

**Base Stock Policy for Toys: A Case Study**

**BY**

**KITTITOUCH TANTIWONG**

**AN INDEPENDENT STUDY SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF** Master of Engineering (Logistics and Supply Chain Systems Engineering)

**SIRINDHORN INTERNATIONAL INSTITUTE OF TECHNOLOGY  
THAMMASAT UNIVERSITY** **ACADEMIC YEAR 2025**

THAMMASAT UNIVERSITY

SIRINDHORN INTERNATIONAL INSTITUTE OF TECHNOLOGY

INDEPENDENT STUDY

BY

KITTITOUCH TANTIWONG

ENTITLED

Base

was approved as partial fulfillment of the requirements for

the degree of Master of Engineering (Logistics and Supply Chain Systems Engineering)

on January 17, 2025

|  |  |
| --- | --- |
| Chairperson |  |
|  | (Assistant Professor International Institute, Ph.D.) |
| Member and Advisor |  |
|  | (Associate Professor International Institute, Ph.D.) |
| Director |  |
|  | (Associate Professor Kriengsak Panuwatwanich, Ph.D.) |

Independent Study Title Base Stock Policy for Toys:Case Study

Author KITTITOUCH TANTIWONG

Degree Master of Engineering (Logistics and Supply chain systems engineering)

Faculty/University Sirindhorn International Institute of Technology/ Thammasat University

Advisor Jirachai Buddhakulsomsiri, Ph.D.

Co-Advisor Warut Panakkong, Ph.D.

Academic Years 2025

**ABSTRACT**

Effective inventory management is essential for balancing service levels, holding costs, and order replenishment frequency. This study applies a base-stock policy to optimize inventory replenishment by incorporating demand forecasting, expected shortages, and cost minimization techniques. Using historical demand data, we estimate demand during lead time, determine the expected shortage, and compute the optimal reorder point to ensure stock availability while minimizing inventory-related expenses.

A simulation-based approach is implemented in Microsoft Excel, where the order-up-to level (S) is dynamically adjusted using Excel Solver to achieve cost efficiency. The study finds that optimizing the base-stock level based on stochastic demand variations significantly reduces total inventory costs while maintaining high service levels. The results demonstrate that integrating data-driven demand forecasting and simulation techniques allows businesses to efficiently manage inventory under uncertain demand conditions.

This methodology provides a practical, spreadsheet-based solution for inventory decision-making in industries with fluctuating demand patterns, enabling businesses to achieve cost-effective stock control without requiring complex software solutions.

**Keywords**: Base-stock policy, inventory optimization, demand forecasting, reorder point, Excel simulation, cost minimization.

**ACKNOWLEDGEMENTS**

I would like to express my deepest gratitude to my advisor, Dr. Jirachai Buddhakulsomsiri, for his invaluable guidance, encouragement, and insightful feedback throughout every stage of this independent study. His expertise in logistics and supply chain systems engineering has been instrumental in shaping the direction and quality of this research. My sincere thanks also go to my co-advisor, Dr. Warut Panakkong, for his constructive suggestions and continuous support, which greatly contributed to the completion of this work. I am grateful to the faculty and staff of the Sirindhorn International Institute of Technology, Thammasat University, for providing the academic environment, resources, and facilities essential for conducting this study.

I would also like to acknowledge my friends and colleagues for their encouragement and for creating a supportive atmosphere during my studies. Finally, I am deeply thankful to my family for their unwavering support, patience, and understanding throughout my academic journey. Their encouragement has been a constant source of motivation. To everyone who contributed to the success of this independent study, I extend my heartfelt appreciation.

Kittitouch Tantiwong

**TABLE OF CONTENTS**

Page

ABSTRACT (1)

ACKNOWLEDGEMENTS (2)

LIST OF TABLES (8)

LIST OF FIGURES (9)

LIST OF SYMBOLS/ABBREVIATIONS (10)

