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Doctoral Dissertation

A demand-oriented model for worker reallocation in assembly lines

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Abstract

Assembly lines (ALs) are of great importance in most actual production systems and thus continue attracting strong research interest. In fact, assembly line balancing (ALB) continues to be an active area of optimization research in industrial engineering, operations management, operations research, and related fields. We address a real industry scenario where the aim of the line is to target a production output that meets, as much as possible, a given demand forecast. To the best of our knowledge, the existing literature has not tackled this problem, and we denominated it the *demand-driven assembly line rebalancing problem* (DDALRP). In this work, we define the DDALRP, provide a classification framework for the problem variants, developed two non-linear, multi-objective, combinatorial optimization models, and tested the models in the straight assembly line, providing useful insights about the dynamics of worker reallocation.

In a nutshell

Purpose: Introduce the *demand-driven assembly line rebalancing problem* (DDALRP).
Academic implication: This paper contributes to the body of knowledge in the field of assembly line balancing (ALB) / rebalancing (ALR) by introducing a new family of problems (DDALRP).
Originality/value: The rebalancing mechanism: We rebalance an assembly line (AL) over a planning horizon (multi-period rebalancing) via worker reallocation, taking into consideration a demand forecast, as well as workers' learning and forgetting (L&F) curves.
Method: Non-linear, multi-objective, combinatorial optimization model solved by means of a genetic algorithm (GA).
Findings: The results of the numerical experiments reveal insights about the dynamic of worker reallocation over the planning horizon (the length of the demand forecast), under different scenarios: optimistic, most-likely, pessimistic L&F coefficients; experienced and inexperienced workers; and different demand scenarios.
Practical implications:
1) With this method, it is possible to adjust the production output of the AL without the need of reengineering the line; i.e., without modifying the original assignment of tasks to stations.
2) Worker reallocation implies job rotation, which leads to job enrichment and multi-skilled, motivated workers.
Limitations: This model is limited to manual ALs organized in straight layout (I-shaped configuration). The investigation of the DDALRP in ALs having other types of layout (U-shaped ALs, two-sided ALs, ALs with parallel stations, etc.) is part of the upcoming research agenda.

Research content

Ford's assembly line at Highland Park is one of the most influential conceptualizations of a production system [1]. Formally, an assembly line is a production system where the bill-of-material parts and components are attached one by one to a unit in a sequential way by a series of workers [2]; these units or workpieces visit stations successively as they are moved along the line usually by some kind of transportation system, e.g., a conveyor belt [3, 4]. The main objective of an assembly system is to increase production efficiency by maximizing the ratio between throughput and cost [5].

The extensive literature on assembly line balancing (ALB) has focused on maximizing line efficiency, overlooking strategic use or neglecting the organization's overall operations effectiveness [1]. Wilson [6, 7] argues that Ford's assembly lines were optimized both 'locally' as individual production systems; and also 'globally' as constituent sub-systems of Ford's larger, vertically integrated supply chain system. Wilson [1] also reveals with data that, in fact, Ford's operations were adaptable to strongly increasing and highly variable demand.

Needless to say, the importance of matching supply with demand is universally recognized [8, 9, 10, 11, 12]. However, to our surprise, demand fluctuations still have not been explicitly considered to perform task assignment and/or worker allocation (to stations) in the assembly line balancing problem (ALBP).

This research introduces the *demand-driven assembly line rebalancing problem* (DDALRP). The proposed models aim to balance and rebalance an assembly system over a planning period, adjusting the production output of the line as much as possible to the forecast market demand, by means of worker allocation and reallocation. At the same time, our models aim to achieve smooth production flow by minimizing the standard deviation of the number of units processed by the stations and minimizing total overproduction or production excess.

Experimental results provided useful insights to understand the dynamic of worker reallocation under different scenarios: (1) optimistic, most-likely, and pessimistic learning and forgetting coefficients; (2) experienced workers (e.g., workers with some initial skill inventory) and inexperienced workers (e.g., workers with no initial skill inventory); (3) different demand forecast trends (increasing, seasonally increasing, and erratic patterns); and (4) different levels of difficulty of the demand forecast (attainable and challenging).

Because our model takes into account the learning curve, due to the learning effect, eventually, all workers will achieve 100% efficiency in all assembly tasks, after several reallocations. When this point is reached, any worker allocation to stations would yield nearly the same number of units of production output from the line. So, the proposed model should be particularly useful during *production ramp-up*, the period from completed initial product development to maximum capacity utilization. The core idea in this research is to assertively match learning curve improvements with variable (changing) demand.

Research purpose

Previous research in ALB has focused solely on maximizing the efficiency of the assembly line, without taking into consideration the number of units that are actually needed, orders placed by customers, or any kind of demand forecast.

The originality standing points of this work consists of a balancing mechanism of the assembly line that aims at both, achieving high efficiency, and adapting the production output of the assembly line to some given demand forecast. As a consequence, this work addresses by the first time a problem that we have named DDALRP.

Different from other balancing methods, which attempt to evenly distribute workload among the stations of the line by performing a *one-time* assignment of *tasks to stations*, our balancing mechanism is performed repeatedly (*multi-period*) by allocating and re-allocating *workers* (to stations) over some planning horizon (the length of the forecast horizon), considering dynamic processing times of tasks due to the learning and forgetting curves of workers.

We hope that the DDALRP will become an important research topic within the field of assembly line balancing (ALB) / rebalancing (ALR).

Keywords

- Assembly line rebalancing
- Demand forecast
- Learning and forgetting curves
- Non-linear, multi-objective, combinatorial optimization model
- Worker reallocation

Dedication

To my parents,
Luis Marcelino (1953~2021) and María Verónica.

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Contents

Abstract i

Dedication iv

Acknowledgment v

List of Figures vii

List of Tables viii

List of Symbols (notation) x

List of Abbreviations xii

1 Introduction 1
- 1.1 Background . . . 2
  - 1.1.1 Historical background . . . 2
  - 1.1.2 Academic background . . . 2
- 1.2 Motivation . . . 3
- 1.3 Problem statement . . . 5
- 1.4 Research objectives . . . 5
- 1.5 Scope . . . 6
- 1.6 Organization of chapters . . . 7

2 Literature Review 8
- 2.1 Assembly line balancing and worker (re)allocation . . . 8
- 2.2 Worker (re)allocation with learning and forgetting effects . . . 9
- 2.3 Assembly line balancing and multi-objective optimization . . . 10
- 2.4 Assembly line balancing and market demand . . . 11

3 The Demand-Driven Assembly Line Rebalancing Problem 13
- 3.1 Preliminaries . . . 13
- 3.2 Problem description . . . 15
- 3.3 DDALRP typology . . . 18

4 A Demand-Driven Model to Minimize Lost Sales 20
- 4.1 Proposed model . . . 20
  - 4.1.1 Objective functions . . . 20
  - 4.1.2 Normalization of objective functions . . . 21
  - 4.1.3 Incorporation of learning and forgetting effects . . . 23
  - 4.1.4 Constraints . . . 24
- 4.2 Numerical experiments . . . 26

4.2.1 Experimental design . . . 26
4.2.2 Solution implementation . . . 27
4.2.3 Results . . . 29

5 A Demand-Driven Model to Minimize Back Orders 41
5.1 Proposed model . . . 41
5.1.1 Objective functions and normalization procedure . . . 41
5.1.2 Constraints and learning and forgetting effects . . . 42
5.2 Numerical experiments . . . 42
5.2.1 Experimental design . . . 42
5.2.2 Results . . . 42

6 Concluding Remarks 54
6.1 Conclusions . . . 54
6.2 Contributions . . . 55
6.2.1 Practical implications . . . 55
6.2.2 Academic implications . . . 55
6.2.3 Contribution to Knowledge Science . . . 55
6.3 Directions for future research . . . 56

Bibliography 58

List of Figures

1.1 Scope of this research 6
1.2 Structure of this dissertation 7

3.1 Solution to the example: Assembly of the Boeing 737 electrostatic wing 14
3.2a A worker is assigned to station 1. As long as this worker remains in station 1, he/she will be making progress in his/her production output rate according to some learning curve. 15
3.2b When this worker is moved from station 1 to a different station (say, for instance, station 2), a new learning curve begins a progress while, at the same time, the previously learned skill starts deterioration. 16
3.2c Considering the learning and forgetting curves of all workers, our aim is to find the best assignment of workers to stations in every working period, so as to match a given demand forecast as much as possible. 16

4.1 Flowchart of the genetic algorithm implemented in this study 29
4.2 Model A (lost sales): 36 cases of the Jackson problem 31
4.3 Model A (lost sales): 36 cases of the Buxey problem 32
4.4 Model A (lost sales): 36 cases of the Gunter problem 33
4.5 Model A (lost sales): 36 cases of the Kilbrid problem 34
4.6 Model A (lost sales): 36 cases of the Hahn problem 35
4.7 Model A (lost sales): 36 cases of the Tonge problem 36
4.8 Model A (lost sales): 36 cases of the Arcus 1 problem 37
4.9 Model A (lost sales): 36 cases of the Mukherjee problem 38
4.10 Model A (lost sales): 36 cases of the Arcus 2 problem 39
4.11 Model A (lost sales): 36 cases of the Bartholdi 1 problem 40

