12-2016

Modeling and Optimizing of Strategic/Tactical Production Planning Problems

Naresh Gupta Uppala
Clemson University

MODELING AND OPTIMIZING OF STRATEGIC/TACTICAL PRODUCTION PLANNING PROBLEMS

A Thesis
Presented to
the Graduate School of
Clemson University

In Partial Fulfillment
of the Requirements for the Degree
Master of Science
Industrial Engineering

---

by
Naresh Gupta Uppala
December 2016

Accepted by:
Dr. Burak Eksioglu, Committee Chair
Dr. Kevin Taaffe, Committee Co-chair
Dr. Sandra Eksioglu

ABSTRACT

Satisfying customer demand at an optimal cost is the most important concern for the high-level management of every company. This dissertation details i) the development of a strategic/tactical model for the distribution of production responsibilities to different sites/factories and ii) the design of an inter-area logistics flow ensuring demand satisfaction, by consider the production capabilities of each site, while minimizing the total costs of production output. A mixed integer program, which includes the supply of raw materials and the distribution of finished products in the respective markets, was proposed to manage this production problem. This concept encompassed two case studies: the first involved a scenario in which setup costs were identical (Case 1); the second entailed setup costs that differed from product to product (Case 2) to determine the optimal costs by understanding the role of the setup costs.

This model also simultaneously automatically assigns a production job to a particular factory and transports the finished goods among the sites, if the production costs at those sites are relatively higher than the transportation costs. CPLEX solver, used for the numerical analysis, determined that this proposed formulation could indeed manage such a complex problem. These experiments were also used to predict the role of Fixed and Setup costs on the percentage of products transferred among the companies for purposes of satisfying the demand.

Key Words: Strategic/Tactical model; Setup Costs; Transportation Costs; CPLEX.

ACKNOWLEDGMENTS

I feel extremely blessed and honored to be at this point in my career. I express my deep sense of respect and gratitude to Dr. Alain Quilliot, Dr. Burak Eksioglu and Dr. Kevin Taaffe for their meticulous guidance, ever willing help, continuous support, creative ideas, well timed advice, extreme patience, good understanding, forgiving and guiding spirit throughout the journey in fulfilling the requirements of this degree. Without their cooperation and advice, I would not have been able to reach this far in the research.

I deeply appreciate Helene Toussiant, Sreenath Chalil Madathil, and Dr. Jon Lowe for their well-timed support and help rendered at various stages of my work in writing programming codes which made the successful completion of this research. Thanks are also due to my lab colleague Sid Ahmed Hamadi for his help. I appreciate Severine Miginiac for her help in assisting through different kinds of paperwork.

I want to acknowledge my parents Krishna Kumar and Vijaya Kameswari, my brother Vishnu Vardhan for their constant encouragement, support, and prayers. Special thanks to my cousin Sai Sree & well-wisher Abhishek Kumar for their support. I also appreciate each and everyone who has helped me by person or by moral support or by any other means, without any of the help I received from you all I would not have been able to fulfill my degree.

TABLE OF CONTENTS

Table of Contents (Continued)

Page

LIST OF TABLES

LIST OF FIGURES

CHAPTER ONE

INTRODUCTION

Every business/company operates according to a plan. Planning is very important and plays a very significant role to achieve the goals which are set during the start of a business. These goals are incorporated into the business strategies and then a planning process for the company is proposed keeping the goals in mind. There are three types of plans namely Strategic, Tactical and Operational. The three types of plans can be stepping stones as the relationship between one another helps in aiding the achievements of organizational goals. Operational plans are necessary to attain tactical plans and tactical plans lead to the achievement of strategic plans. The main challenges or difficulties of planning lies in choosing the type of model for the framework, conditions while dealing with uncertainties and designing strategic plans in such a way that there exists a relationship between all three types of plans- Strategic, tactical and Operational.

Strategic planning is a long range planning and is done before production planning. The planning time ranges from 1-3years (These years are for Michelin Inc. and the numbers changes for every organization) and is designed by the top level managers keeping the entire organization in mind. The main purpose of strategic planning is it gives a broad view while production planning gives overall details of production. Strategic planning co-ordinates the production plan with the overall plans and strategies of the organization. It is the plan in which the top management which considers possible markets, company facilities, company financial capability and company expertise for the next 1-3 years.

But there are some type of questions that arise at this point like, (Bradley, Hax, and Magnanti, 1977) what kind of decisions are to be taken for new product facilities, capacity extension of existing facilities, acceptance of long-term contracts, and development of marketing and distribution strategies? What is the total time horizon to consider? Etc. Different authors assume different time periods according to their length of the plan for achieving their respective organizational goals. Goetschalckx (2002) included one of the main decisions of strategic network planning describing the locations for opening and closing new and existing production sites respectively as well as the manufacturing point for a particular product to satisfy the demand of the customer in a particular zone in every time period. Assigning products to the plant locations and installing flexible production capacity are the fundamental tasks for strategic production planning.

Tactical planning is a medium range planning where the planning time ranges from 2 months to 1 year which supports strategic plans. These are designed by lower level managers and are responsible for achieving the goals set by the top level managers. Operational plans come under short range planning, where the planning time is no more than 2 months, perhaps a week or two and are designed by the front line managers and will take care of day to day activities in the company with high level of detail.

CHAPTER TWO

STATEMENT OF THE PROBLEM

Strategic decisions should mainly concentrate on future markets. A strategic and tactical model has to be developed for Michelin Inc. to optimize its production and transportation activities by minimizing costs and not to fail in meeting the customer demands in four different zones namely Europe, North America, South America and Asia. There is also a logistics part included for meeting demand from one zone to another zone, if in case the later area was unable to meet the customer demand. The strategic decision to be proposed must consider two levels, one for logistics and the other for production capacities.

In the first level, production is distributed to different zones and then a design for inter-area logistics is required in order to meet demand by considering the capacity of zones and minimize the costs at the same time. The second level focuses on production capacities of different zones and by also considering the changes in the distribution of machines (if necessary) inside the sites/factories for achieving required production. The secondary result of the model must give information on capacity and flexibility utilization. Hence several decisions like lowering investments in new facilities and better usage of existing facilities for satisfying the customer demands should be included in the model. The aim of this integrated model is to determine the production and transportation activities and also the shortfalls by minimum costs under the consideration of uncertain demands. The secondary result of the model gives information on the expected utilization of the flexibility and capacity defaults. This result can only be determined by anticipation of demand. Vidal and Goetschalckx (2000) discussed uncertainties that exist in global production networks such as product demands, product life cycles, and transportation and production costs which are identified by Santoso (2003).

There is also a need for a tactical model in Michelin Inc. to include the factors like uncertainty in product demand and product technologies and also must be able to include the system's adaptability for changes in capacity. There must also be an involvement of medium-term uncertainties applications like accessibility of primary products, changes in technology like advancement in machinery and products like the emergence of new products. Bihlmaier et al. (2008) distinguished between technical and organizational capacities to distinguish the adaptation of tactical planning from strategic planning. Technical capacity is the maximal quantity that can be produced by a manufacturing facility and Organizational capacity concerns about the utilization of the manufacturing facility. For capacity dimensioning process, technical or organizational planning options are needed to be applied for the installed capacities to get adjusted to the market situations. Technical planning options usually linked to a high cost which include the addition of new equipment to the productions lines, incorporating new technology or altering the production line cycle time whereas organizational options include flexibility of workforce like the variation in shift length, staff working overtime etc. For fully exploiting the impact of these additional attributes of the tactical planning, it is necessary to anticipate them in the strategic planning and this must be done in such a way that there in not much change in the planning complexity. According to Jordan and Graves (1995), flexibility and capacity may be substitutable and hence strategic planning model must involve the decisions for strategic and tactical planning simultaneously.

CHAPTER THREE

OVERVIEW OF DIFFERENT MODELS IN PRODUCTION PLANNING

In this chapter, a brief description of different kinds of models and approaches considered based on the kind of problems arise in a company were presented. Selecting a model which suits for a particular problem also plays an important role in strategic planning for getting accurate decisions. Yves Pochet (2001) presented the modelling elements that are to be considered in most of the production planning problems namely, sizing and timing decisions for production lots, resource availability, allocating resources to production lots, satisfying forecasting demand, maximizing performance in terms of production and inventory costs and customer service level and finite planning horizon. And also pointed some complicating modeling elements namely, multiple items interacting through shared resources, multiple items interacting through multi-level product structures, demand backlogging and startup or switching capacity utilization.

There are various kinds of models proposed in strategic planning based on the type of problem like models linking tactical planning and strategic planning, deterministic models, simulation models, optimization models, models incorporating uncertainties etc.

Deterministic Models:

Deterministic models are models in which variables are known and specified. The output of the model is based on the initial conditions and the given parameter values.

Why Linear Programming and Mixed Integer Programming?

Most of the models are currently modeled with Integer Linear Programming (LP) or Mixed Integer Programming (MIP). Decision variables are restricted to integers in Mixed Integer Programming which makes them different when compared to LP models. MIP is used in contexts which emphasizes on human resource planning, facility location, production planning, assignment problems and timetabling etc. MIP's and LP's widely used in developing models as they are easy to model and the best features include their ability to represent the real world system and finding effective configuration Goetschalckx (2001). Various important problem features can be captured with linear models and moreover many powerful solution methods for them are readily available. These programs require lesser solution times compared to other models.