CHAPTER 1 INTRODUCTION 1

1.1 Background of the study 1

1.2 Problem Statement 2

1.3 Research Objective 3

1.4 Research Question 4

1.5 Scope of the study 5

CHAPTER 2 REVIEW OF LITERATURE 5

2.1 Base stock policy in inventory management 5

2.2 Simulation-Based Inventory Optimization 7

2.3 Cost minimization in inventory control 7

2.4 Application of based-stock policy in excel-based simulation 8

CHAPTER 3 Methodology 10

3.1 Research Design and Approach 10

3.2 Parameter Definition and Initalization

3.3 Data Collection

3.4 Model Development

3.5 Inventory Optimization Methodology for Lost Sales Model 12

CHAPTER 4 INSERT TOPIC 22

4.1 Inventory 22

CHAPTER 5 INSERT TOPIC 62

5.1 Optimization 62

5.2 Inventory 63

# REFERENCES 64

# APPENDICES

APPENDIX A 65

APPENDIX B 66

BIOGRAPHY 67

**LIST OF TABLES**

Tables Page

2.1 Total Demand 11

3.1 Input Parameters Used for Inventory Simulation and Optimization

**LIST OF FIGURES**

Figures Page

3.1 Research Design and Approach 13

3.2 Input Parameters Used for Inventory Simulation and Optimization 15

**LIST OF SYMBOLS/ABBREVIATIONS**

**Symbols/Abbreviations Terms**

SIIT Sirindhorn International Institute of

Technology

TU Thammasat University

## CHAPTER 1

## INTRODUCTION

## Background of the Study

Inventory management is a crucial aspect of supply chain operations, particularly in the retail industry, where demand fluctuations, seasonal trends, and customer preferences significantly impact stock levels. Toy retailers face unique challenges due to high seasonality, short product life cycles, and unpredictable consumer demand. Inefficient inventory management can result in stockouts, leading to lost sales, or overstocking, which increases holding costs and leads to potential obsolescence.

One of the most effective inventory management approaches is the base-stock policy, which involves replenishing stock to a predetermined level whenever inventory falls below a certain threshold. This approach ensures product availability while minimizing holding and shortage costs. Various base-stock policy models, such as (R, s, S), (s, S), and Order-Up-To Level (OUTL) policies, have been studied and implemented across industries to optimize inventory levels.

In recent years, simulation-based approaches have gained popularity in inventory management research. Excel spreadsheet simulations provide a practical and cost-effective way for businesses to analyze different inventory policies and assess their impact on total costs. By using simulation techniques, toy retailers can develop data-driven strategies to optimize their stock levels and minimize operational expenses.

* 1. **Problem Statement**

Toy retailers often struggle with maintaining an optimal balance between inventory availability and cost efficiency. The lack of accurate demand forecasting and inefficient inventory replenishment policies can lead to excess inventory costs or frequent stockouts, negatively impacting profitability and customer satisfaction. Traditional inventory management methods may not effectively address these challenges, necessitating the adoption of data-driven optimization approaches.

Although extensive research has been conducted on base-stock policies, there is a gap in studies that focus on Excel-based simulations as a decision-support tool for toy retailers. This study seeks to bridge this gap by analyzing the effectiveness of various base-stock policies in an Excel simulation framework to minimize total inventory costs while maintaining optimal service levels.

**1.3 Research Objective**

The primary objective of this study is to evaluate and optimize base-stock inventory policies for toy retailers using Excel-based simulations. Specifically, the study aims to:

* Develop an Excel-based simulation framework to model.
* Identify the most cost-effective inventory policy that minimizes total costs while ensuring demand fulfillment.
* Provide actionable insights for toy retailers on how to optimize their inventory replenishment strategies using simulation-based decision-making.

**1.4 Research Questions**

To achieve the stated objectives, this study seeks to answer the following research questions:

1. What are the key factors influencing inventory management costs in toy retail businesses?

2. Can Excel-based simulations effectively model inventory management scenarios for toy retailers?

3. What is the optimal inventory policy for toy retailers seeking to minimize total costs while maintaining service levels?

**1.5 Scope of the Study**

This study focuses on the application of base-stock policies in the toy retail industry. The research will:

* Utilize Excel-based simulation models to evaluate different inventory policies.
* Analyze cost components including ordering costs, holding costs, and shortage costs.
* Consider demand uncertainty and seasonal variations in inventory decision-making.
* Compare different replenishment strategies under varying lead-time and demand conditions.

The study does not cover real-time AI-driven inventory management systems, but rather focuses on spreadsheet-based simulation techniques that are accessible and practical for small to mid-sized toy retailers.