5.1 Model B (back orders): 36 cases of the Jackson problem 44
5.2 Model B (back orders): 36 cases of the Buxey problem 45
5.3 Model B (back orders): 36 cases of the Gunter problem 46
5.4 Model B (back orders): 36 cases of the Kilbrid problem 47
5.5 Model B (back orders): 36 cases of the Hahn problem 48
5.6 Model B (back orders): 36 cases of the Tonge problem 49
5.7 Model B (back orders): 36 cases of the Arcus 1 problem 50
5.8 Model B (back orders): 36 cases of the Mukherjee problem 51
5.9 Model B (back orders): 36 cases of the Arcus 2 problem 52
5.10 Model B (back orders): 36 cases of the Bartholdi 1 problem 53

List of Tables

3.1 Example: Assembly of the Boeing 737 electrostatic wing 13
3.2 Solution to the example: Assembly of the Boeing 737 electrostatic wing 14
3.3 Example of an output or solution representation 17
3.4 Example data to illustrate the backlog portion of Equation (3.4) 19
3.5 DDALRP typology 19

4.1 Main characteristics of the examined problem instances 26
4.2 Deployment of cases run 28

List of Symbols (notation)

Indexes

j	stations, $j = 1, 2, 3, \ldots, J$
k	workers, $k = 1, 2, 3, \ldots, K$
ℓ	planning periods, $\ell = 0, 1, 2, \ldots, L-1$

Input parameters and intermediate variables related to the learning curve (skill improvement)

r_k	the learning coefficient of worker k
β_k	the learning slope of worker k
$S_{jk}^{initial}$	the initial skill level of worker k in station j
S_{jka}^{rem}	the skill level that worker k had in station j when he/she was assigned to that station (period a)
S_j^{max}	the theoretical maximum level of skill at station j
S_j^{UB}	the achievable upper level or skill upper bound in station j
δ_j	the skill upper bound threshold value for station j

Input parameters and intermediate variables related to the forgetting curve (skill deterioration)

f_k	the forgetting coefficient of worker k
γ_k	the forgetting slope of worker k
S_{jkd}	the skill level that worker k had in station j when he/she departed last time (period d) from that station
S_j^{min}	the theoretical minimum level of skill at station j
S_j^{LB}	the achievable lower level or skill lower bound in station j
ϵ_j	the skill lower bound threshold value for station j

Other input parameters

$D(\ell)$	the market demand forecast for period ℓ, $\ell = 1, 2, 3, \ldots, L$
WIP_{min}	the minimum work-in-process inventory necessary to assure smooth production flow at the beginning of each period ℓ
h	the inventory holding cost per unit per period
h_{FP}	the cost of holding one unit of finished product one period
h_{WIP}	the cost of holding one unit of work-in-process inventory one period
g	the unit cost of lost sale
z_1^ℓ, z_1^u	the lower and upper limits that define the satisfaction of objective function 1
z_2^ℓ, z_2^u	the lower and upper limits that define the satisfaction of objective function 2
z_3^ℓ, z_3^u	the lower and upper limits that define the satisfaction of objective function 3

Other intermediate variables

$WIP(j,\ell)$	the work-in-process inventory between stations $j-1$ and j accumulated at the end of period ℓ
$P(j,\ell)$	the theoretical number of units that can be processed in station j in period ℓ
$Q(j,\ell)$	the actual number of units processed by station j in period ℓ
$\overline{Q}(\ell)$	the average number of units processed among all stations in period ℓ
$Q(bn,\ell)$	the number of units processed by the bottleneck station in period ℓ
$Q_e(j,\ell)$	the number of units processed in excess by station j in period ℓ
$Q_e(\ell)$	the total number of units processed in excess by all stations (the whole assembly line) in period ℓ
$I_i(\ell)$	(initial inventory) the amount of inventory of finished goods at the beginning of period ℓ
$I_f(\ell)$	(final inventory) the amount of inventory of finished goods at the end of period ℓ
$Std.Dev(\ell)$	the standard deviation of the number of units processed by all stations in period ℓ

Output: the decision variables and the value of the objective functions

$x_{jk\ell}$	the decision variable: 1 if worker k is assigned to station j in period ℓ; 0 otherwise
Z_1	the value of objective function 1: total lost sales (or total back orders)
Z_2	the value of objective function 2: total standard deviation (the sum of the S.D. of the number of units processed by all stations during the whole planning period)
Z_3	the value of objective function 3: total production excess
SL_1, SL_2, SL_3	the satisfaction levels of objective functions 1, 2, and 3

List of Abbreviations

ABC	Artificial Bee Colony
ACO	Ant Colony Optimization
AL	Assembly Line
ALB	Assembly Line Balancing
ALBHW	Assembly Line Balancing with Hierarchical Worker Assignment
ALBP	Assembly Line Balancing Problem
ALR	Assembly Line Rebalancing
ALRP	Assembly Line Rebalancing Problem
ALS	Assembly Line System
ALWABP	Assembly Line Worker Assignment and Balancing Problem
ALWIBP	Assembly Line Worker Integration and Balancing Problem
AWALBP	Accessibility Windows Assembly Line Balancing Problem
BOM	Bill of Materials
BPP	Bin Packing Problem
B&B	Branch and Bound
BB&R	Branch, Bound, and Remember
CMS	Cellular Manufacturing System
DDALRP	Demand Driven Assembly Line Rebalancing Problem
DE	Differential Evolution
DPSO	Discrete Particle Swarm Optimization
GA	Genetic Algorithm
GALBP	Generalized Assembly Line Balancing Problem
HAL	Hull Assembly Line
IDPSO	Improved Discrete Particle Swarm Optimization
IFG	Inventory of Finished Goods
ILP	Integer Linear Programming model
LALBP	Assembly Line Balancing Problem with Learning effects
LFFRM	Learning-Forgetting-Fatigue-Recovery model
L&F	Learning and Forgetting
LS	Lost Sales
MILP	Mixed Integer Linear Programming model
MIP	Mixed Integer Programming
MO	Multi-Objective
MOACO	Multi-Objective Ant Colony Optimization
MOEA	Multi-Objective Evolutionary Algorithm
MODO	Multi-Objective Differential Evolution
MOGA	Multi-Objective Genetic Algorithm
MOO	Multi-Objective Optimization

OM	Operations Management
OR	Operations Research
PBABC	Pareto-based Artificial Bee Colony (algorithm)
PE	Production Excess
PSO	Particle Swarm Optimization
SALBP	Simple Assembly Line Balancing Problem
SD	Standard Deviation
SL	Satisfaction Level
TSALBP	Time and Space constrained Assembly Line Balancing Problem
TSP	Traveling Salesman Problem
TWALBP	Traveling Worker Assembly Line (re)Balancing Problem
T&E	Tooling and Equipment
ULBP	U-type Line Balancing Problem
VNS	Variable Neighborhood Search
WIP	Work-in-Process

Chapter 1

Introduction

An *assembly line* (AL) is a flow-oriented production system in which a job or workpiece is put together and joined with other parts, components, and materials, progressively, along one ore more stations until finally completing a finished product at the end of the line [2, 5]. The assembly line was first introduced by Henry Ford in the early 1900's [13, 14]. It was designed to be an efficient, highly-productive way of manufacturing a particular product. Today, ALs are widely employed as mass production systems in order to increase speed and efficiency, reduce the unit production cost, and facilitate production control and the transformation of raw materials into a finished product. In addition, as pointed by Boysen et al. [3, 4], nowadays, ALs are of great importance in both, the industrial production of high-quantity standardized commodities, and in the low-volume production of customized products (mass-customization).

Assembly lines can have different kinds of layouts: straight, U-shaped, S-shaped, or multiple-U layout; single- or two-sided configuration; parallel workstation(s), parallel line, or a configuration without parallelization; main line only or main line with feeder line(s) (sub-assembly and main assembly operations); multi-station or single-station (i.e., a manufacturing cell); etc. Readers are referred to the works of Battaïa and Dolgui [15], Boysen et al. [4], Boysen et al. [3], and Becker and Scholl [16] for reviews and surveys on types of assembly lines and classification of assembly line systems (ALSs). All ALs, regardless of their intended physical layout or configurations, have to address the same problem: Which tasks are to be assigned to which station (while respecting both, cycle time and precedence relations)? This problem is referred to as the *assembly line balancing problem* (ALBP).

Depending on the assumptions under consideration, the ALBP can be classified in two main categories: the *simple assembly line balancing problem* (SALBP), and the *generalized assembly line balancing problem* (GALBP). The SALBP is further divided into four problems: 1) SALBP-1 seeks to minimize the number of stations when the cycle time is given, 2) SALBP-2 seeks to minimize the cycle time when the number of stations is given, 3) SALBP-E seeks to maximize the efficiency of the assembly line, and 4) SALBP-F seeks a feasible solution.

While SALBP focuses on the core configuration problem (i.e., the assignment of tasks to stations) with numerous simplifying assumptions, GALBP is the extended ALBP with additional characteristics such as different line layouts and configurations, mixed-model production, different objective functions, and related problems (equipment selection, parts feeding, material supply, etc.) simultaneously considered on top of the core problem.

Assembly line balancing (ALB) is an active area of optimization research in operations management. ALB directly affects production flow, the movement of the product through a facility. According to Zandin [17], production flow strategies are strongly related to the layout of the facility. There are five basic types of layouts: continuous flow layout, product layout (also known as line layout), cellular layout, process layout (also known as functional layout), and fixed position layout [17].