LP and MIP incorporates the view that the innovation in technology does not permit such a decision where fixing one quantity of input and determining the remaining quantities of input and output. For minimization or maximization problems, one way to go accurately is through Linear Programming models. When it comes to long-term planning for big companies under certain constraints and limitations, linear programming is extremely useful for optimizing objectives under this circumstances. A. C. Hax (1977) presented a formal and integrated system which deals with logistic decisions in an aluminum company. They stated that linear-programming model becomes the most appropriate model when production activities are continuous and involving large number of interactions in the planning process.

Jolayemi and Olorunniwo (2003) developed a deterministic mixed integer linear programming model with extension capacities for planning production and transportation activities in a multi-plant and multi-warehouse environments. This model integrates production, transportation, warehouse capacity and inventory systems which result in preparing and optimal production plan and increased profits. This model helps in determining production mix and in maximizing overall profits during a finite planning horizon and can be able to meet shortfalls by either subcontracting or by the use of inventory. After solving the model with LINDO software, it helps in determining the following:

a) The quantity of each product production at each plant

b) The quantity of each product to be transported from each plant to each warehouse

c) The quantity of each product to be subcontracted at each warehouse and

d) The quantity of each product to be kept in inventory at each warehouse.

Bihlmaier et al. (2008) presented a two-stage stochastic, mixed integer program for coping up with complex real world problems in the automotive industry from a capacity and production planning perspective. They proposed mathematical formulations of strategic network planning problems under uncertain demands by presenting a deterministic and stochastic model and then extended the deterministic model to tactical workforce planning by linearized approximation scheme which incorporates workforce planning via detailed shift models to emphasize the necessity of anticipating consecutive stages in a hierarchical process. In the first stage of the program, it includes strategic decisions containing decisions about product allocation and capacity dimensioning and in the second stage, it includes tactical and operational decisions to determine the net present value of the profits. They presume that only demand quantities are uncertain with known probability distributions for extending the deterministic planning problem to two-stage stochastic, mixed integer program which indeed makes it computationally tractable. They used applied Benders decomposition as solution approach and later presented numerical results showing a great decrease in solution time when compared to standard methods.

Fleischmann et al. (2006) presented a multi-period, mixed integer model for strategic planning of BMW’s global production network for optimizing its product allocation globally during a 12-year planning horizon. They considered various factors responsible for uncertainty like exchange rates, demand and cost related factors. During the first phase, they integrated load planning process into their existing strategic planning process and in the second phase they incorporated financial variable, investment decisions, and a greater detail in considering capacity and flexibility reserves. The succeeded in choosing the net present value in objective function which allowed them for comparing their optimal solution with manually computed strategies.

Santoso et al. (2004) developed a two-stage stochastic, mixed integer programming model for realistically solving supply chain design network problems and was successful in solving the realistic complexity of stochastic network design problem in acceptable time for a large number of scenarios. In the first stage of the program, they included decisions related to opening and closing of the manufacturing and distribution centers as well as allocation production to the plants by setting capacity levels. They considered the factors causing uncertainties like costs, demands, capacities, supply quantities, exchange rates and transfer costs. They included them in the tactical decisions in the second stage of the program for getting optimal values for production and transportation quantities. They integrated a sampling strategy known as Sampling Approximation Scheme (SAA) with an accelerated Benders decomposition method for minimizing computing time for computing large number of scenarios. Computational analysis was performed at the end in order to feature stochastic model significance and the solution strategy efficiency.

Bashiri et al. (2011) proposed a mixed integer linear programming model for strategic and tactical planning in four-echelon, multiple-commodity production-distribution network including suppliers, production units, warehouses and customers with different time resolutions for both strategic and tactical decisions and network expansion is planned based on cumulative net incomes in budget constraint. This model deals with network design and expansion planning at the strategic level and deals with distribution and production horizon at the tactical level. This model can make decisions on production and distribution quantities, capacities, selecting suppliers, raw material quantity, facility location and expansion planning in long time horizon. At the end, they analyzed results for a numerical example for explaining applications of the model. Badri et al. (2012) also proposed a mixed integer linear programming model for network design and planning expansions of a four-echelon multiple commodity supply chain with a long-term horizon. They considering some features such as minimum and maximum utilization of facilities, public warehouses and locations for private warehouses and the same decisions as of Bashiri et al. (2011). But Badri et al. (2012) proposed a solution approach that is based on a Lagrangian Relaxation (LR) method.

Thanh et al. (2008) proposed a dynamic mixed integer linear programming model for a four-echelon supply chain which comprises of suppliers, plants, warehouses and customers for designing a new network or making changes in an existing network or for evaluating a strategic decision. Bill of materials and multiple products have been taken into consideration. They make a distinction between private warehouse (owned by the company) and the public warehouse (hired by the company). It also includes the same strategic decisions of Bashiri et al. (2011). Different time resolutions and cumulative net incomes in the budget constraint are the main differences between the proposed model and Bashiri et al. (2011).

Arntzen et al. (1995) proposed a multi-period, mixed integer model for global supply chain planning which incorporates a global, multi-product bill of materials for supply chains. The model includes detailed production, inventory and transportation planning and strategic decisions as product allocation with related fixed costs without considering investment requirements. The main feature of the model is its focus on international aspects like duties and exchange rates, duty drawbacks or import taxes etc. The objective function is a combination of cost and time where it minimizes costs as well as weighted production and shipping times. This model was applied to Digital Equipment Corporation, where the model saved millions of dollars for restructuring.

Stochastic Models:

Galbraith (1973) defines uncertainty as the difference between the amount of information required to perform a task and the amount of information already processed. The development of market demand, prices, tariffs, cost factors, lead times and exchange rates over a long-term planning horizon is highly uncertain. Let us consider an example of unknown market demand behavior to illustrate the importance of taking uncertainty into account. See the case study of Parsons (2004). This behavior has vital importance in supply chain design as it gives an indication of future markets, sales and production quantities in a geographical area as well as matching demand with supply. The case study deals with the number of NFL replica jerseys produced by Reebok during an event. It is important to procure inventory before the start of the season, and demand for jerseys changes based on the hot players in the team as well as unexpected teams success on the baseball field.

Ho (1989) categorizes the real world forms of uncertainties affecting the production process into environmental uncertainty and system uncertainty. Demand uncertainty and supply uncertainty comes under environmental uncertainty whereas uncertainties of operation yield, production lead time, quality etc. comes under system's uncertainty. These uncertainties require different ways to counteract. Graves (2003) considered uncertainties in the quantity and timing of replenishment orders of a single item with non-stationary demand. They developed a near-optimal heuristic and later compared it with an infinitesimal perturbations analysis (Glasserman and Tayur, 1995) which is a simulation based optimization procedure. For existing literature for production planning models under uncertainty, refer to Mula et al. (2006) where the authors gave a general classification of different methods to cope up with different forms of uncertainty. They are tabulated in Table 1.

The significance of uncertainty has prompted numerous researchers to address stochastic parameters in tactical level supply chain and production planning. Stochastic programming with recourse models is well suited for analyzing resource acquisition planning problems because of their inherited randomness, versatility and as well as they

Conceptual Models	*Analytical Models*
Yield factors	Hierarchy Process
Safety Stocks	Mathematical Programming
Safety lead times	Stochastic Programming
Hedging	Deterministic approximations
Over planning	Laplace Transforms
Line requirements planning	Markov decision processes
Flexibility	
Intelligence artificial based models	*Simulation Models*
Expert systems	Monte Carlo Techniques
Reinforcement learning	Probability Distributions
Fuzzy set theory	Heuristic methods
Fuzzy logic	Freezing parameters
Neural network	Network modelling
Genetic algorithms	Queuing theory
Multi-agent systems	Dynamic systems

Table 1: Classification of general types of uncertainty models in manufacturing systems

combine deterministic mathematical programming models for allocating resources optimally with decision analysis models (S.A. MirHassani et al., 2000). The question which often arises at this point of time is, how uncertainty is represented? Once the strategic and the tactical model is developed for an organization, the model is then extended to a stochastic model which represent uncertainties with known probabilistic distributions. There will be no change in the strategic or tactical part of the model, but there will be a change in the constraints of the respective uncertainties. Let us consider the example of Bihlmaier et al. (2008). They considered only demand quantities are uncertain and they modified only demand constraint (11) in the deterministic model and replaced with scenario-dependent demand, d_{npmt} in the stochastic model.

S.A. MirHassani et al. (2000) considered a two-stage model for multi-period capacity planning of a supply chain networks. The first stage decisions are concerned with opening and closing of plants and distribution centers and setting their capacity levels needed to be decided before the realization of future demands. Then production and decisions are made optimally upon the realization of a particular demand scenario. The second stage deals with operational decisions like production quantities, packaging quantities, and transportation amounts. The main objective is the minimization of costs of the first stage strategic decisions and the expected production and distribution costs over the uncertain demand scenarios. For solution approach, they used Benders decomposition to solve the resulting stochastic integer program.

Tsiakis et al. (2001) considered a two- stage stochastic programming model with uncertain demand. They modeled a mixed integer linear programming optimization problem for determining decisions related to locations and capacity of distribution centers and warehouses to be established, transportation as well as flows and production rate of materials. The overall objective is to minimize the total cost of the network and presented a case study illustrating the applicability of the model in three different European countries.