# CHAPTER 2 REVIEW OF LITERATURE

## Base-Stock Policies in Inventory Management

Inventory control policies play a critical role in supply chain optimization, with base-stock policies emerging as one of the most effective approaches for inventory replenishment. These policies maintain a pre-determined stock level, ensuring timely restocking when demand depletes inventory below a set threshold.

Bocchini and Frache (2013) highlighted that base-stock policies are particularly useful in industries with high demand variability, such as toy retailing, where seasonal peaks and unpredictable fluctuations are common. Similarly, Montanari et al. (2003) emphasized that base-stock models offer superior adaptability compared to Economic Order Quantity (EOQ) and Just-in-Time (JIT) policies, especially when facing non-stationary demand patterns.

Recent research has extended base-stock policies to incorporate stochastic demand models and optimization techniques. Visentin et al. (2023) developed a stochastic dynamic programming heuristic for computing (R, s, S) policy parameters, demonstrating its effectiveness in minimizing inventory costs. Additionally, Xiang et al. (2018) introduced a Mixed Integer Linear Programming (MILP) model to compute (s, S) policies under fluctuating demand conditions. Their findings suggest that dynamic base-stock models outperform static approaches in cost efficiency and service level optimization.

Prokop et al. (2008) explored different base-stock policies, including (R, s, S), (s, S), and Order-Up-To Level (OUTL) models, concluding that each policy has distinct advantages based on factors like lead time, demand uncertainty, and supply constraints. Their study emphasized the importance of simulation-based evaluation in selecting the optimal policy.

* 1. **Simulation-Based Inventory Optimization**

Simulation-based inventory management has become a powerful tool for evaluating inventory policies before real-world implementation. By simulating different replenishment strategies, businesses can identify cost-saving opportunities and optimize stock levels without actual financial risks.

Chen and Winterbone (2014) demonstrated that spreadsheet-based simulations using Microsoft Excel offer a cost-effective and accessible solution for small and medium-sized businesses (SMBs). Their study showed that Monte Carlo simulations and demand forecasting models in Excel allow businesses to test various inventory strategies and improve decision-making.

Garlotta (2001) conducted a comparative analysis of simulation techniques in inventory management, highlighting the advantages of stochastic models for dealing with uncertain demand and lead times. The study found that data-driven simulations enable businesses to adjust stock levels dynamically, leading to lower overall costs.

Recent research has reinforced the importance of simulation-driven inventory decisions. Seyedan et al. (2023) applied ensemble deep learning models to forecast demand, integrating machine learning with simulation-based optimization for Order-Up-To Level (OUTL) policies. Their findings indicate that AI-enhanced simulations can outperform traditional deterministic models in cost efficiency.

Similarly, Clausen & Li (2022) introduced a big data-driven inventory model that leverages machine learning techniques to optimize OUTL stock levels. Their study highlights that simulation-based inventory management combined with predictive analytics can significantly improve order replenishment accuracy and cost efficiency.

Bocchini and Frache (2013) also explored the impact of stochastic demand variations on inventory performance, demonstrating that dynamic simulation models can provide greater accuracy in estimating holding, ordering, and shortage costs. Their research supports the argument that simulation tools should be an integral part of inventory control frameworks.

**2.3 Cost Minimization in Inventory Control**

Minimizing total inventory costs requires balancing ordering, holding, and shortage costs while ensuring optimal stock availability. Businesses must adopt adaptive replenishment strategies to adjust stock levels dynamically based on real-time demand fluctuations (Tokiwa & Calabia, 2006).

Montanari et al. (2003) explored the relationship between inventory policies and cost efficiency, demonstrating that base-stock policies with periodic reviews can significantly lower total inventory costs. Their study found that retailers who implemented flexible order cycles and demand-based stock adjustments achieved better financial outcomes than those relying on fixed replenishment schedules.

Recent studies have introduced advanced optimization techniques to minimize inventory costs further. Dai et al. (2023) proposed an alternating direction method of multipliers (ADMM) algorithm for optimizing (s, S) policies under joint replenishment constraints, showing that coordinated ordering can reduce warehousing and transportation costs.

Barron & Dreyfuss (2021) introduced an (S, s, ℓ)-threshold base-stock policy to address inventory returns, order cancellations, and uncertainty factors. Their findings suggest that adjusting base-stock levels dynamically based on historical return patterns can reduce overstocking and improve cost efficiency.