Product layouts are dedicated assembly lines (ALs) used for manufacturing big volumes of one specific product [17]. If there is need for small varieties, so as to produce different product models, minor adjustments can be made in the dedicated production line, provided that minimal setup times are achieved [17]. However, as already pointed by Boysen et al. [3, 4], assembly lines have already gained importance in the low-volume production of commodities with customized varieties. In fact, the authors classify assembly lines depending on the degree of variation of the product models being manufactured, and identify three categories: (a) *single-model* ALs (one homogeneous product is manufactured), (b) *mixed-model* ALs (several variations of a basic product family are manufactured simultaneously and continuously), and (c) *multi-model* ALs (different products are manufactured in separate batches).

For a product flow layout to perform efficiently, the assembly line needs to be balanced. In general terms, the objective of balancing an assembly line is to achieve approximately the same workload in the different stations, so that production flows smoothly along the line [15]. To perform an optimum (or near-optimum) balance, the best possible assignment of tasks and operators to workstations must be identified by means of optimization (or heuristic) techniques.

The ALBP is an NP hard combinatorial optimization problem. The solution for an ALBP consists of finding the best assignment of tasks to operators, and the best assignment of operators to workstations, so that the precedence relations among tasks are satisfied and some measure of effectiveness is optimized. The simpler version of this problem (SALBP, *simple assembly line balancing problem*) was first defined by Baybars [18]. Its main assumptions are: each task can be assigned in any station, the line produces only one homogeneous product, stations are equally equipped in respect to machinery and workers, the line is considered serial, no parallel stations or feeder lines exist, there is only one workplace per station. Today, the ALBP is a well established research topic in the Operations Research literature.

1.1 Background

1.1.1 Historical background

Assembly lines

The assembly line was invented in 1913 and has been in continuous operation ever since. It has spread to every industrial nation and has become the most familiar form of mass production [19]. Some corporations that adopted it made enormous profits; other went bankrupt. It has been praised as a boom to all working men and women, yet it has also been condemned as a merciless form of exploitation. The assembly line was reinvented in Japan and exported back to the United States [20].

The assembly line emerged in a specific place (Detroit), at a specific time (1913), in a specific industry (the automobile industry) [19, 21].

1.1.2 Academic background

Assembly line balancing problem

The ALBP belongs to the general class of sequencing problems [22] and can be seen as a bin packing problem (BPP) with additional side constraints, as precedence relations between tasks. These precedence constraints establish an implicit order of bins, deriving in a sequence of operations.

The *assembly line balancing problem* (ALBP) has been studied intensively in academia for over six decades. The search for ways to increase labor productivity in industrial enterprises with flow organization of production led to the appearance in the 1950's of the idea of controlling the assembly line on the basis of a mathematical model that would allow the production process to be optimized. The first mathematical formalization of this problem was made by Salveson [23] in 1955. Since then, different line configurations with various considerations have been investigated, and different approaches have been proposed, enriching the field. However, one gap in the existing literature is the lack of interest in assembly line practice before Salveson's work; despite universal acknowledgement ([24, 25, 26, 27, 28, 29]) of Ford's fundamental contribution in implementing these systems.

The ALBP is the generalized form of the *bin packing problem* (BPP) [30], which involves no precedence relations among tasks. In a BPP, the aim is to pack uni-dimensional objects of various sizes into the smallest possible number of containers of a given capacity.

Learning curves

Learning curves have been studied for more than eight decades. The learning curve phenomenon was first reported in the literature by Wright [31] in 1936. Wright observed in the aircraft industry that the time required to process one job decreases as the operator processes more jobs. Wright also described the favorable effect of learning on reducing production costs. Different types of learning effects have been demonstrated and extensively studied in a number of areas. However, the effects of learning in the context of production scheduling were investigated by first time by Biskup [32].

1.2 Motivation

Balancing an assembly line is an essential role that organizations must workout. Consider, for instance, the automobile assembly industry. A car consists of approximately 30,000 parts, and its assembly operations represent a substantial portion of the entire production process. The vehicle assembly process comprises welding, painting, prefabrication, and final entire-vehicle assembly, making the labor force for the assembly line the largest group involved in the process. Thus, labor force requirements need to be appropriately organized and production efficiency must be improved by effectively implementing assembly line balancing [33].

Consider the apparel industry. Garment manufacturing consists of a variety of product categories, materials, and styling. The joining of garment pieces by using thread, known as the sewing process, is the most labor-intensive division of the clothing manufacturing process. Even today, in spite of the efforts to adapt automation in the clothing system, the sewing process continues demanding a considerably large number of human resources. Because of its critical importance, line balancing in the sewing process needs to be planned and executed carefully in order to achieve small stocks in the sewing lines and increase the efficiency of the clothing manufacturing system.

Consider shoemaking, the process of making footwear, a traditional handmade product. The footwear industry manufactures a range of products, including shoes, moccasins, sandals, clogs, slippers, boots, and safety footwear (in different sizes and in different styles). A variety of materials are used in the process, including leather, textiles, rubber, plastics, wood, cork, and plaiting materials, which are all assembled through a production line. Substantial labor is dedicated along the processes of cutting, stamping, stitching, assembling (the core component of the shoemaking process), and finishing touches (i.e., oil and dirt are washed off, cream is applied and shoes are polished to a high shine, etc.). Because the production rate of operators will be changing constantly due to the effect of the learning curve, an appropriate allocation and reallocation of the labor force becomes necessary to balance and rebalance the assembly line, so that it operates with smooth flow and high efficiency.

Labor-intensive manufacturing cells are characterized by the presence of lightweight, small, inexpensive machines and equipment where continuous operator attendance and involvement is required. Consequently, cell performance is affected by the performance of operators. Thus, operator issues like skill levels, skill-based operation times, and learning curves become important matters to consider. Therefore, it is essential and worthwhile to assign and reassign workers in order to increase the production rate of the bottleneck workstation in each cell, and hence improve the efficiency of the cellular manufacturing system (CMS).

In short, assembly line systems are commonly found in most manufacturing and production systems; and hence, assembly line balancing continues to be an optimization problem of significant industrial importance. For this reason, over the last decades, enormous academic effort has been done towards solving assembly line balancing problems efficiently. In fact, finding the best solution for this problem is a fundamental task for maintaining the competitive advantage of an organization. As Falkenauer [34] argues, the efficiency difference between an optimal and a sub-optimal assignment can yield economies (or loses) reaching millions of dollars per year.

There are two more motivational perspectives: value for society (a positive contribution to community), and a personal motivataion.

Motivation (ii): Value for society, higher living standards

Manufacturing, at the *macro* level and from a global perspective, is regarded as an essential and uniquely powerful economic force. In advanced economies and developed nations, manufacturing drives productivity growth and trade; manufactured goods are the clear, tangible expression of innovation and competitiveness. In emerging economies and developing countries, manufacturing is recognized as the engine of development, the pathway to higher living standards which raises agrarian populations out of poverty, turning poor nations into players in the global economy [35].

At the *micro* level, from a community-size perspective, manufacturing is at the heart of our daily lives. Manufacturing supports the satisfaction of our basic needs. For instance, assembly lines produce heavy machinery used in industrialized agriculture and intensive farming -necessary to bring the food to our table. The benefits of manufacturing also play a vital role in providing ease, comfort, and convenience; for example, the production of washing and drying machines. In short, production systems and manufacturing plants are producing products every day to enhance the well-being of society. Therefore, manufacturing ultimately determines how well we live.

Motivation (iii): Personal motivation

In my first job as Plant Engineer at Knitwear S.A. (a garment manufacturing company in Nicaragua), I worked at the Engineering Department. One area within the Engineering Department dealt with the training of new hires (new operators without previous sewing experience or semi-skilled workers with previous experience in sewing operations). Some of my tasks included to perform time and motion studies, monitor the actual progress of the learning curves of operators, and compare such progress against theoretical learning curves and the production plan.

In the training lines, operators used to remain at one particular station (i.e., one specific sewing machine) until achieving 100% efficiency. I noticed that this situation caused bottlenecks and inefficiencies during the training period (because different sewing operations have different learning curves with different pattern or shape of progress). At all stations the job that needed to be executed was the sewing of a portion of the garment. However, due to certain particularities and specific movements that the operator needed to do, the learning curve at each station was different. Hence, the progress in the production output rate of an operator was different depending on which machine (station) he/she was allocated. As a consequence, along time, the output rate of operators progressing at different rhythm or pace, caused accumulation of work-in-process (WIP) inventory in some stations, or starvation in other stations.

In order to alleviate the situation, I proposed to examine exchanging workers among stations. If the current arrangement of workers into stations was creating accumulation of jobs at some stations, and starvation in others, then, assigning workers differently along the line would modify the flow of jobs, hopefully, in a more efficient way.

I started to notice that I was performing balancing differently from the way learned in my undergraduate education. In my bachelor program we solved problems on assembly line balancing by distributing tasks to stations; not by reallocating workers. To me, the reallocation of workers to balance the assembly line became a very interesting topic which highly stimulated my intellectual curiosity. In addition, I visualized a practical and positive implication of reallocating workers: due to a different assignment of workers to stations, workers would be exposed to more than one type of sewing machine, thus, creating the additional advantage of training multi-skilled workers. This practical implication also motivated me to keep going further in my proposal.