Chopra and Meindl (2001) suggested a way to deal with uncertainty by controlling a combination of two factors namely production capacity and inventory. It is evident that it is impossible to eliminate uncertainty completely, but incorporating more comprehensive decision support approaches can minimize its effect on the performance of supply chain.

Simulation Models:

Simulation is something that represents imitation of the functioning of one system to another in the real world. The objective of the simulation models is determining the most effective strategies for an organization. There are three simulation techniques which are widely used namely, Discrete Event Simulation (DES), System Dynamics (SD) and Agent-Based Simulation (ABS). These are incorporated accordingly depending on the type of issues that arise during production planning. Table 2 (Jeon and Kim, 2016) emphasizes applicable simulation techniques for the production planning problems. DES can be modeled in discrete time whereas SD can be modeled in continuous time. The reason is, the state changes are aroused by events in DES while the state changes smoothly over time in SD. Simulation models which often based on DES models are able to achieve the following (Carteni and Lusa, 2011):

a) To overcome mathematical limitations of optimization approaches

b) To support computer-generated policies and make them relatively easy to understand and

c) To support decision makers in a daily decision processes through a 'what-if' approach.

In production planning, a number of models were being used to link strategic and tactical levels and it's being difficult considering the increasing complexity and globalization of manufacturing environment. So, simulation modeling is a better technique for approaching this kind of problems based on its ability to adapt to complex manufacturing situations.

Production Planning problems		Applicable Simulation techniques
Facility resource Planning	Location determination	DES
	Layout design	DES
Capacity Planning	Resource management	DES, SD, ABS
	Optimal quantity determination to produce product over planning horizon	DES
	Forecasting problem for demand uncertainties	SD
	Optimal capacity selection to determine total cost and product revenues	DES, SD
Job planning	Equipment planning	DES, ABS
	Job-shop planning and management	DES, ABS
	Machine job sequence planning	DES, ABS
	Bottleneck problems	DES
Process planning	Process sequence planning	DES
	Machine routing	DES, ABS

Shop floor Scheduling	Material processing planning Shop floor scheduling Schedule management (slack time, queuing, due date)	DES, ABS DES, ABS DES, ABS, SD

Table 2: Applicable simulation techniques for production planning problems

Kotevski et al. (2015) developed a descriptive event simulation model for the companies dealing with different kinds of wastes, delays, overstock, bottlenecks and loss of time in production planning environment. They used methodology of Banks (1998) for this simulation model. Then the model was created using Siemens Plant Simulation Software by considering different percentages of scrap that forms the end product. They verified model and results are presented at the end.

Carteni and Lusa, (2011) presented microscopic discrete event simulation models for addressing strategic and tactical planning modeling issues and focused on finding the best technique to adapt to simulate time duration in elementary handling activities in a container terminal. They broke down the terminal operations into elementary activities and then analyzed each and every operation and modeled through stochastic approach. They addressed different kinds of modeling issues that may arise during different planning horizons such as real time, short term, medium term and long term. They proposed four microscopic DES models for a terminal in southern Italy which only differences in estimating handling activity duration times. Later they are validated on the calibration date set through global performance indicators to point out the strengths and weaknesses of the considered approaches.

For more literature on Simulation models, Jeon and Kim (2016) presented a detailed literature review on state-of-the-art applications of simulation techniques and illustrated their applicability to modern manufacturing issues in production planning between 2002 and 2014. They enclosed three types of simulation techniques namely DES, SD and ABS, and eight production planning and control (PPC) issues namely facility resource planning, job planning, capacity planning, process planning, production and process design, inventory management, scheduling, purchase and supply management. They defined issues in PPC and provided the characteristics of simulation techniques along with their applications in PPC problems.

CHAPTER FOUR

METHODS USED IN PRODUCTION PLANNING MODELS

In this chapter, we are interested in dealing with different kinds of approaches used to solve production planning problems. Some of the methods used are Optimization methods, Lagrangian relaxation, Column generation, Benders and Dantzig-Wolfe decomposition methods etc.

The main purpose of optimization methods is to find optimal solutions for the proposed models or near to the optimal solutions with a performance guarantee usually expressed in terms of the objective value's deviation percentage from the optimal value. Most of them are based on easy to solve relaxations of the initial problem. Lagrangian relaxation is simply a relaxation method which approximates a complex problem of a constrained optimization model by a simpler problem. Hence it approximates the solution of the complex problem with the solution of the simpler problem. Column generation is an algorithm which is used to solve larger linear programs. Martunez-Costa et al. (2014) stated that most of the authors used dynamic programming techniques, approximate algorithms or specially designed heuristics like Lagrangian-relaxation heuristics for solving models until 2000. Later many software's came into existence such as CPLEX, MS- Excel, IBM product, Genetic Algorithms for tackling issues like complexity of the model, computational time etc.

Yves Pochet (2001) presented a detailed literature review on optimization models where the relaxation is done with different methods namely Lagrangian relaxation, Dantizig-Wolfe or column generation methods. Shapiro (1989) presented a literature review on Lagrange multiplier and decomposition methods for several large scale production planning and scheduling models. Crainic et al. (1999) reported on the performance of different relaxations and dual optimization methods to solve network design problems.

Monte Carlo method was used by Bihlmaier et al. (2008) in two-stage stochastic, mixed integer program. It is involved in log-normal distribution calculations of product life cycles along with considering correlations among the other products. They applied Bender’s decomposition approach for solving a master problem. As presented earlier, Badri et al. (2012) proposed a solution approach that is based on a Lagrangian Relaxation (LR) method. Jolayemi and Olorunniwo (2003) solved their reduced model with LINDO software. Santoso et al. (2004) integrated a sampling strategy known as Sampling Approximation Scheme (SAA) for uncertain data with an accelerated Benders decomposition method for minimizing computing time for computing a large number of scenarios for solving supply chain design issues.

Example of Bihlmaier et al. (2008):

Let us consider the model proposed by Bihlmaier et al. (2008) as an example for better understanding of the link between strategic and tactical models. They described capacity planning problem in the automotive industry which is facing a market situation involving uncertainty and dynamic change. They integrated workforce planning via detailed shift models. They modeled the problem as a deterministic and a two-stage stochastic mixed integer program and then this deterministic model is extended by a detailed model of tactical workforce planning.

Model Notation:

A complete list of sets used in the model is presented in Table 3. Every element $p \in P$ represents raw material, intermediate or a final product. An element $f \in F$ represents a facility transforming a product $p \in P$ into another $p' \in P$. A stage $s \in S$ denotes the stage where capacity is to be initialized for the production line.

Symbol	Definition
P	Set of products produced and transported
F	Set of facilities (plants/production lines)
S^f	Set of capacity-initializing stages for line $f \in F$
M	Set of markets
T	Set of time-periods in the planning horizon
N	Set of demand scenarios
W	Set of shift models

Table 3: List of Indexes

Cost based and quantity based parameters are given in Tables 4 and 5 and miscellaneous parameters are shown in Table 6 which depends on corporate policy settings. Cost based parameters represent both single period payment flows which involve strategic decisions like one-time costs for setting up machinery and continuously payment flows which involve tactical decisions like fixed and variable costs. MU refers to the unit of measurement for cost parameters, CU refers capacity units and QU refers to quantity units.

Symbol	Definition	Unit
r_t	Interest rate for the calculation of the capital value in period t	%
k^{PI}_{pf}	Amount of product specific investment, if product p is allocated to facility f	MU
k^{KI}_{sf}	Amount of capacity based investment, if technical capacity stage s is initialized in facility f	MU
k^{PV}_{psft}	Variable production costs of product p, in capacity stage s, facility f and period t	MU/QU
k^{PF}_{pft}	Production based fixed costs of product p in facility f and period t	MU
k^{KF}_{sft}	Capacity based fix costs of the initialized capacity stage s, that occur, if it is actually deployed in facility f and period t	MU
$k^{TI}_{pff\prime t}$	Cost rate for internal transport of one unit of product p from facility f to facility f ′ in period t	MU/QU
k^{TE}_{pfmt}	Cost rate for external transport of one unit of product p from facility f to market m in period t	MU/QU
k^{SF}_{pmt}	Opportunity costs for shortfall of one unit of product p in market m and period t	MU/QU
k^{MIN}_{sft}	Cost to reduce the capacity of stage s in facility f and period t using organizational instruments by one unit (linear approximation)	MU/QU
k^{MAX}_{sft}	Cost to increase the capacity of stage s in facility f and period t using organizational instruments by one unit (linear approximation)	MU/CU

Table 4: Cost Parameters

Symbol	Definition	Unit
d_{pmt}	Demand of product p in market m and period	QU
c_{sf}^{K}	Capacity of stage s in facility f per period in regular working time	CU
c_{pf}^{EFF}	Factor that reflects the loss of efficiency induced by flexible production of product p in facility f	%
c_{pf}^{AV}	Factor that reflects the loss of capacity in the first period of production of product p in facility f	%
c_{psf}^{KB}	Amount of capacity units of stage s needed to produce one unit of product p in facility f	CU/QU
c_{f}^{MK}	Technical capacity per period in facility f in maximal working time	CU
$c_{p'p}^{BOM}$	Number of units of product p to produce one unit of product p (bill of material)	QU/QU