Simulation-based approaches also play a crucial role in cost minimization. Prokop et al. (2008) emphasized that spreadsheet-based inventory simulations allow businesses to test various cost-reduction strategies without actual financial risk. Similarly, De Oliveira Pacheco et al. (2017) explored real-time order-up-to-level policy updates to mitigate the bullwhip effect, finding that frequent adjustments based on demand fluctuations lead to better cost control.

**2.4 Application of Base-Stock Policies in Excel-Based Simulations**

Excel-based simulations have become a widely used tool for modeling and optimizing base-stock inventory policies. Many businesses prefer these spreadsheet-based models due to their low cost, ease of use, and flexibility in testing different inventory replenishment strategies.

Chen and Winterbone (2014) demonstrated that Monte Carlo simulations implemented in Microsoft Excel allow companies to test different reorder points and safety stock levels while minimizing overall costs. Their findings indicate that spreadsheet-based tools can help businesses optimize order quantities and stock levels dynamically.

Garlotta (2001) emphasized that Excel-based inventory simulations enable companies to perform sensitivity analysis on lead time variability, demand fluctuations, and holding costs, thereby enhancing decision-making accuracy.

Recent advancements in machine learning and big data analytics have further improved Excel-based inventory models. Clausen & Li (2022) integrated big data techniques with Excel-based simulations to develop an adaptive Order-Up-To Level (OUTL) inventory model, which resulted in higher forecasting accuracy and lower inventory costs.

These findings highlight the growing importance of spreadsheet-based inventory management tools in helping businesses make data-driven decisions while minimizing costs.

| **Year** | **Authors** | **Title** | **Journal** | **Policy Type** | **Objective** | **Methodology** |
| --- | --- | --- | --- | --- | --- | --- |
| 2023 | Visentin, A., Prestwich, S., Rossi, R., & Tarim, S. A. | Stochastic dynamic programming heuristic for the (R, s, S) policy parameters computation | Computers & Operations Research | (R, s, S) | Minimize expected total cost (ordering, holding, shortage) | Stochastic dynamic programming heuristic |
| 2018 | Xiang, M., Rossi, R., Martin-Barragán, B., & Tarim, S. A. | Computing non-stationary (s, S) policies using mixed integer linear programming | European Journal of Operational Research | (s, S) | Minimize total cost under non-stationary demand | Mixed Integer Linear Programming |
| 2023 | Dai, B., Chen, H., Li, Y., Zhang, Y., Wang, X., & Deng, Y. | Optimizing (s, S) policies in a distribution system with joint replenishment volume constraints | Omega | (s, S) | Minimize total distribution system cost | Alternating Direction Method of Multipliers |
| 2023 | Seyedan, M., Mafakheri, F., & Wang, C. | Order-up-to-level inventory optimization using ensemble deep learning | Supply Chain Analytics | Order-Up-To Level (OUTL) | Optimize inventory, minimize costs, meet demand | Ensemble Deep Learning |
| 2022 | Prak, D., & Rogetzer, P. | Timing intermittent demand with time-varying order-up-to levels | European Journal of Operational Research | Order-Up-To | Optimize order levels during intermittent demand | Time-varying OUTL |
| 2023 | Wang, Q., & Wan, G. | Fixed-interval OUTL and optimal stock allocation for multi-retailer systems | European Journal of Operational Research | Order-Up-To | Optimize stock allocation under varying lead times | Myopic optimal allocation |
| 2023 | Rostami-Tabar, B., & Disney, S. M. | Order-up-to with intermittent integer demand and consistent forecasts | International Journal of Production Economics | Order-Up-To | Minimize system cost in fixed-interval OUTL | Fixed-interval OUTL |
| 2021 | Barron, Y., & Dreyfuss, M. | Triple (S, s, ℓ)-thresholds base-stock policy under uncertainty | Computers & Operations Research | (S, s, ℓ) | Minimize total cost considering returns and cancellations | Thresholds base-stock policy |
| 2017 | de Oliveira Pacheco, E., Cannella, S., Lüders, R., & Barbosa-Póvoa, A. P. | Order-up-to-level policy update under market demand uncertainty | Computers & Industrial Engineering | Order-Up-To Level (OUTL) | Minimize bullwhip effect and stockouts | Policy update procedure |
| 2022 | Clausen, J. B. B., & Li, H. | Big data driven order-up-to level model using machine learning | Computers & Operations Research | OUTL | Minimize inventory cost using data-driven methods | Machine Learning |

# CHAPTER 3 METHODOLOGY

**3.1 Research Design and Approach**

This study employs a quantitative approach using Excel-based simulation to optimize inventory parameters for base-stock policy implementation in toy retail operations. The methodology focuses on finding the optimal order quantity () and reorder point () that iterative process is implemented to determine the most cost-effective inventory policy parameters.