At my workplace, I started to modify the position of workers, initially, twice per week; and later on, every day, from Monday to Friday. There were positive results in terms of job efficiency (reduced work-in-process inventory, increased production output), and in terms of personnel satisfaction (more worker motivation, workers acquiring skills in more than one sewing operation).

Since those days, the mathematical formalization of a model has always been a goal that I wanted to achieve. For this reason, in these Ph.D. studies, without hesitation, I focused on the worker reallocation problem, considering not only learning and forgetting effects, but also a demand forecast, creating, thus, the *demand-driven assembly line rebalancing problem.*

1.3 Problem statement

Simply, the problem can be stated as follows: Identify the most appropriate allocation of workers to stations for every working period, in such a way that the production output of the assembly line adapts as much as possible to a given demand forecast while simultaneously aiming a smooth production flow.

1.4 Research objectives

1. Propose a framework to formally define the new model and its related problem variants.
2. Develop specific mathematical models to balance assembly lines and meet demand forecasts via worker reallocation.
3. Validate the models and obtain insights about the dynamic of worker reallocation.

Make contributions to Knowledge Science and the field of ALB by creating *new, useful,* and *practical* knowledge.

As for objective 1, the formal definition of the *demand-driven assembly line rebalancing problem* and DDALRP typology are presented in Chapter 3. As for objectives 2 and 3, two mathematical models were proposed and tested in numerical experiments. Those two models are detailed in Chapters 4 and 5.

1.5 Scope

In order to visualize and understand the scope of this work, we have to think of an assembly system taking into consideration three core components; namely: machines, people, and information.

1. Machines: In this research, we treat assembly lines that are organized in straight layout (also known as assembly systems organized under an I-shaped configuration) and are operated by human workers (labor-intensive assembly lines). Robotic or semi-automated assembly lines are out of the scope of this research. Moreover, other kinds of layouts or configurations (U-shaped lines, two-sided lines, assembly lines with parallel stations, etc.) are also out of the scope of this research.

2. People: Regarding human factors, we take into consideration the experience / inexperience of workers (e.g., the fact of having or lacking some initial skill inventory) as well as their learning and forgetting curves. Other kinds of human factors (for instance: fatigue-recovery, motivation-boredom, age, gender, etc.), are out of the scope of this research.

3. Information: The actual operation of an assembly system is sustained thanks to information systems that support decision-making regarding both, in-bound logistics decisions (such as the material supply or the feeding of parts and components to the assembly line), and out-bound logistics decisions (such as the expected production output or number of units that shall be produced by the assembly line). In this research, we take into consideration a demand forecast that indicates the expected production output. In this research, the demand forecast is the main driver of the worker reallocation decision. Information other than the demand forecast is out of the scope of this research.

Figure 1.1 schematically depicts the scope of this research.

Figure 1.1: Scope of this research

1.6 Organization of chapters

After the introductory chapter, the rest of this dissertation is structured as follows: Chapter 2 presents the literature review. We review related works on assembly line that are linked to: (1) assignment or allocation of workers (to stations), (2) learning and forgetting effects, (3) assembly line balancing with multi-objective optimization, (4) demand forecast. Then, Chapter 3 defines the *demand-driven assembly line rebalancing problem* (DDALRP) and proposes a classification framework to define four kinds of DDALRPs. Next, Chapter 4 presents the mathematical formulation and numerical experiments of a demand-driven model that aims to minimize lost sales. Afterwards, Chapter 5 presents the mathematical formulation and numerical experiments of a demand-driven model that aims to minimize backlog or back orders. Finally, Chapter 6 summarizes the contributions of this dissertation to industry, academia, and the Knowledge Science community; and provides conclusions and directions for future research. This organization of chapters (or structure of this dissertation) is depicted in Figure 1.2.

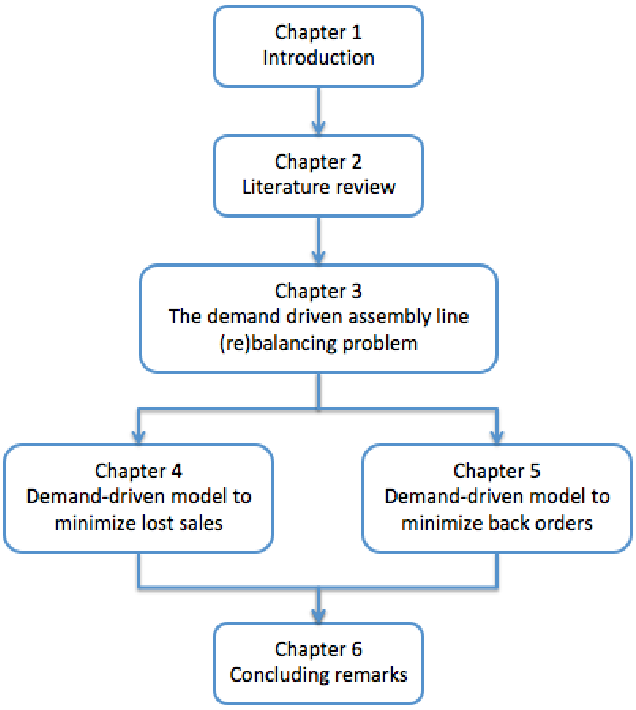


Figure 1.2: Structure of this dissertation

Chapter 2

Literature Review

2.1 Assembly line balancing and worker (re)allocation

In 2007, Miralles et al. [36] introduced the *assembly line worker assignment and balancing problem* (ALWABP). The ALWABP appears in real assembly lines in which not every worker is capable of executing any task, and the operation time of each task differs depending upon who executes the task. Traditionally, the aim in the ALBP has been the assignment of tasks to stations. In the ALWABP the balancing of the line consists of a double assignment: (1) tasks to stations (respecting the precedence relations among tasks), and (2) workers to stations (respecting the incompatibilities among tasks and workers). The authors presented the mathematical model for the ALWABP and a case study based on a Spanish sheltered workcenter for disabled workers.

Miralles et al. [37] proposed a basic branch-and-bound procedure with three possible search strategies and different parameters for solving the ALWABP. Chaves et al. [38, 39] proposed a clustering-search-based hybrid solution approach for solving the problem, which was implemented using simulated annealing to generate solutions in the clustering process. Blum and Miralles [40] presented an algorithm based on beam search for solving the problem. Moreira et al. [41] developed a constructive heuristic framework based on task and worker priority rules defining the order in which the tasks and workers should be assigned to the stations. Mutlu et al. [42] developed an iterative genetic algorithm. Borba and Ritt [43] and Vilà and Pereira [44] proposed branch-and-bound procedures for solving the ALWABP.

In 2015, Moreira et al. [45] introduced the *assembly line worker integration and balancing problem* (ALWIBP). While the ALWABP was inspired in a workcenter for disabled workers –where most of the workers have limitations–, the scenario seen in the ALWIBP is quiet more similar to that of the ordinary company –where only few disabled workers have to be integrated. The authors presented mathematical models and heuristic methodologies to solve the problem. Moreira et al. [46] proposed the use of Miltenburg's regularity criterion to evenly distribute workers with special characteristics along the line, as well as two fast heuristics in order to assign tasks and workers to stations and solve the ALWIBP.

In 2013, Calleja et al. [47] introduced a novel ALBP: the *accessibility windows assembly line balancing problem* (AWALBP). Usually, in the literature concerning ALBPs, it is assumed that each station accesses and processes one workpiece at a time and that each workpiece can only be processed by one station at a time. In contrast, the AWALBP addresses the situation where the length of the workpieces is larger than the width of the stations. This is the case of the assembly of large buses, trucks, and ambulances, where, at any time, a station cannot access one whole workpiece, but is restricted to a portion of it or to two consecutive workpieces. The authors formalized the AWALBP and its variants and proposed a mixed integer linear programming (MILP) model for the two-sided assembly line to solve the AWALBP.

Sungur and Yavuz [48] introduced a new ALBP in which tasks differ with respect to their qualification requirements and the qualification levels of workers are ranked hierarchically. In the hierarchical workforce structure, a lower qualified worker can be substituted by a higher qualified one at the expense of higher cost. The resulting problem was named *assembly line balancing with hierarchical worker assignment* (ALBHW). The ALBHW problem consists of finding the optimal assignment of tasks and workers to stations in such a way that the total cost is minimized. The authors formulated an integer linear programming model to solve this problem and carried out computational experiments in order to investigate the effects of time and cost on the total cost and the total number of different types of workers assigned to the stations.

More recently, Stall Sikora et al. [49] introduced the *traveling worker assembly line (re)balancing problem* (TWALBP). This new problem variation arises if workers can be assigned to more than one station. Hence, workers are able to move between stations, allowing them to perform tasks from different regions of the precedence diagram. Each worker limits the cycle time by the sum of the processing times of the tasks assigned to him/her and his/her movement times between stations. The authors presented a mixed integer linear programming model with a traveling salesman problem (TSP) formulation integrated in the balancing model to solve the problem.

2.2 Worker (re)allocation with learning and forgetting effects

The importance of considering learning effects in ALB was first discussed by Globerson and Shtub [50], followed by Chakravarty and Shtub [51] and Cohen and Dar-El [52].