Table 5: Quantity based parameters

Symbol	Definition	Unit
ρ_n	Probability of scenario n	
d_{sf}^{KMIN}	Minimal relative capacity reduction by organizational instruments in capacity stage s and facility f	%
d_{sf}^{KMAX}	Maximal relative capacity increase by organizational instruments in capacity stage s and facility f	%
d_{pft}^{PMIN}	Lower bound on the amount of product p produced in facility f and period *t*	
d_{pft}^{PMAX}	Upper bound on the amount of product p produced in facility f and period t	
d_{pft}^{LE}	Upper bound on product allocation variable y_{pft}^{PA}, which indicates the allocation of product p to facility f in period t (if set to 0, y_{pft}^{PA} is fixed to 0)	
d_{pft}^{LF}	Lower bound on product allocation variable y_{pft}^{PA}, which indicates the allocation of product p to facility f in	

	period t (if set to 1, y^{PA}_{pft} is fixed to 1)	

Table 6: Miscellaneous parameters

Symbol	Definition
y^{PI}_{pft}	Indicator variable: 1, if the allocation of product p to facility f is initialized in period t, 0 otherwise
y^{PA}_{pft}	Indicator variable: 1, if the product p is produced in facility f period t, 0 otherwise
y^{KI}_{sft}	Indicator variable: 1, if the technical capacity stage s in facility f is initialized in period t, 0 otherwise
y^{KA}_{sft}	Indicator variable: 1, if the technical capacity stage s in facility f is deployed in period t, 0 otherwise
x^{P}_{psft}	Real nonnegative variable: amount of product p produced in facility f and period t using capacity stage s
$x^{TI}_{pff\prime t}$	Real nonnegative variable: amount of product p transported from facility f to facility f' in period t (internal transport)
x^{TE}_{pfmt}	Real nonnegative variable: amount of product p transported from facility f to market m in period m (external transport)
x^{MIN}_{sft}	Real nonnegative variable: amount of which the capacity of stage s in facility f is reduced by organizational instruments
x^{MAX}_{sft}	Real nonnegative variable: amount of which the capacity of stage s in facility f is increased by organizational instruments
z^{SF}_{pmt}	Real nonnegative variable: shortfall of product p on market m in period t

Table 7: Decision Variables

Strategic decisions are involved in Yes/No decisions represented by a binary code while all tactical decisions are represented by continuous real-valued variables for approximating the real problem.

Model Formulation for the example considered:

- *Deterministic Model:* Deterministic formulation of the optimization model is presented below. ZFS (t) represents the formulations for strategic decisions on payment flows which only involves investments and fixed costs, while ZFT (t) represents the formulations for tactical decisions on payment flows involving variable costs and cause running expenses and profits.

$$\min \mathrm{ZF} = \sum_{T} \frac{ZF^{S}(t) + ZF^{T}(t)}{(1+r_t)^t} \tag{1}$$

$$\begin{aligned} \text{with } \mathrm{ZF}^{\mathrm{S}}(t) = {} & \Sigma_{\mathrm{P}}\Sigma_{\mathrm{F}}\,(\mathrm{k}^{\mathrm{PI}}_{\mathrm{pf}}\mathrm{y}^{\mathrm{PI}}_{\mathrm{pft}} + \mathrm{k}^{\mathrm{PF}}_{\mathrm{pft}}\mathrm{y}^{\mathrm{PA}}_{\mathrm{pft}}) \\ & + \Sigma_{\mathrm{S}}\Sigma_{\mathrm{F}}\,(\mathrm{k}^{\mathrm{KI}}_{\mathrm{sf}}\mathrm{y}^{\mathrm{KI}}_{\mathrm{sft}} + \mathrm{k}^{\mathrm{KF}}_{\mathrm{sft}}\mathrm{y}^{\mathrm{KA}}_{\mathrm{sft}}) \end{aligned} \tag{2}$$

$$\begin{aligned} \text{and } \mathrm{ZF}^{\mathrm{T}}(t) = {} & \Sigma_{\mathrm{S}}\Sigma_{\mathrm{F}}\,(\mathrm{k}^{\mathrm{MIN}}_{\mathrm{sft}}\mathrm{x}^{\mathrm{MIN}}_{\mathrm{sft}} + \mathrm{k}^{\mathrm{MAX}}_{\mathrm{sft}}\mathrm{x}^{MAX}_{sft}) \\ & + \Sigma_{\mathrm{P}}\Sigma_{\mathrm{S}}\Sigma_{\mathrm{F}}\,\mathrm{k}^{\mathrm{PV}}_{\mathrm{psft}}\mathrm{x}^{\mathrm{P}}_{\mathrm{psft}} \\ & + \Sigma_{\mathrm{P}}\Sigma_{\mathrm{F}}\Sigma_{\mathrm{F'}}\,\mathrm{k}^{\mathrm{TI}}_{\mathrm{pff't}}\,\mathrm{x}^{\mathrm{TI}}_{\mathrm{pff't}} \\ & + \Sigma_{\mathrm{P}}\Sigma_{\mathrm{F}}\Sigma_{\mathrm{M}}\,\mathrm{k}^{TE}_{\mathrm{pfmt}}\mathrm{x}^{\mathrm{TE}}_{\mathrm{pfmt}} \\ & + \Sigma_{\mathrm{P}}\Sigma_{\mathrm{M}}\,\mathrm{k}^{SF}_{\mathrm{pmt}}\mathrm{z}^{\mathrm{SF}}_{\mathrm{pmt}} \end{aligned} \tag{3}$$

Subject to (4) – (17)

Constraints (4) and (5) enforces the indispensable dependencies of strategic decisions and capacity decisions allow only one of the given set of options can be utilized for each production facility (6).

$$Y^{PA}_{pft} \leq \Sigma t' \leq t \ \ y^{PI}_{pft'} \quad \forall\, p, f, t \tag{4}$$

$$y^{KA}_{sft} \leq \Sigma t' \leq t \ \ y^{KI}_{sft'} \quad \forall\, s, f, t \tag{5}$$

$$\Sigma_S \Sigma_T \ y^{KI}_{sft} \leq 1 \quad \forall\, f \tag{6}$$

Constraint (7) gives the decisions about the links determining the disposition of production feasibilities to lines or locations. Constraints (8) – (10) deals with the capacity decisions. Constraint (11) ensures demand satisfaction. Constraints (12) and (13) ensures material balance.

$$c^{KB}_{psf} x^{P}_{psft} \leq c^{MK}_{f} y^{PA}_{pft} \quad \forall\, p, s, f, t \tag{7}$$

$$\Sigma_P \Sigma_S \ c^{KB}_{psf} x^{P}_{psft} \leq \Sigma_S \left(c^{K}_{sf} y^{KA}_{sft} + x^{MAX}_{sft} - x^{MIN}_{sft} \right) \quad \forall\, f, t \tag{8}$$

$$x^{MAX}_{sft} \leq d^{KMAX}_{sf} c^{K}_{sf} y^{KA}_{sft} \quad \forall\, s, f, t \tag{9}$$

$$x^{MIN}_{sft} \leq (1 - d^{KMAX}_{sf}) \, c^{K}_{sf} y^{KA}_{sft} \quad \forall\, s, f, t \tag{10}$$

$$z^{SF}_{pmt} + \Sigma_F \, x^{TE}_{pfmt} \geq d_{pmt} \quad \forall\, p, m, t \tag{11}$$

$$\Sigma_{F'} \ x^{TI}_{pff't} = \Sigma_S \Sigma_{P'} \ c^{BOM}_{p'p} x^{P}_{p'sft} \quad \forall\, p, f, t \tag{12}$$

$$\Sigma_S \ x^{P}_{psft} = \Sigma_{F'} \ x^{TI}_{pff't} + \Sigma_M \ x^{TE}_{pfmt} \quad \forall\, p, f, t \tag{13}$$

Constraint (14) represents that some product allocation decisions might be fixed, prohibited or technologically impossible. Constraint (15) enforces, if given, a frame for the feasible output of several manufacturing facilities.

$$d^{LF}_{pft} \leq y^{PA}_{pft} \leq d^{LE}_{pft} \quad \forall\, p, f, t \tag{14}$$

$$d^{PMIN}_{pft} \leq \Sigma_S \ x^{P}_{psft} \leq d^{PMAX}_{pft} \quad \forall\, p, f, t \tag{15}$$

In long term capacity planning, whole capacity in years of product launches is not available for each affected production line and hence the capacity will be reduced by c^{AV}_{pf} in constraint (16). Flexibility in production refers to the production of different types of products on the same line. Efficiency loses that incurs while producing different products on the same production line is represented in constraint (17) by rate c_{pf}^{EFF}. Inequalities (18) and (19) are added to reduce the required solution time.

$$c_{sf}^{K} y_{sft}^{KA} + x_{sft}^{MAX} - x_{sft}^{MIN} \leq (1 - \Sigma_P \; c_{pf}^{AV} y_{pft}^{PI}) \; c_{sf}^{MK} \quad \forall \, s, f, t \tag{16}$$

$$c_{sf}^{K} y_{sft}^{KA} + x_{sft}^{MAX} - x_{sft}^{MIN} \leq (1 - \Sigma_P \; c_{pf}^{EFF} y_{pft}^{PA}) \; c_{sf}^{MK} \quad \forall \, s, f, t \tag{17}$$

$$\Sigma_T \; y_{pft}^{PI} \leq 1 \quad \forall \, p, f \tag{18}$$

$$\Sigma_T \; y_{sft}^{KI} \leq \Sigma_T \Sigma_P \; y_{pft}^{PI} \quad \forall \, s, f \tag{19}$$