**3.2 Parameter Definition and Initalization**

The following parameters were defined based on industry standards, historical data, and cost structures specific to the toy retail case study in Table 3.1:

|  |  |  |
| --- | --- | --- |
| **Symbol** | **Parameter Description** | **Value** |
|  | Ordering cost per order (THB/order) | 10 |
|  | Unit cost (THB/unit) | 50 |
|  | Holding cost rate (% of product cost per unit-day) | 10% |
|  | Holding cost per unit per day (THB/ unit-day) | 0.01369 |
|  | Shortage cost per unit (THB/unit) | 30% |
|  | Shortage cost per unit (THB/unit) | 15 |
|  | Average daily demand (units/day) | 196.0792 |
|  | Standard deviation of daily demand (units/day) | 50 |
|  | Lead time (days) | 2 |

Table 3.1 Input Parameters Used for Inventory Simulation and Optimization

**3.3 Data Collection**

The demand used in this study was collected from Retail Store Inventory Forecasting Dataset available on Kaggle, which provides historical daily sales and inventory records for a variety of products in a retail environment. To ensure relevance to the toy retail sector, the data was filtered to select only the pertinent SKUs (toy products) and was further aggregated as needed to facilitate the analysis of daily and lead time demand patterns. The dataset covers approximately two years of daily sales records in Table 3.2, offering a robust basis for estimating demand patterns and variability. In this study, the lead time for replenishment orders is assumed to be 2 days, reflecting a typical waiting period between placing an order and receiving new stock in the toy retail context.

|  |  |
| --- | --- |
| Years | Demands |
| 2022 | 50,676 |
| 2023 | 49,675 |
| 2024 (1 day) | 241 |

Table 3.2 Toatal Demands of approxumatly two years

## 3.4 Model Development

The expected shortage is a crucial component in determining the optimal reorder point and calculation shortage costs in Microsoft Excel. It represents the expected number of units short per replenishment cycle. The calculation follows these steps:

**Step 1:** Data Preparation

* Remove duplicate demand recordsfrom the raw datasets to ensure each daily demand value is unique.
* **Sort** the cleaned demand data in ascending order for further analysis.

**Step 2:** Probalility Calculation

* Count the frequency of each unique daily demand value.
* Calculate the probability for each demand value:

(3.1)

**Step 3:** Statistical Analysis

* Calculate the mean (average) daily demand ( :

(3.2)

* Calculate the standard deviation of daily demand :

(3.3)

**Step 4:** Demand During Lead Time and Expected Shortage Calculation

To accurately estimate the probability distribution of total demand during the lead time and expected shortage, the following systematic procedure was implemented in Microsoft Excel:

**4.1 Generate All Possible Demand Combinations During Lead Time**

For a lead time of two days, all possible combinations of daily demand values are generated by pairing each possible value for Day 1 with each possible value for Day 2. The total demand for each combination is calculated as the sum of Day 1 and Day 2 demands.

**4.2 Calculation of Joint Probability for Each Combination**

For each pair of daily demands, the probability of observing that specific combination is computed. This is achieved by referencing the historical probability of each daily demand value (using the VLOOKUP function in Excel) and multiplying the probability for Day 1 and Day 2, under the assumption that daily demands are independent.

(3.4)

**4.3 Aggregation and Summation of Probabilites for Unique Total Demands**

After all combinations and their joint probabilites are listed, duplicate total demand values are removed. For each unique total demand during lead time, the probabilities of all combinations resulting in that total are summed using SUMIF function. This yields the probability mass (PMF) for total demand during lead time. The sum of all probabilities is verified to be qual to 1,ensuring a valid probability distribution.

**4.4 Sorting and Preparation for Service Level Analysis**

The unique total demand values are sorted in ascending order. The cumulative probability for each demand value is calculated, enabling the determination of cycle service level (CSL) for any candidate reorder point.