Toksarı et al. [53] introduced the learning effect into the ALBP and showed that polynomial solutions can be obtained for both, the SALBP and the U-type line balancing problem (ULBP).

In 2014, Otto and Otto [54] combined the well-known *simple assembly line balancing problem* (SALBP) [55] with learning effects, creating a new problem class, named: *assembly line balancing problem with learning effects* (LALBP). The assumption of deterministic task times persistent in the literature was modified, allowing for individual learning curves for each task. The authors developed an exact solution method for small- and medium-sized problems, as well as an effective and fast heuristic for larger problem instances.

Koltai and Kalló [56] proposed a model to calculate the throughput time of a production run when a learning effect influences task times. The authors explored the effects of an exponential learning function, presented an algorithm to determine the throughput time, and examined the sensitivity of the throughput time with respect to the learning rate.

In the process of learning, if the work or operation is temporally stopped for some period of time, then forgetting phenomenon could take place. Different investigations have recognized the actual existence of the forgetting phenomenon in industrial settings. For example, Globerson et al. [57] carried out laboratory experiments in order to examine the forgetting phenomenon. The result of their experiments showed that the forgetting of a task depends on the length of the break or interruption and the amount of experience accumulated before the break or interruption.

Bailey [58] investigated relearning in a laboratory setting. The study revealed that, using a one-time break in the learning process, the level of forgetting a task is directly influenced by the amount of learning achieved before the task was interrupted, a forgetting rate, the time duration of the interruption, and the nature of the task itself.

Toksarı et al. [59] introduced simultaneous effects of learning and linear deterioration in the ALBP. The authors proposed a mixed, nonlinear, programming formulation to minimize the number of stations for a given cycle time. The same learning and deterioration rates were used for all stations. The authors used the learning curve introduced by Biskup [32], which means that the time required to perform a task decreases with the number of repetitions.

Worker allocation with the consideration of learning and forgetting effects has been investigated mainly in manufacturing cells. Liu et al. [60] developed an integrated model that minimizes the sum of back-order cost and inventory holding cost of a manufacturing cell, by assigning and reassigning operators over a planning period, considering multi-skilled workers and learning and forgetting effects. The authors extended the model of Mazur and Hastie [61] (an individual learning model), and its modified version made by Nembhard and Uzumeri [62] (modified to include forgetting effects) to represent the learning and forgetting behavior of heterogeneous workers who process different operations.

Süer and Tummaluri [63] proposed a multi-phase hierarchical approach for loading labor-intensive cells and assigning operators to operations by considering operator skill levels, operator-operation times, and learning and forgetting issues. In their study, the number of consecutive weeks an operator performs or does not perform a particular operation was used as the criterion for skill improvement or deterioration. The authors represented learning as an ordinal scale, with assumed values for the time it takes to improve or deteriorate the skill level along with an associated probability, which indicates the chance that an operator will improve (or deteriorate) his/her skill level after he/she has (not) been performing that operation for a specified number of consecutive weeks.

2.3 Assembly line balancing and multi-objective optimization

Multi-objective optimization has attracted research attention in comparison with single-objective problems [64]. In fact, in recent years, the basic ALBP has been extended a large number of multi-objective scheduling problems for the demands of manufacturing flexibility, just-in-time, and lean production [65].

Song et al. [66] built a model with three objectives (minimize the standard deviation of operation efficiency, maximize production line efficiency, and minimize total operation efficiency waste) to find the optimal operator allocation in a hybrid (serial/parallel) assembly line (or "*pstat*" -parallelized stations-, following the classification scheme of Boysen et al. [3]). The authors used both single- and multiple-skilled operators, and assumed that different operators have different efficiency on the same operation; this is, each operator has his/her own skill inventory.

Nearchou [67] addresses a solution for the multi-objective single-model deterministic ALBP. Two bi-criteria objectives are considered: (1) minimize the cycle time of the AL and the balance delay time of the workstations, and (2) minimize the cycle time and the smoothness index of the workload of the line. The author proposes a new population heuristic to solve the problem based on the general differential evolution (DE) method. The efficiency of the proposed multi-objective DE (MODE) was compared to that of two other previously proposed population heuristics, namely, a weighted-sum Pareto genetic algorithm (GA) [68], and a Pareto-niched GA [69]. The experimental comparisons showed a promising high quality performance of the MODE approach.

Hamta et al. [64] addressed multi-objective (MO) optimization of a single-model AL where the operation times of tasks are unknown variables and the only known information is the lower and upper bounds of operation times of each task. The authors used the learning curve introduced by Biskup [32], and considered three objectives functions: minimize the cycle time, minimize total equipment cost, and minimize the smoothness index. In their research, it was assumed that (a) task times depend on workers' learning, and (b) sequence-dependent setup time exists between tasks. The authors proposed a new solution method based on the combination of a particle swarm optimization (PSO) algorithm and a variable neighborhood search (VNS) algorithm to solve the problem. The performance of their proposed hybrid algorithm showed superior efficiency.

Rada-Vilela et al. [70] adapted eight multi-objective ant colony optimization (MOACO) algorithms to solve the TSALBP-m/A by optimizing their operation with respect to the number of workstations and the maximum physical area these require, and compared their performance on ten well-known problem instances. The comparison was performed in terms of the quality of results found by two variants of the algorithms: one in which ants utilize the commonly used heuristic functions within their transition rules (heuristic variant), and another in which such functions are simply excluded (non-heuristic variant). The non-heuristic variants always outperformed the heuristic ones in a time-limited setup where both had the same computational resources and time to perform as many iterations as possible.

Saif et el. [71] address the single model assembly line balancing problem with uncertain task times and multiple objectives. Their research aims to minimize the cycle time, maximize the probability that completion time of tasks on stations does not exceed the cycle time, and minimize the smoothness index. The authors propose a Pareto-based artificial bee colony (PBABC) algorithm to get Pareto solution of the multiple objectives. The performance of the proposed PBABC algorithm was compared with a famous multi-objective optimization algorithm, NSGA II [72, 73]. Computational results show that the proposed PBABC algorithm outperforms NSGA II in terms of both, quality of Pareto solutions and computational time.

Yuguang et al. [65] developed a model for the hull assembly line (HAL) that aims to minimize the cycle time, minimize the static load balancing between workstations, minimize the dynamic load balancing in all workstations, and minimize the multi-station associated complexity. The authors also developed an improved discrete particle swarm optimization (IDPSO) algorithm for scheduling of the multi-objective problem. The performance of their proposed hybrid algorithm was compared against that of a discrete PSO algorithm (DPSO) [74] and a multi-objective genetic algorithm (MOGA) [75]. Comparative results showed a promising higher performance for the IDPSO in terms of quality of the solutions.

Zacharia and Nearchou [76] presented a multi-objective evolutionary algorithm (MOEA) for the solution of the ALWABP with two objectives to be minimized: the cycle time and the smoothness index. The efficiency of the proposed MOEA was evaluated over a set of benchmarks test problems taken from the open literature, obtaining very satisfactory performance in terms of solution quality.

2.4 Assembly line balancing and market demand

Chica et al. [77] introduced novel robustness functions to measure how robust an AL configuration -number of stations and stations area- (found by a multi-objective optimization method) is when production plans change due to variable and uncertain demand. The authors also introduced a graphical representation to plot the values of the robustness functions in order to offer a picture of the robustness of different AL configurations for the problem under consideration, and evaluate the convenience of the solutions. The authors tackled the *time and space constrained assembly line balancing problem* (TSALBP) introduced by Bautista and Pereira [78], specifically the TSALBP-1/3 variant.

Bautista and Pereira [78] introduced a new family of ALBPs, called TSALBPs, that arise in the automobile industry. In addition to the cycle time constraint, the authors considered space limitations by associating each task i with a required area a_i, and by associating each station j with an available area A_j. Based on the variables: number of stations j, cycle time c, and the total area A available, and depending on which variables are set as fixed values and which are set as optimization variables, eight variants of the TSALBP were proposed by the authors:

1. TSALBP-F (feasible): given j, c, and A, find a feasible solution.
2. TSALBP-1: minimize j given c and A.
3. TSALBP-2: minimize c given j and A.
4. TSALBP-3: minimize A given j and c.

5. TSALBP-1/2: minimize j and c given A.
6. TSALBP-1/3: minimize j and A given c.
7. TSALBP-2/3: minimize c and A given j.
8. TSALBP-1/2/3: minimize j, c, and A.

The authors formulated a model for the TSALBP-1 variant and proposed an ant algorithm for solving the problem. The algorithm was tested by comparing its solutions offered with that of the branch-and-bound procedure SALOME [55], two tabu search implementations [79], and a previous ant algorithm approach developed by the authors [80], obtaining clearly superior results.

Chica et al. [81] proposed the *robust model for the time and space assembly line balancing problem* (r-TSALBP), a multi-objective model for ALB that searches for the most robust solution when demand changes. In their model, the authors used the demand vector $\overrightarrow{d} = (d_{1\epsilon}, d_{2\epsilon}, \ldots, d_{I\epsilon})$ of product $i \in I$ in production plan $\epsilon \in E$ to compute the average processing time and required area of each task $j \in J$ for production plan ϵ. These two average values are then used in two of the three objective functions, for computing, respectively, the cycle time of the line and the area of the line.