- *Extension to tactical workforce planning*: Now the above deterministic model is extended for integrating tactical work force planning. They used shift models for planning workers shifts (for example day, evening and night) for considering realistically the workforce planning task. The additional parameters for this extension are shown in Table 8. This extension must be already anticipated at the strategic level. This must be done without not much difference in solution time. Hence they considered linear approximation scheme which guarantees acceptable solution time. As this approximation is not sufficient for determining total life-cycle costs, they extended the model in such a way that it supports both identification of optimal capacity adaptation paths and calculation of life-cycle costs for a given network structure and demand realization. Equation (20) represents new objective function after adjusting original model by capacity adaptation cost.

$$
\begin{aligned}
ZF^{T}(t) = \quad & \Sigma_F \Sigma_W \Sigma_S \left(r^{SM}_{wsft} k^{WF}_{f} x^{WF}_{wsft} \right. \\
& \left. + k^{HWF}_{f} x^{HWF}_{ft} + k^{FWF}_{f} x^{FWF}_{ft} \right) \\
& + \Sigma_P \Sigma_S \Sigma_F \, k^{PV}_{psft} x^{P}_{psft} \\
& + \Sigma_P \Sigma_{P'} \Sigma_F \Sigma_{F'} \, k^{TI}_{pff't} x^{TI}_{pp'ff't} \\
& + {}_P \Sigma_F \Sigma_M \, k^{TE}_{pfmt} x^{TE}_{pfmt} \\
& + \Sigma_P \Sigma_M \, k^{SF}_{pmt} z^{SF}_{pmt}
\end{aligned}
\qquad (20)
$$

Symbol	Definition	Unit
y^{SM}_{wsft}	Indicator variable: 1, if shift model w is chosen in capacity stage s, facility f and period t, 0 otherwise	
x^{WF}_{wsft}	Real nonnegative variable: number of employees deployed in shift model w,capacity stage s, facility f and period t	
x^{HWF}_{ft}	Real nonnegative variable: number of employees hired in facility f in period t	
x^{FWF}_{ft}	Real nonnegative variable: number of employees dismissed in facility f in period t	
r^{SM}_{wsft}	Cost parameter: factor for the shift model bonus of shift model w, capacity stage s, facility f in period t (it is multiplied with employee's wage k^{WF}_{f} to obtain time, shift model, and capacity stage dependent costs)	%
k^{WF}_{f}	Cost parameter: wage per employee in facility f	MU
k^{HWF}_{f}	Cost parameter: hiring costs per employee in facility f	MU
k^{FWF}_{f}	Cost parameter: dismissal costs per employee in facility f	MU
c^{SM}_{wsft}	Capacity parameter: amount of capacity available in shift model w and stage s, facility f and period t	CU
d^{WF}_{wsft}	Workforce parameter: minimal number of employees required to deploy shift model w in capacity stage s, facility f and period t	

Table 8: Additional parameters and decision variables in workforce planning extension

Constraints (21) – (26) are capacity adaptation constraints and are obtained after replacing them with constraints (8), (9), (10), (16), (17). Constraint (21) determines suitable shift model. Constraint (22) ensures, choosing at most one shift model for a capacity stage s deployed in time period t and facility f. Constraint (23) prevents the number of employers x_{wsft}^{WF} from falling below the required workforce for a chosen shift model. Constraint (24) deals with hiring and dismissing workers. Constraints (25) and (26) are the equivalents to constraints (16) and (17) in the original model.

$$\sum_P c_{psf}^{KB} x_{psft}^{P} \leq \sum_W c_{wsft}^{SM} y_{wsft}^{SM} \quad \forall\, s, f, t \tag{21}$$

$$y_{wsft}^{SM} \leq y_{sft}^{KA} \quad \forall\, s, f, t \tag{22}$$

$$x_{wsft}^{WF} \geq d_{wsft}^{WF} y_{wsft}^{SM} \quad \forall\, w, s, f, t \tag{23}$$

$$\sum_W \sum_S x_{wsft}^{WF} = x_{ft}^{HWF} - x_{ft}^{FWF} + \sum_W \sum_S x_{wsf(t-1)}^{WF} \quad \forall\, f, t \tag{24}$$

$$\sum_W c_{wsft}^{SM} y_{wsft}^{SM} \leq (1 - \sum_P c_{pf}^{AV} y_{pft}^{PI})\, c_{sf}^{MK} \quad \forall\, s, f, t \tag{25}$$

$$\sum_W c_{wsft}^{SM} y_{wsft}^{SM} \leq (1 - \sum_P c_{pf}^{EFF} y_{pft}^{PA})\, c_{sf}^{MK} \quad \forall\, s, f, t \tag{26}$$

The authors used applied Bender's Decomposition scheme for solving the model. The model is split into a master problem and n subproblems, where all strategic decisions are included in the master problem and each subproblem includes tactical decisions for a single demand scenario. Demand scenarios are generated and computed by using Monte Carlo Method and an abstract algorithmic strategy was presented for finding optimal values of strategic decisions. Bender's decomposition scheme solved each and every demand scenario by iterating and solving the extended master problem and the subproblems. After every iteration, the best solution if the strategic variables are stored and are passed to the subproblems and dual solutions of the remaining subproblems are computed. Shift model planning task is performed for strategic decisions and each and every demand scenarios after solving the main problem.

Firstly Bihlmaier et al. (2008) succeeded in improving the efficiency of the process. The above two models when compared in a case study gave the same strategic decisions, which justifies the use of an approximation of the stochastic model during uncertainty. There are few more questions that arise to the users. They neglected uncertainty factors like dynamics of markets as they are associated with high levels of uncertainty. They considered only uncertainty in production and demand but didn’t consider uncertainty in the entire supply chain. The authors neglected exchange rates, duty and import taxes in the model which limits it to the production in a single country. Authors stated that they are hiring and dismissing workers according to the optimal plan, which is not easy in the real world scenario as it is involved with so many regulations. Some of the factors like sub-contracting, scheduling are also not incorporated in the model. They used applied Benders decomposition as solution approach and later presented numerical results which showed, that the demonstrated method decreases computational effort which in turn enabling the handling of large scale problems in a reasonable amount of times. They concluded their work with a performance study followed by a case study.

In this paper, I developed a mixed strategic and tactical model for planning production and transportation quantities in multi-plant environments. The main objective is to prepare a low-cost optimal model satisfying demand and production quantities in a multi-plant environment integrating two different means of satisfying customer demands, namely production, transportation and logistics. To cope with the complex real-world problems, a mixed-integer program is presented in the next section. This representation is developed by considering the disintegration of a process within the factory as well as total integrated layout for designing inter-area logistics flow. We considered two cases during the modeling namely one with the same setup cost for the production of different products and the second with different setup costs for different products. The model will be formulated under the assumption of 1 time period.

CHAPTER FIVE

MODEL FORMULATION

<u>Definition of Symbols:</u>

The symbols used in this model are divided into 2 categories namely input parameters and decision variables. Let P be the set of products produced and I be the set of sites (factories/plants) where the manufacturing plants (factories) are located. Overview of the production sites is shown in Figure 1. An element $i \in$ I represents a facility transforming raw materials into final products. Raw materials are transported to each and every factory from site 0 and production/manufacturing takes place in the sites 1, 2, …, S. Let *nFact* is the total number of factories which also includes factory at site 0. Therefore we can say *nFact* = S+1. For every $p \in$ P, represents different types of raw materials or intermediate or final products being produced in those factories.

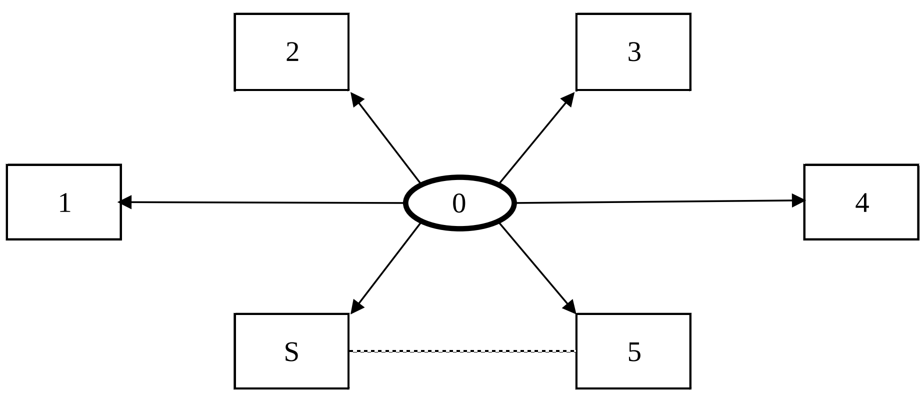

Figure 1: Overview of production sites

Input parameters and decision variables are shown in the Tables 9 and 10 respectively. There is also a miscellaneous variable which is, R_{pi} the rank (order in the line) for the product p in site i used in the setup constraint in case 2.