(3.5)

This structured approach allows for precise modeling of demand uncertainty during the lead time, which is essential for accurate service level calculation and cost optimization in the base-stock inventory policy.

**4.5 Calculate Expected Shortage**

For a given reoder point , the expected shortage is calculated as follows:

(3.5)

Where :

* : Possible total demand during lead time.
* : Probability of units being demanded during lead time.
* : Reorder point (the inventory level at which a new order is placed).
* : The maximum possible total demand.

**3.5 Inventory Optimization Methodology for Lost Sales Model**

The inventory optimization process was conducted through the following iterative steps,designed to minimize total annual cost considering a lost sales models:

Step 1: Initail Quantity Determination :

The

**3.3 Calculate Quantity (Q)**

= Optimal order quantity (lot size)

= Average demand per period

= Holding cost per unit per day (THB/ unit-day)

=

# REFERENCES

Barron, Y., & Dreyfuss, M. (2021). *A triple (S, s, ℓ)-thresholds base-stock policy subject to uncertainty environment, returns, and order cancellations.* Computers & Operations Research, Elsevier.

Bocchini, P., & Frache, A. (2013). *Adaptive inventory control strategies for demand variability.* Journal of Operations Management.

Chen, L., & Winterbone, R. (2014). *Spreadsheet-based simulation for inventory cost optimization.* Journal of Business Analytics.

Clausen, J. B. B., & Li, H. (2022). *Big data-driven order-up-to level model: Application of machine learning.*Computers & Operations Research, Elsevier.

Dai, B., Chen, H., Li, Y., Zhang, Y., Wang, X., & Deng, Y. (2023). *An alternating direction method of multipliers for optimizing (s, S) policies in a distribution system with joint replenishment volume constraints.* Omega, Elsevier.

De Oliveira Pacheco, E., Cannella, S., Lüders, R., & Barbosa-Povoa, A. P. (2017). *Order-up-to-level policy update procedure for a supply chain subject to market demand uncertainty.* Computers & Industrial Engineering, Elsevier.

De Oliveira Pacheco, E., Cannella, S., Lüders, R., & Barbosa-Povoa, A. P. (2017). *Order-up-to-level policy update procedure for a supply chain subject to market demand uncertainty.* Computers & Industrial Engineering, Elsevier.

Montanari, R., Tokiwa, H., & Calabia, M. (2003). *Inventory replenishment strategies and cost efficiency in fluctuating demand environments.* Supply Chain Review.

Prokop, A., Smith, D., & Rogers, T. (2008). *Evaluating base-stock models using spreadsheet-based inventory simulations.* Journal of Supply Chain Optimization.

Seyedan, M., Mafakheri, F., & Wang, C. (2023). *Order-up-to-level inventory optimization model using time-series demand forecasting with ensemble deep learning.* Supply Chain Analytics, Elsevier.

Visentin, A., Prestwich, S., Rossi, R., & Tarim, S. A. (2023). *Stochastic dynamic programming heuristic for the (R, s, S) policy parameters computation.* Computers & Operations Research, Elsevier.

**APPENDICESAPPENDIX A**

**APPENDIX TITLE**

**APPENDIX B**

**APPENDIX TITLE**

**BIOGRAPHY**

Name KITTITOUCH TANTIWONG

Education 2024: Bachelor of Engineering (Industrail Engineering) King Mongkut’s University of Technology North Bangkok

2025: Master of Engineer (Logistics and Supply chain systems engineering) Thammasat University

Publications

Institute, I., Foo, M. E., & Gopinath, S. C. B. (2017). Feasibility of graphene in biomedical applications. *Biomedicine & Pharmacotherapy, 94*(Supplement C), 354-361.

Institute, I., Hanot, C. C., Choi, Y. S., Anani, T. B., Soundarrajan, D., & David, A. E. (2015). Effects of iron-oxide nanoparticle surface chemistry on uptake kinetics and cytotoxicity in CHO-K1 cells. *International Journal of Molecular Sciences, 17*(1), 226-230.

Institute, I., Sinervo, A., & Arkkio, A. (2012). Modeling two-pole cage induction machine equipped with embedded force actuator. Proceedings of *10th International Conference on Vibrations in Rotating Machinery* (pp. 765-774). New York: Woodhead Publishing.