Simaria et al. [82] developed a two-stage methodology for designing flexible U-shaped lines. In the first stage, the required number of stations is computed based on the highest forecast demand (this guarantees that the line will be capable to respond to all the demand scenarios) and tasks are assigned to stations. The second stage consists in determining the assignment of workers to stations. The configuration task-station defined in the first stage is maintained; so, whenever demand changes, the only modification in the line is the number of workers. The second stage is repeated for every demand scenario of the problem. The solution procedure for both stages is based on ANTBAL, an ant colony algorithm previously developed by the authors [83].

Chapter 3

The Demand-Driven Assembly Line Rebalancing Problem

3.1 Preliminaries

Traditionally, ALB has tackled the problem of assigning tasks to stations. This implies that a station is designed and built-up with specific functionality depending on which tasks will be performed in it. In fact, in many industrial settings, each station of an assembly system is a well-defined area equipped with specific tooling for executing a specific subset of operations of the whole assembly process. Furthermore, because the cost of installing an assembly line is high, its configuration is carefully planned in advance.

Configuration planning comprises all decisions related to equipping and aligning the productive units for a given production process, before the actual assembly can start. This includes (a) *defining the line layout* (will the line operate on a straight, U-shaped, or S-shaped layout? Single- or two-sided configuration? Will it have some parallel stations, full parallel line, or a configuration without parallelization? Etcetera), (b) *setting the system capacity* (cycle time, number of stations, equipment for each station), and (c) *assigning the work content to productive units* (task assignment, sequence of operations) [3]. Hence, the configuration of the assembly line is a long-term decision for the operation of the production system; and therefore, rebalancing the line in terms of regrouping tasks differently becomes undesirable and, often, unfeasible.

For instance, to give a simple and extreme example, consider Boeing 737, the world's most popular commercial airplane, which is produced on a moving production line traveling at 2 inches per minute through the final assembly process [10]. Table 3.1 provides the task times and precedence relations for the assembly of the electrostatic wing of Boeing 737. Boeing determines that there are 480 productive minutes of work available per day. Furthermore, the production schedule requires that 40 units of the wing component be completed each day. With this information on hand, Boeing now wants to

Table 3.1: Example: Assembly of the Boeing 737 electrostatic wing

Task	Task time (min)	Predecessor
A	10	-
B	11	A
C	5	B
D	4	B
E	12	A
F	3	C, D
G	7	F
H	11	E
I	3	G, H

Source: Heizer and Render [10]

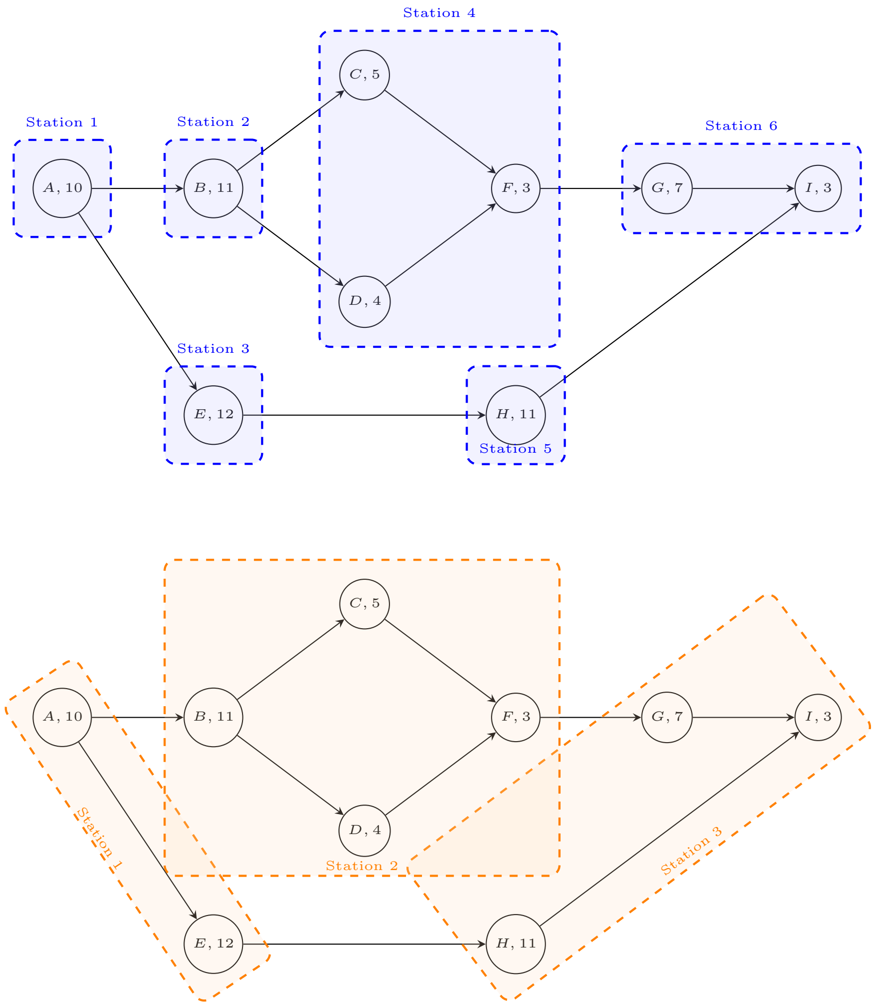


Figure 3.1: Solution to the example: Assembly of the Boeing 737 electrostatic wing

Solution A: 6 stations. Solution B: 3 stations.

Table 3.2: Solution to the example: Assembly of the Boeing 737 electrostatic wing

Solution A: 6 stations				
Station	Tasks assigned	Working time	Idle time	Utilization
1	A	10	2	83%
2	B	11	1	92%
3	E	12	0	100%
4	C, D, F	$5+4+3=12$	0	100%
5	H	11	1	92%
6	G, I	$7+3=10$	2	83%
Solution B: 3 stations				
Station	Tasks assigned	Working time	Idle time	Utilization
1	A, E	$10+12=22$	2	92%
2	B, C, D, F	$11+5+4+3=23$	1	96%
3	G, H, I	$7+11+3=21$	3	88%

group the tasks into stations. Solution: The cycle time is 480 minutes $\div$ 40 units $=$ 12 minutes/unit. The minimum number of stations is computed by dividing the total task time by the cycle time, $\lceil 66 \div 12 \rceil = 6$ stations. An appropriate grouping of tasks is provided in Figure 3.1 (A) and in Table 3.2 (A).

What if demand increases (or decreases)? What would be an appropriate balancing if the production schedule were 20 units of the wing component per day? Solution: The cycle time is 480 minutes $\div$ 20 units = 24 minutes/unit. So, the minimum number of stations is $\lceil 66 \div 24 \rceil = 3$. An appropriate grouping of tasks is provided in Figure 3.1 (B) and in Table 3.2 (B).

Can the reader visualize how cumbersome and inconvenient it would be for Boeing to redesign the working area for the assembly of the electrostatic wing from 6 stations to 3 stations? Tooling and equipment (T&E) for station 1 (embracing task A only, in solution A) were already in place. In the new configuration (solution B), T&E for station 1 would now include two tasks, A and E; meaning that T&E of task E (station 3 in solution A) have to be moved into station 1, in some convenient, coherent, and effective arrangement.

Often, the movement of a machine is not technically impossible, but rather associated with movement costs [4]. Time and effort spent in redesigning the working area could significantly offset the benefits of the new balance. As a matter of fact, often, the cost exceeds the benefit [84]. In addition, there is risk that the machine malfunctions if it is constantly moved and reorganized withing the factory or plant, when it is supposed to be installed in a fixed position. Hence, once resources are allotted to stations, heavy machinery is not usually reallocated [4]. In short, rebalancing is rare in industry because of prohibitively high costs [84].

Falkenauer [34] already observed that in real-world balancing, workstations cannot be eliminated (i.e.: "redesigned" from, say, 6 to 3 stations, as illustrated in the example above) because workstations have *identities* in terms of the operations that can be carried out there, heavy equipment already installed which cannot be moved, space, and other characteristics that define a workstation's identity. The problem is *not* balancing a new line by the first time, but *rebalancing* an *existing* assembly line. For this reason, Falkenauer [34] indicates that assuming that the problem to be solved involves a new, yet-to-be-built AL, has been the gravest oversimplification ever made.

Taking into consideration this fact pointed by Falkenauer, we have proposed a model to perform assembly line rebalancing (over a planning horizon), different from the traditional approach of assigning tasks to stations. In this regard, our model shows a way for dealing with worker allocation and reallocation as a mean to balance and rebalance an AL over a planning period taking into consideration a demand forecast and learning and forgetting effects.

3.2 Problem description

In this subsection, we describe the problem, including the characteristics of the assembly line, its stations, the flow of the jobs or workpieces throughout the stations, the assumptions regarding the demand forecast, workers and their learning and forgetting curves, and the logic behind the worker reallocation decision. A brief description of the scenario is shown in Figure 3.2.

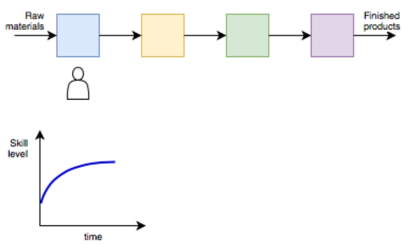


Figure 3.2a: A worker is assigned to station 1. As long as this worker remains in station 1, he/she will be making progress in his/her production output rate according to some learning curve.