Symbol	Definition
CF_{ip}	Fixed production cost of product *p* in site *i*
CL_{ip}	Linear production cost of product *p* in site *i*
S_i	Setup cost at site *i* (does not depend on the type of products produced)
$S_{ipp'}$	Setup cost for changing production from product *p* to product *p'* in site *i*
D_{ip}	Demand for product *p* in site *i*
C_{ip}	Capacity of the batch of product *p* in site *i*
CAP	Capacity of a truck carrying products *p* from site *i* to site *j*
DIST(i,j)	Distance between the sites *i* and *j*

Table 9: Input Parameters

Symbol	Definition
x_{ip}	Quantity of products *p* produced in site *i*
V_{ip}	Number of batches of products *p* in site *i*
U_{ij}	Number of trucks transporting products from site *i* to site *j* and $i \neq j$
Z_{pij}	Number of products being transferred from site *i* to site j
y_{ip}	a binary variable which is 1 if the product *p* is produced in site *i* and 0 otherwise
$w_{ipp'}$	a binary variable which is 1 if the set of products *p* and *p'* are processed consecutively and 0 otherwise
$w_{i\phi p}$	a binary variable which is 1 if *p* is the first processed set of products and 0 otherwise

Table 10: Decision Variables

The Model (Case 1):

In Case 1, we are formulating the mixed strategic and tactical model using the notation described above. Here we are assuming that there is no setup cost for producing different kinds of products on the same production line.

The Objective Function:

The objective function of the model is the minimization of total costs which includes production, transportation and setup costs, which are represented by the following expression:

$$\text{Minimize} \sum Costs = \sum_{i=o}^{nFact-1} \sum_p CF_{ip} V_{ip} + \sum_{i=o}^{nFact-1} \sum_p CL_{ip} x_{ip} + \sum_{i=0}^{nFact-1} \sum_{\substack{j=0 \\ i \neq j}}^{nFact-1} DIST(i,j) U_{i,j} + \sum_{i=0}^{nFact-1} S_i \left(\sum_p y_{ip}\right) \qquad (27)$$

Subject to (28) – (33).

The first two terms represent production costs followed by transportation and setup costs respectively.

Demand Constraint:

$$D_{ip} = x_{ip} + \sum_{\substack{j=1 \\ j \neq 0 \\ j \neq i}}^{nFact-1} Z_{jip} - \sum_{\substack{j=1 \\ j \neq 0 \\ j \neq i}}^{nFact-1} Z_{ijp} \quad \forall\, i, p \qquad (28)$$

In order to satisfy demand in all the sites, sometimes there arises a necessity of transferring products from one site to another site in order to avoid backlogs. Hence for every site and a product, demand must equal the production as well as the difference between the transferred and received products shown in Equation (28).

Production Constraints:

$$x_{ip} = Z_{0ip} \quad \forall\, i, p \tag{29}$$

$$x_{ip} \le V_{ip}\, C_{ip} \quad \forall\, i, p \tag{30}$$

As mentioned before that all the primary products or raw materials are transferred from site 0 to all the remaining sites where the final production takes place. Therefore Equation (29) represents that for every site *i* and product *p*, the products produced at all the manufacturing sites must be equal to the number of primary products that have been received from the site 0. As we are implementing production in batches, the Equation (30) states that for every site *i* and product *p*, total production must be at most equal to the product of the batch size and the number of batches being produced.

Transportation Constraint:

$$CAP * U_{i,j} \ge \sum_p Z_{ijp} \quad \forall\, i, j;\ i \ne j \tag{31}$$

In order to minimize the cost of transportation, we have to concentrate on the number of trucks traveling between one site to another site. As the capacity of each truck is already constant, for every site *i* and *j* where *i* is different from *j*, the product of capacity and number of trucks must be at least equal to the number of products carrying from site *i* to site *j* represented in Equation (31).

Setup Cost Constraints:

$$V_{ip} \le y_{ip}\, Vmax \quad \forall\, i, p \tag{32}$$

$$Vmax = \frac{\sum_{i=0}^{nFact-1} \sum_p D_{ip}}{min_{i,p}\, C_{ip}} \quad \forall\, i, p \tag{33}$$

Setup cost mainly depends on the different types of products produced in a particular site and in turn depends on the maximum number of batches produced. The maximum number of batches can be calculated by dividing total demand with the minimum capacity of a batch for every product in site *i* as shown in Equation (33).

Nonnegativity of the variables:

All the variables should be nonnegative.

<u>The Model (Case 2):</u>

The only difference between the model in Case 1 and Case 2 is the difference in the assumption of setup cost. In case 2, there is a setup cost included for different kinds of products produced on the production line. But we neglected the time taken for changing the setup for one product to another.

The Objective Function:

The objective function of the model is the minimization of total costs which includes production, transportation and setup costs, which are represented by the following expression:

$$\text{Minimize} \sum Costs = \sum_{i=o}^{nFact-1} \sum_p CF_{ip} V_{ip} + \sum_{i=o}^{nFact-1} \sum_p CL_{ip} x_{ip} + \sum_{i=0}^{nFact-1} \sum_{\substack{j=0 \\ i \neq j}}^{nFact-1} DIST(i,j)\, U_{i,j} + \sum_{i=0}^{nFact-1} \sum_p \sum_{p'} S_{ipp'} w_{ipp'} \quad (34)$$

Subject to (28) – (31) & (35) – (39)

The first two terms represents production costs followed by transportation and setup costs respectively. Demand, Production and Transportation constraints are the same as in Case 1. Setup Cost constraints are the one which differs from the Case 1.

Setup Cost Constraints:

$$w^i_{p,p'} \le y^i_p \quad \forall\, i, p, p' \tag{35}$$

$$w^i_{p,p'} \le y^i_{p'} \quad \forall\, i, p, p' \tag{36}$$

$$\sum_{p'} w^i_{p,p'} = \sum_{p'} w^i_{p',p} \ge y^i_p \quad \forall\, i, p \tag{37}$$

$$w^{\,i}_{\phi,p} - R^i_p \le 0 \quad \forall\, i, p \tag{38}$$

$$w^i_{p,p'} - R^i_{p'} - R^i_p \le 0 \;\; \forall\, i, p, p' \tag{39}$$

Setup cost in this scenario depends on the different types of products processed consecutively on the production line. Equations (35) and (36) ensures the consecutive processing of two products *p* and *p'* in site *i*. Equation (37) shows the number of different kinds of products processed other than type *p* in site *i*. If product *p* is the first product in the line, it must be numbered 1 which is represented in Equation (38). And for every product *p*, there is another product following *p'* whose rank must be next to rank of product *p* which is represented in Equation (39).

Nonnegativity of the variables:

All the variables should be nonnegative.

CHAPTER SIX

NUMERICAL EXPERIMENTS

<u>Description:</u>

For fixed Demand values and fixed Capacities, results are going to depend on the different types of costs that arise during production and distribution. Assuming fixed total Production Costs in all the sites, the results will now depend on the Setup and Transportation Costs which determines whether the production takes place at each and every site or the production taking place in some of the sites and transporting the finished products to the rest of the sites. Several numerical experiments are conducted on the model (Case 1) which aims to experimentally show the percentage of the number of finished products transferred within the sites for satisfying demands in those respective sites. The experimental computations were run using CPLEX on an Intel® Core™ i7 GHz PC with 16.0 GB Ram running Windows 7 operating system.

A number of numerical experiments were conducted for different values of Setup and Transportation costs. The input data for these experiments are generated through random function using C++. For these experiments, 6 sites (out of which 5 are production sites and the other is dummy site which supplies raw materials) and 3 different kinds of products being produced were considered. The values considered are uniform for the fixed value parameters for the 3 products in the respective sites are presented below.

Capacity of the trucks = 30

Fixed Production Cost = UNIF[20,30]

Linear Production Cost =UNIF[30,40]

Capacity of batches = UNIF[15,30]

Demand = UNIF[200,500]

The OPL codes for the model and data for the first experiment with Average Transportation Cost of 750.86 where the data considered is uniform between 700 and 800 and Average Setup Cost is 24.6 where the data considered is uniform between 20 and 30 is presented in Appendix A - D.

Results:

The results of the experiments with all the different Setup and Transportation costs are tabulated in Table 11. For example, let's consider the first experiment. After solving the model, the obtained optimal cost and the number of products transferred within the sites are 228626 and 68 products respectively. The total demand for all types of products in all the sites is 5319. Hence the percentage of products transferred within the sites will be 68/5319 = 1.27%. This process continuous for 10 cases with different transportation costs and different Setup Costs.

It is obvious from the case 1 about the less percentage of products transferred. As the Setup costs are lesser than the transportation costs, every site has its own production and even though there is a change in fixed costs, there won't be any change in the percentage of products transferred for the fewer Setup costs transportation costs. But there is a gradual increase in optimal Costs due to increased Setup Costs in all the cases.

Until case 4, we can see the constant values for the percentage of products transferred with lesser Setup costs. But in Case 5, we can observe the gradual increase and then the decrease in the percentage of products transferred which in turn is the appropriate maximum number of products transferred within the sites for any Setup Cost.

