & Barsoum, 2009; Elamvazuthi et al., 2009; Peidro & Vasant, 2010; Elamvazuthi, Vasant, & Ganesan, 2010; Peidro & Vasant, 2011; Cebi et al., 2012; Dostal, 2013; Guerry, 1999). However, in practice, several complexities are realized in manpower systems modeling.

In the real world, we are often unable or unwilling to describe a manpower system structure and behavior using humanistic or linguistic expressions, such as high demand, somewhat high demand, or increasing demand, among others. In large corporations, vagueness of future demand for human resources is. In most cases, caused by dynamic market growth which. In turn, directly influences the need to develop robust recruitment policies in accordance with the ensuing manpower demand behavior. As an illustration. In times of growth or decline of business, manpower policy makers must recruit human resources cautiously, paying attention to the lack of numerical precision in the variables that affect the behavior of manpower systems (Guerry, 1999). In fact, this is critical in the sense that robust policies can avoid huge costs associated with understaffing due to under-investment in human resource recruitment and training, and overstaffing due to over-investment in human resources. Therefore, a judicious trade-off between loss of business due to under-investment in human resources in times of business growth and overstaffing costs due to over-investment in human resources in times of business decline. Robust computing approaches are essential in complex and uncertain environments in order to design, evaluate and implement appropriate human resource planning policies.

In addition to lack of exact numerical precision, the estimation of future manpower demand often requires data collection over a considerable period of time so as to develop a useful statistical model. However. In practice, the relevant data may not be readily available for the development of a satisfactory statistical model. Moreover. In dynamic and turbulent times, past data is quickly outdated due to dynamic changes in the factors that led to the generation of the data. The dynamic interactions and causal linkages between various factors in the system may be too complex to be modeled using statistical or probabilistic methods. Therefore, the development of dynamic models which address dynamic and fuzzy variables is imperative. In other words, there is need for a joint approach to addressing problems that are characterized by dynamic and fuzzy variables in order to enhance cautious policy evaluation and optimization in manpower systems. System dynamics is a potential systems modeling and analysis tool for evaluating long-term decision alternatives in dynamic business management problems (Forrester, 1961). Since its inception in the 1960's, system dynamics has been applied successfully to various policy and strategy problems. Some of the areas of the application of this methodology include supply chain management (Sterman, 2004), healthcare systems, manpower systems (Hafeez & Aldelmeguid, 2003), military systems (Gass, 1991), healthcare manpower systems (Mutingi & Mbohwa, 2012), and dynamic manpower forecasting (Park et al., 2008). In most of these applications, the concept of decision making under fuzziness or imprecision is not particularly addressed.

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