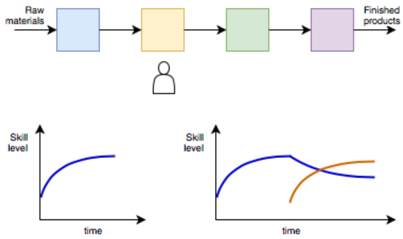


Figure 3.2b: When this worker is moved from station 1 to a different station (say, for instance, station 2), a new learning curve begins a progress while, at the same time, the previously learned skill starts deterioration.

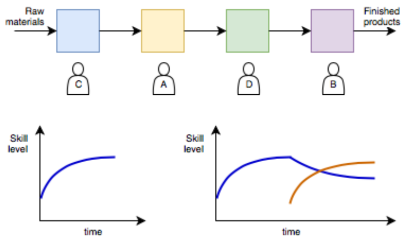


Figure 3.2c: Considering the learning and forgetting curves of all workers, our aim is to find the best assignment of workers to stations in every working period, so as to match a given demand forecast as much as possible.

Input description

The assembly line and its stations

This study considers an assembly line that consists of a specified number of stations $j = 1, 2, 3, \ldots, J$, which are arranged in an I-shaped configuration; i.e., the stations are organized in straight layout. We assume the production of one homogeneous product. This is, we deal with a *single-model* assembly line. The production of this homogeneous product requires several assembly operations $i = 1, 2, 3, \ldots, I$. We assume that these tasks have already been assigned to the stations in the original design and creation of the assembly line. Therefore, each station is equipped with specific instruments and tools, so as to provide them with the functionality they are intended to have in order to execute that particular subset of tasks that belongs to each station. Main assumption / simplification: Stations are assumed to be reliable. Preventive maintenance of machines as well as unplanned breakdowns or downtimes are not considered.

The flow materials throughout the stations

Regarding the movement of materials along the assembly line, we deal with an *unpaced* assembly line. This is, jobs or workpieces move from one station to the next as soon as the worker completes the assembly tasks. Between two consecutive stations there is a buffer. The buffer located at the backside of a station contains the jobs or workpieces to be processed by that station. The buffer located at the frontside of a station contains the jobs or workpieces processed by that station. For the purpose of assuring a smooth production flow and as a measure to avoid the waiting time of feeding the line at the beginning of each working period, each station has to secure a minimum WIP inventory, WIP_{min}, for the next station at the end of each working period. The jobs or workpieces become finished products at the end of the assembly line, after the bill-of-material (BOM) parts and components had progressively been assembled throughout the stations. Main assumption / simplification: We assume unlimited buffer capacity.

The market demand

For each working period $\ell = 1, 2, \ldots, L$ of the planning horizon, a forecast market demand, $D(\ell)$, is a given input. The demand data, if plotted against time, may have different patterns, including: increasing, decreasing, seasonal, erratic, etc. Demand is served at the beginning of each period using the inventory of finished goods (IFG) available at the end of the previous period, $I_f(\ell - 1)$. (For example, the units produced in period 0 are used to satisfy the market demand of period 1; the units produced in period $L - 1$ are used to satisfy the market demand of period L.) When IFP is not enough to cope with the market demand, lost sales occur. Back orders are cleared at the beginning of the next period or later period, when inventory of finished goods is available. Main assumption / simplification: Demand data is deterministic and is known with certainty. Stochastic demand and demand uncertainty are not considered.

Workers

In the factory, there is a fixed number of workers, K, that will occupy a position in one station. These workers may (or may not) have an initial skill inventory, $S_{jk}^{initial}$, defined as the number of units that worker k would be able to process (in one working period) in his/her first assignment to station j. This capacity improves (according to some learning parameter r) as long as the worker continues performing on the same station, or deteriorates (according to some forgetting parameter f) if he/she discontinues performing on that station. (The formulas for computing skill improvement and skill deterioration are presented in section 4.1.3.)

Throughput description

The throughput refers to the mechanisms that will be implemented in order to process the input and provide the output or final solution. In this work we have employed a genetic algorithm (GA) to solve the problem. Details of the implemented GA is provided in Section 4.2.2.

Output description

The output refers to the allocation of workers along the planning period. An example of an output or solution representation is shown in Table 3.3.

By assigning workers to stations, the AL should be balanced in the best possible way in each planning period $\ell = 0, 1, 2, \ldots, L - 1$ in order to satisfy $D(\ell + 1)$, the forecast market demand of the next period. (The units produced in period 0 are used to satisfy the market demand of period 1; the units produced in period $L - 1$ are used to satisfy the market demand of period L.)

Table 3.3: Example of an output or solution representation

	Period, ℓ											
Station	0	1	2	3	4	5	6	7	8	9	...	51
j_1	3	1	1	2	2	2	3	1	2	2	...	2
j_2	1	3	2	1	1	3	2	2	1	1	...	1
j_3	2	2	3	3	3	1	1	3	3	3	...	3

Problem statement

Given the five main inputs described above (tasks and stations, workers, minimum WIP inventory, learning and forgetting parameters, and the demand forecast of a planning period), what is the assignment of workers to stations for each period that best fits or adapts to the forecast market demand while achieving the highest possible production flow?

3.3 DDALRP typology

The solution to a DDALRP intends to match the production output of the AL to the forecast market demand. The units of finished products available at the end of period ℓ, $I_f(\ell)$, are used to satisfy the market demand of the next period, $D(\ell+1)$. If $I_f(\ell) < D(\ell+1)$, then the factory would be losing sales in period $\ell+1$. The solution to a DDALRP intends to minimize the number of lost sales. Hence, the first objective function is:

$$\text{Min } Z_1 = \sum_{\ell=0}^{L-1} \max\left\{0, D(\ell+1) - I_f(\ell)\right\} \tag{3.1}$$

Equation (3.1) represents the first objective (objective A: minimize lost sales) of type I (units). In the analysis of objective A, it may also be of interest to minimize lost sales in terms of money. Every unit of unmet demand represents an economic (business) loss for the factory. In order to reduce the likelihood of losing sales, the AL should build sufficient inventory. However, inventory also represents money; it is an operating cost which, ideally, should be as small as possible. Therefore, a trade-off clearly emerges: to reduce the likelihood of lost sales, enough inventory should be built. On the other hand, if the amount of inventory is kept very low in order to reduce the cost of holding inventory, then lost sales may occur. Therefore, an appropriate balance between both elements is crucial.

If $I_i(\ell)$ and $I_f(\ell)$ are respectively the inventory of finished goods at the beginning and at the end of period ℓ, then, $\left[I_i(\ell) + I_f(\ell)\right] \div 2$ is the average inventory held in period ℓ. If h represents the unit cost of holding inventory, and g, the unit cost of lost sale, then, objective function A (minimize lost sales) of type II (cost) can be written as:

$$\text{Min } Z_1 = g\sum_{\ell=0}^{L-1} \max\left\{0, D(\ell+1) - I_f(\ell)\right\} + h\sum_{\ell=0}^{L} \frac{I_i(\ell) + I_f(\ell)}{2} \tag{3.2}$$

Furthermore, if the analysis of objective function A shall include the cost of WIP inventory along the stations, then, the previous equation can be extended to:

$$\text{Min } Z_1 = g\sum_{\ell=0}^{L-1} \max\left\{0, D(\ell+1) - I_f(\ell)\right\} + h_{FP}\sum_{\ell=0}^{L} \frac{I_i(\ell) + I_f(\ell)}{2} + h_{WIP}\sum_{\ell=0}^{L}\sum_{j=2}^{J} \frac{WIP_i(j,\ell) + WIP_f(j,\ell)}{2} \tag{3.3}$$

where h_{FP} is the unit cost of holding inventory of finished products and h_{WIP} is the unit cost of holding WIP inventory. Notice that station 1 is excluded from the WIP computation because station 1 is fed by raw materials, not by WIP inventory.

Under the analysis of objective function A, unmet demand is a lost sale. However, if customers are willing to receive their products (some time) later (implying some economic penalty for the factory), then, the unmet demand becomes a backlog or back order. Since there is a penalty for supplying units late, the number of back orders should be minimized. Again, to reduce the likelihood of backlog, enough inventory should be built, and some appropriate balance between the penalty of back orders and the cost of (holding) inventory should be sought.

$$\text{Min } Z_1 = b\sum_{\ell=0}^{L-1} \max\left\{0, \sum_{\ell'=0}^{\ell}\left[D(\ell'+1) - Q(J,\ell')\right]\right\} + h\sum_{\ell=0}^{L} \frac{I_i(\ell) + I_f(\ell)}{2} \tag{3.4}$$

where b is the unit cost of backlog (the economic penalty for delaying one unit of finished product one period), and $Q(J,\ell)$ is the actual number of units processed by the last station J in each period ℓ.

As a short example of the backlog portion of Equation (3.4), consider the data of Table 3.4.