S. No	Average Transportation Cost	Average Setup Cost	Total Optimal Cost	No. of Products transferred within the sites	% of Products transferred within the sites
1	750.86 UNIF[700,800]	24.6	228626	68	1.27
		44.2	228920	68	1.27
		65	229232	68	1.27
		86.8	229559	68	1.27
		104.6	229826	68	1.27
		195.6	231191	68	1.27
		292.8	232649	68	1.27
		405.6	234069	606	11.39
		446	234579	1054	19.81
2	661.13 UNIF[600,700]	24.6	222877	518	9.73
		44.2	223181	428	8.04
		65	223483	518	9.73
		86.8	223804	698	13.12
		104.6	224052	698	13.12
		195.6	228127	1057	19.87
		292.8	229296	1058	19.89
		405.6	230584	1058	19.89
		446	231071	1056	19.85
3	557.93 UNIF[500,600]	24.6	216290	968	18.19
		44.2	216545	1057	19.87
		65	216796	1053	19.79
		86.8	217030	1057	19.87
		104.6	217276	1058	19.89
		195.6	218413	1057	19.87
		292.8	219567	1057	19.87
		405.6	220863	1057	19.87
		446	221350	1060	19.92

S. No	Average Transportation Cost	Average Setup Cost	Total Optimal Cost	No. of Products transferred within the sites	% of Products transferred within the sites
4	456.46 UNIF[400,500]	24.6	207917	1508	28.35
		44.2	208181	1507	28.33
		65	208432	1507	28.33
		86.8	208667	1597	30.02
		104.6	208870	1597	30.02
		195.6	209907	1597	30.02
		292.8	210961	1597	30.02
		405.6	212149	1597	30.02
		446	201765	1949	36.64
5	347.66 UNIF[300,400]	24.6	198014	2578	48.46
		44.2	198224	2578	48.46
		65	198450	2578	48.46
		86.8	198683	2578	48.46
		104.6	19887	2578	48.46
		195.6	199779	2849	53.56
		292.8	200571	2927	55.02
		405.6	201442	2889	54.31
		446	201765	2884	54.22
6	279.66 UNIF[250,300]	24.6	192388	2764	51.96
		44.2	192581	2764	51.96
		65	192790	2758	51.85
		86.8	193000	2764	51.96
		104.6	193187	2758	51.85
		195.6	193984	2946	55.38
		292.8	194763	2940	55.27
		405.6	195640	2901	54.54
		446	195931	3444	64.74

S. No	Average Transportation Cost	Average Setup Cost	Total Optimal Cost	No. of Products transferred within the sites	% of Products transferred within the sites
7	172.73 UNIF[150,200]	24.6	182849	3191	59.99
		44.2	182995	3263	61.34
		65	183142	3254	61.17
		86.8	183283	3269	61.45
		104.6	183416	3263	61.34
		195.6	183966	3826	71.93
		292.8	184440	4225	79.43
		405.6	184781	4515	84.88
		446	184784	4437	83.41
8	95.46 UNIF[50,150]	24.6	174804	4244	79.78
		44.2	174887	4323	81.27
		65	174967	4300	80.84
		86.8	175049	4300	80.84
		104.6	175117	4467	83.98
		195.6	175387	4492	84.45
		292.8	175690	4487	84.35
		405.6	176029	4514	84.86
		446	176122	4481	84.24
9	52.20 UNIF[25,75]	24.6	170432	4511	84.80
		44.2	170487	4500	84.60
		65	170545	4490	84.41
		86.8	170611	4479	84.20
		104.6	170670	4479	84.20
		195.6	170940	4479	84.20
		292.8	171251	4466	83.96
		405.6	171582	4490	84.41
		446	171675	4500	84.60

S. No	Average Transportation Cost	Average Setup Cost	Total Optimal Cost	No. of Products transferred within the sites	% of Products transferred within the sites
10	23.73 UNIF[15,35]	24.6	167061	4487	84.35
		44.2	167116	4458	83.81
		65	167174	4458	83.81
		86.8	167240	4486	84.33
		104.6	167305	4479	84.20
		195.6	167569	4486	84.33
		292.8	167872	4487	84.35
		405.6	168211	4485	84.32
		446	168304	4505	84.69

Table 11: Percentage of products transferred within the sites for different Transportation and Setup Costs.

The maximum percentage of products transferred according to the considered example is around 84%. The main reason behind it is in the later cases, when the transportation costs are lesser when compared to Setup costs, then the production will occur in only 1 site for a particular product and then it is transferred to all of the remaining sites. Here, before transferring products to the other sites, it also satisfies its own demand which is the remaining 16% of the total demand. That is the reason why the percentage of products transferred within the sites won't be able to reach 100 as the sites where the production takes place has to satisfy its own demand too. The percentage of products transferred within the sites and its gradual increase and decrease with respect to Transportation and Setup costs are represented in a graph in Figure 2.

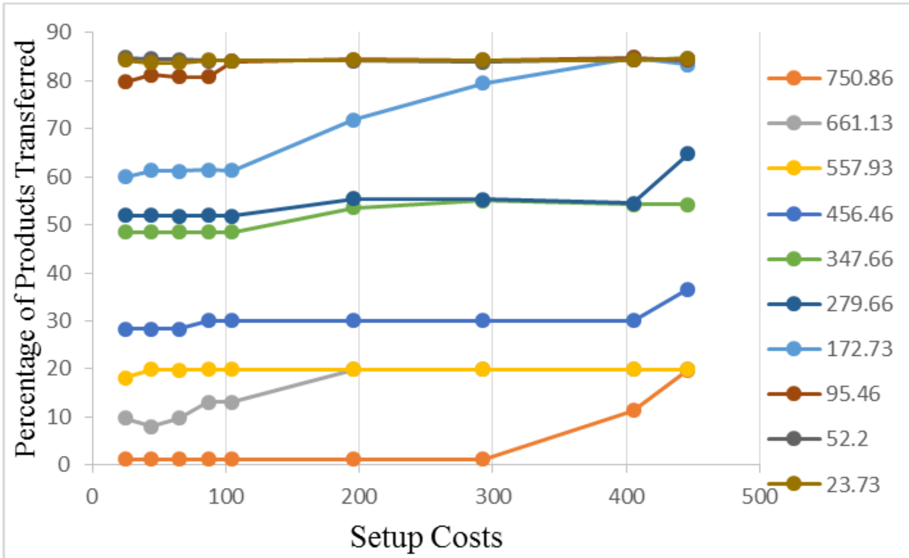

Figure 2: Transportation Vs Setup Costs showing the percentage of products transferred

By observing the pattern of the percentage of products transferred between the sites for different setup and transportation costs as shown in the Figure 2, we can also say that there is no or little change in the percentage of products transferred until some point and after that there is higher increase in the percentage of products transferred. This implies that there must be a threshold value after which we can find drastic increase in the percentage of products transferred. It is also evident that the increase in setup costs doesn't effect the percentage of products transferred when the transportation costs are too low.

CHAPTER SEVEN

CONCLUSION AND FUTURE SCOPE

The main purpose of this work is to study different strategic and tactical models and to develop a strategic/tactical model for a production planning problem in a company by designing inter-logistics flow for distributing production at optimal costs. The model was created by considering same and different Setup costs for various kinds of products and encoded in CPLEX to check its consistency.

Later, different numerical experiments were conducted to test the model as well as to find the role of Setup and Transportation costs on the optimal costs is studied by fixing all the other costs, capacities, and demands. There is a continuation of this research which included in developing an Integrated Strategic model for the same set of factories. Once it was encoded, the results of both the Strategic as well as Strategic/Tactical model must be close to each other by conducting the same type of experiments. There is also a scope for considering uncertain demand in the tactical model as it plays a prominent role in real world planning models.

There is more scope in future for models considering various kinds of uncertainties. Authors must come up with such kind of models and at the same time taking measures of decreasing their complexity and methods for lesser solution times. Another point is to take into consideration the possibility of moving production of different kinds of products to other regions according to the demand of the product in a particular region.

APPENDICES

Appendix A

OPL Model for Case1

```
int m =...;
int n = ...;
int CAP=30;

range sites = 1..m;
range products = 1..n;

float CF[sites,products]=...; //CFip
float CL[sites,products]=...; //CLip
float C[sites,products]=...; //Cip
float D[sites,products]=...; //Dip
float DIST[sites,sites]=...; //DIST(i,j)
float S[sites]=...; //Si



dvar float+ x[sites,products];
dvar float+ V[sites,products];
dvar float+ U[sites,sites];
dvar float+ Z[sites,sites,products];
dvar float+ Vmax;
dvar int y[sites,products] in 0..1;

maximize (sum(i in sites:i!=1,p in products)(CF[i,p]*V[i,p])) +
        (sum(i in sites:i!=1,p in products)(CL[i,p]*x[i,p])) +
        (sum(i,j in sites:(i!=j && i!=1 && j!=1))(DIST[i,j]*U[i,j])) +
        (sum(i in sites:i!=1,p in products)(S[i]*(y[i,p])));

subject to
{

  forall(i in sites,p in products)
    {
                D[i,p] == x[i,p]+ (sum(j in sites:(j!=i && j!=0))(Z[j,i,p]))
                  - (sum(j in sites:(i!=j && i!=0))(Z[i,j,p]));  // : i!=1 && j!=1 && i!=j
    }

  forall(i in sites,p in products)//
    {
                x[i,p] == Z[1,i,p];
```

```
                  x[i,p] <= V[i,p]*C[i,p];
    }

  forall (i,j in sites:i!=j)
         {
                  CAP*U[i,j] >= (sum(p in products)(Z[i,j,p]));
         }

  forall(i in sites: i!=1,p in products)
    {
                  V[i,p] <= y[i,p]*Vmax;
                  Vmax  == sum(i in sites, p in products: i!=1)(D[i,p]) / min(i in sites,p in
products: i!=1)(C[i,p]);
    }

};
```

Appendix B

OPL Model for Case 2

```
int m =...;
int n = ...;
int CAP=30;

range sites = 1..m;
range products = 1..n;

float CF[sites,products]=...; //CFip
float CL[sites,products]=...; //CLip
float C[sites,products]=...; //Cip
float D[sites,products]=...; //Dip
float DIST[sites,sites]=...; //DIST(i,j)
float S[sites,products,products]=...; //Si,p,q

dvar float+ x[sites,products];
dvar float+ V[sites,products];
dvar float+ U[sites,sites];
dvar float+ Z[sites,sites,products];
dvar float+ R[sites,products];
dvar int y[sites,products] in 0..1;
dvar int w[sites,products,products] in 0..1;

maximize (sum(i in sites:i!=1,p in products)(CF[i,p]*V[i,p])) +
        (sum(i in sites:i!=1,p in products)(CL[i,p]*x[i,p])) +
        (sum(i,j in sites:i!=j)(DIST[i,j]*U[i,j])) +
        (sum(i in sites:i!=1,p,q in products)(S[i,p,q]*w[i,p,q]));

subject to
{

   forall(i in sites,p in products)
     {
                    D[i,p] == x[i,p] + sum(j in sites:j!=i && j!=1)(Z[j,i,p])
                      - sum(j in sites:i!=j && i!=1)(Z[i,j,p]);
     }

   forall(i,j in sites,p in products)
     {
          x[i,p] == Z[1,i,p];
          x[i,p] <= V[i,p]*C[i,p];
```

```
    }

        forall (i,j in sites:i!=j)
         {
                CAP*U[i,j] >= (sum(p in products)(Z[i,j,p]));
         }

  forall(i in sites, p,q in products)
    {
                w[i,p,q] <= y[i,p];
                w[i,p,q] <= y[i,q];
                (sum(q in products)(w[i,p,q])) == (sum(q in products)(w[i,q,p])) >=
y[i,p];
                w[i,1,p] - R[i,p] <= 0;
                w[i,p,q] - R[i,q] - R[i,p] <= 0;
        }
};
```

Appendix C

Data File for Case 1

```
m = 6;
n = 3;
CF = [ [0,0,0],
 [22,28,27],
 [21,20,25],
 [24,28,20],
 [20,25,21],
 [22,21,25]];
CL = [ [0,0,0],
 [32,38,37],
 [31,30,35],
 [34,38,30],
 [30,35,31],
 [32,31,35]];
C = [ [0,0,0],
 [17,33,42],
 [16,35,30],
 [39,33,25],
 [15,30,26],
 [27,16,30]];
D = [ [0,0,0],
 [352,218,377],
 [201,310,455],
 [404,428,450],
 [230,485,271],
 [422,411,305]];
DIST = [ [0,575,589,572,540,599],
 [575,0,596,533,567,542],
 [589,596,0,564,512,505],
 [572,533,564,0,549,572],
 [540,567,512,549,0,554],
 [599,542,505,572,554,0]];
S = [0,22,28,24,26,23];
```

Appendix D

Data File for Case 2

```
m = 6;
n = 3;
CF = [ [0,0,0],
 [22,28,27],
 [21,20,25],
 [24,28,20],
 [20,25,21],
 [22,21,25]];
CL = [ [0,0,0],
 [32,38,37],
 [31,30,35],
 [34,38,30],
 [30,35,31],
 [32,31,35]];
C = [ [0,0,0],
 [17,33,42],
 [16,35,30],
 [39,33,25],
 [15,30,26],
 [27,16,30]];
D = [ [0,0,0],
 [352,218,377],
 [201,310,455],
 [404,428,450],
 [230,485,271],
 [422,411,305]];
DIST = [ [0,575,589,572,540,599],
 [575,0,596,533,567,542],
 [589,596,0,564,512,505],
 [572,533,564,0,549,572],
 [540,567,512,549,0,554],
 [599,542,505,572,554,0]];
S = [ [[17,33,42],[42,17,33],[33,42,17]],
 [[16,35,30],[30,16,35],[35,30,16]],
 [[39,33,25],[25,39,33],[33,25,39]],
 [[15,30,26],[26,15,30],[30,26,15]],
 [[27,16,30],[30,27,16],[16,30,27]],
 [[31,30,35],[35,31,30],[30,35,31]]];
```

REFERENCES

A.C Hax (1973) Integration of strategic and tactical planning in the Aluminum industry. Operations Research Center, M.I.T. Working paper 026-73

Arntzen BC, Brown GG, Harrison TP, Traffton LL (1995) Global supply chain management at digital equipment corporation. Interfaces 25(1):69–93

Banks, J. (Ed.). (1998). Handbook of simulation. New York: Wiley

Bradley, Hax, and Magnanti (Addison-Wesley, 1977) Applied Mathematical Programming. ISBN-13: 978-0201004649 ISBN-10: 020100464X

Carme Martinez-Costa, Marta Mas-Machuca, Ernest Benedito, Albert Corominas (2014) A review of mathematical programming models for strategic capacity planning in manufacturing. Int. J. Production Economics 153 (2014) 66-85

Chopra, Sunil. Meindl (2001). Supply chain management: strategy, planning and operation -1st
edition. Pearson Prentice Hall.

Crainic, T.G., A. Frangioni, B. Gendron (2001). Bundle-based relaxation methods for multicommodity capacitated fixed charge network design problems. Discrete Applied Mathematics, 112, 73–99

Fleischmann B, Ferber S, Henrich P (2006) Strategic planning of BMW's global production network. Interfaces 36:194–208

Galbraith, J., 1973. Designing Complex Organizations. Addison-Wesley, Reading, MA

Glasserman, P., Tayur, S., 1995. Sensitivity analysis for basestock levels in multiechelon production-inventory systems. Management Science 41, 263–281

Goetschalckx (2001) Strategic Network Planning. BT and Centre for Automotive Industry Research, Cardiff

Goetschalckx M (2002) Strategic network planning. In: Stadtler H, Kilger C(eds) Supply chain management and advanced planning. Springer, Heidelberg, pp 105–122

Graves, S.C., 2003. Replenishment planning in discrete-time, capacitated, non-stationary, stochastic inventory systems. Working Paper of Massachusetts Institute of Technology

Hartmut Stadtler (2004) Supply Chain management and advanced planning-basics, overview and challenges, European Journal of Operations Research 163 (2005) 575-588

Ho, C., 1989. Evaluating the impact of operating environments on MRP system nervousness. International Journal of Production Research 27, 1115–1135.

Hossein Badri, Mahdi Bashiri, Taha Hossein Hejazi (2012) Integrated strategic and tactical planning in a supply chain network design with a heuristic solution method. Computers and Operations research 40 (2013) 1143-1154

J. Mula, R. Poler, J.P. Garcia Sabater, F.C. Lario (2006) Models for production planning under uncertainty: A review. Int. J. Production Economics 103 (2006) 271-285

Joel K. Jolayemi and Festus O. Olorunniwo (2003) A deterministic model for planning production quantities in a multi-plant, multi-warehouse environment with extensible capacities. Int. J. Production Economics 87 (2004) 99-113

Jordan WC, Graves SC (1995) Principles on the benefits of manufacturing process flexibility. Manage Sci 41(4):577–594

Mahdi Bashiri, Hossein Badri, Jafar Talebi (2011) A new approach to tactical and strategic planning in production-distribution networks. Applied Mathematical Modelling 36 (2012) 1703-1717

P. Nga Thanh, B. Bostel, O. Peton, A dynamic model for facility location in the design of complex supply chains, Int. J. Prod. Econ. 113 (2) (2008) 678–693

Parsons, John C. W. (Supervised by Professor Stephen C. Graves) (June 2004). Using a Newsvendor Model for Demand Planning of NFL Replica Jerseys. MLog thesis - Massachusetts Institute of Technology

Ralf Bihlmaier, Achim Koberstein, Rene Obst (2008) Modeling and optimization of strategic and tactical production planning in the automotive industry under uncertainty. OR Spectrum (2009) 31:311-336

S.A. MirHassani, C. Lucas, G. Mitra, E. Messina, C.A. Poojari, Computational solution of capacity planning models under uncertainty, Parallel Computing 26 (2000) 511–538.

Santoso T (2003) A comprehensive model and efficient solution algorithm for the design of global supply chains under uncertainty. PhD Thesis, Georgia Institute of Technology

Santoso T, Ahmed S, Goetschalckx M, Shapiro A (2004) A stochastic programming approach for supply chain network design under uncertainty. Euro J Oper Res 167(1):96–115

Shapiro, J. F., "Mathematical Programming Models and Methods for Production Planning and Scheduling," In Handbooks in Operations Research and Management Science, Volume 4, Logistics of Production and Inventory, edited by S. C. Graves, A. H. G. Rinnooy Kan and P. H. Zipkin, Amsterdam, Elsevier Science Publishers B. V., 1993, pp. 371-443

Tsiakis, P., Shah, N., and Pantelides, C.,C. (2001). Design of multi-echelon supply chain networks under demand uncertainty. Industrial and Engineering Chemistry Research, 40: 3585–3604

Vidal CJ, Goetschalckx M (2000) Modeling the impact of uncertainties on global logistics systems. J Bus Logistics 29(1):95–120

Yves Pochet (2001) Mathematical Programming Models and Formulations for Deterministic Production Planning Problems, CORE and IAG Universit´e Catholique de Louvain, Belgium. Computata. Comb. Optimization, LNCS 2241, pp. 57-111

Zivko Kotevski, Bojan Jovanoski, Robert Minovski (2015) Simulation model for improved production planning and control through quality, cycle time and batch size management. Journal of Engineering Management and Competitiveness (JEMC), Vol. 5, No. 1, 40-45