Table 3.4: Example data to illustrate the backlog portion of Equation (3.4)

ℓ	0	1	2	3	4	5	6
$D(\ell)$		10	12	15	7	20	17
$Q(J,\ell)$	10	10	12	20	15	14	
backlog		0	2	5	0	0	0

Forecast demand data is given for six periods, 1 to 6. Consequently, the AL works from period 0 to 5. In period 0 the AL produced exactly the demand requirement of period 1 (10 units). Hence, backlog is 0: $\sum_{\ell'=0}^{0}\left[D(\ell'+1)-Q(J,\ell')\right]=10-10=0$. The cumulative production of the AL from period 0 to 1 is 20 units. These units are intended to satisfy the demand of periods 1 and 2. However, the cumulative demand requirement of periods 1 and 2 is 22 units. Therefore, there is a backlog of 2 units at the end of period 2: $\sum_{\ell'=0}^{1}\left[D(\ell'+1)-Q(J,\ell')\right]=22-20=2$. At the end of period 3, there is an accumulated backlog of 5 units: $\sum_{\ell'=0}^{2}\left[D(\ell'+1)-Q(J,\ell')\right]=37-32=5$. At the end, $\sum_{\ell=0}^{5}\max\left\{0,\sum_{\ell'=0}^{\ell}\left[D(\ell'+1)-Q(J,\ell')\right]\right\}=7$ units $\cdot$ periods.

To understand the real dynamic of back orders, building a table becomes necessary. 7 units $\cdot$ periods may be interpreted as 7 units delayed 1 period each. However, a careful look at Table 3.4 reveals that 2 units were delayed 2 periods (periods 2 and 3), and 3 units were delayed 1 period (period 3), making a total backlog of 7 units $\cdot$ periods.

If WIP inventory is also considered along all stations, then, Equation (3.4) can be extended to:

$$\text{Min } Z_1 = b\sum_{\ell=0}^{L-1}\max\left\{0,\sum_{\ell'=0}^{\ell}\left[D(\ell'+1)-Q(J,\ell')\right]\right\}+h_{FP}\sum_{\ell=0}^{L}\frac{I_i(\ell)+I_f(\ell)}{2}+h_{WIP}\sum_{\ell=0}^{L}\sum_{j=2}^{J}\frac{WIP_i(j,\ell)+WIP_f(j,\ell)}{2} \tag{3.5}$$

Equations (3.4) and (3.5) address objective function B (minimize back orders) of type II (cost). Objective function B can also be of type I (units):

$$\text{Min } Z_1 = \sum_{\ell=0}^{L-1}\max\left\{0,\sum_{\ell'=0}^{\ell}\left[D(\ell'+1)-Q(J,\ell')\right]\right\} \tag{3.6}$$

The family of DDALRPs is summarized below, in Table 3.5. Two rows display two objective functions (A: lost sale and B: backlog) and two columns display two measures of interest (1: units or 2: money). This 2 x 2 matrix leads to the 4 possible variations of the DDALRP.

Table 3.5: DDALRP typology

	Measure of interest	
Objective	I. Units	II. Cost
A. Minimize lost sales	Type A-I Equation (3.1)	Type A-II Equation (3.2) or (3.3)
B. Minimize back orders	Type B-I Equation (3.6)	Type B-II Equation (3.4) or (3.5)

In this research we focus our attention to examine the model Type I (units). The next Chapter addresses full formulation and numerical experiments for the “lost sale” scenario (problem variant A-I), while Chapter 5 addresses the “backlog” scenario (problem variant B-I).

Chapter 4

A Demand-Driven Model to Minimize Lost Sales

In this Chapter we propose a mathematical formulation for balancing and rebalancing workers over a planning horizon with the aim of minimizing lost sales. The Chapter is composed of two main sections. In Section 4.1 "Proposed model", we incorporate additional objective functions, detail the normalization procedure of the objective functions, explain how learning and forgetting curves were incorporated into the model, and state the constraints of the model. In section 4.2 "Numerical experiments", we describe the experimental design and present and discuss the results obtained.

4.1 Proposed model

4.1.1 Objective functions

The first objective function comprising this formulation is A-I (Equation 3.1), already presented in the previous Chapter. In addition to the minimization of lost sales, the solution to the DDALRP also aims to achieve the smoothest possible production flow. Therefore, workers need to be allocated to stations so as to obtain the most balanced AL with the lowest possible standard deviation of the number of units processed by the stations, and the least possible excess of production. The following two objective functions were modified and adapted from those of Song et al. [66]. If $\overline{Q}(\ell)$ represents the average number of units processed among all stations in period ℓ, then, the degree of how smooth production is flowing along the AL in period ℓ can be expressed by the standard deviation:

$$Std.Dev(\ell) = \sqrt{\frac{1}{J}\sum_{j=1}^{J}\Big[Q(j,\ell) - \overline{Q}(\ell)\Big]^2}$$

Hence, the second objective function consists of minimizing the standard deviation of the number of units processed by the stations along the whole planning horizon, and can be written as:

$$\text{Min } Z_2 = \sum_{\ell=0}^{L-1}\sqrt{\frac{1}{J}\sum_{j=1}^{J}\Big[Q(j,\ell) - \overline{Q}(\ell)\Big]^2} \tag{4.1}$$

The bottleneck station is the station that processes the fewest number of units. The number of units processed by the bottleneck station is $Q(bn) = min\big\{Q(1), Q(2), \ldots, Q(J)\big\}$. The excess of production of station j in period ℓ, represented by $Q_e(j,\ell)$, is defined as the difference between the number of units that station j processed (in period ℓ) and the number of units processed by the bottleneck station (in period ℓ). Mathematically, $Q_e(j,\ell) = Q(j,\ell) - Q(bn,\ell)$. The total production excess (of the whole AL) in period ℓ, represented by $Q_e(\ell)$, is the sum of the production excess of all stations.

$$Q_e(\ell) = \sum_{j=1}^{J} \left[Q(j,\ell) - Q(bn,\ell)\right]$$

Therefore, the third objective function is to minimize the total production excess over the whole planning horizon:

$$\text{Min } Z_3 = \sum_{\ell=0}^{L-1} \sum_{j=1}^{J} \left[Q(j,\ell) - Q(bn,\ell)\right] \tag{4.2}$$

While the unit of measure of objective function 1 is finished products, the unit of measure of objective functions 2 and 3 is units of unfinished products. To adhere to academic rigor, we must make use of some normalization procedure because it facilitates the comparison between data or models having different scales or units of measure. The next subsection specifies a procedure to convert the value of the objective functions into a satisfaction level that ranges between 0 and 1.

4.1.2 Normalization of objective functions

In order to address this problem having a multi-objective formulation, we employ the concept of *membership function*, originally introduced by Zadeh [85] in 1965. In essence, the notion of membership function relates the outcome of an objective function to a number that lies in the interval [0, 1]. In the original work of Zadeh, this value between 0 and 1 represents the "degree of membership" of an element to a fuzzy set. However, in the context of our problem, we will interpret the value as a measure of the *satisfaction level* (SL) achieved by the objective function under consideration. This is, we will use the membership function to transform or map the output value of the objective function into a scale-free value in the interval [0, 1]; thus, normalizing the output value of the three objective functions. The normalization procedure through the concept of membership function works as follows:

Normalization of Z_1 (A-I)

Let z_1 be the number of lost sales expressed as a percentage of the forecast demand.

$$z_1 = \frac{Z_1}{\sum_{\ell=1}^{L} D(\ell)}$$

z_1 should be as small as possible. In the numerical experiments, the ideal case, $z_1 = 0\%$, represents a situation where demand is fully satisfied and no lost sale occurs; this ideal case will receive the maximum satisfaction level of 1. On the other hand, lost sales of 30% or more of the market demand will receive a satisfaction level of 0. Thus, the lower bound is $z_1^\ell = 0\%$ and the upper bound is $z_1^u = 30\%$. Accordingly, the normalization of objective function 1A is as follows (SL stands for satisfaction level):

$$SL_1 = \begin{cases} 1 & \text{if } \frac{Z_1}{\sum_{\ell=1}^{L} D(\ell)} = z_1^\ell \\ 1 - \frac{\frac{Z_1}{\sum_{\ell=1}^{L} D(\ell)} - z_1^\ell}{z_1^u - z_1^\ell} & \text{if } z_1^\ell < \frac{Z_1}{\sum_{\ell=1}^{L} D(\ell)} < z_1^u \\ 0 & \text{if } \frac{Z_1}{\sum_{\ell=1}^{L} D(\ell)} \geq z_1^u \end{cases} \tag{4.3}$$

Or, more simply:

$$SL_1 = \begin{cases} 1 & \text{if } z_1 = z_1^\ell \\ 1 - \frac{z_1 - z_1^\ell}{z_1^u - z_1^\ell} & \text{if } z_1^\ell < z_1 < z_1^u \\ 0 & \text{if } z_1 \geq z_1^u \end{cases} \tag{4.4}$$

A quick inspection of Equation (4.4) reveals the logic behind the concept of membership function: If a response (objective function value) meets or exceeds a given target, then the value of the membership function will be 1. When a response (objective function value) falls within some acceptable or tolerance interval (but not on the target), the corresponding value of membership will lie somewhere between 0 and 1. (As the response approaches the target, the membership value comes closer to 1; and conversely, as the response deviates from the target, the membership value comes closer to 0.) If a response (objective function value) does not reach the acceptable or tolerance interval, then the corresponding membership value (satisfaction level) will be 0.

Normalization of Z_3

The production excess of each station over the whole planning horizon is summed up as Z_3. The average production excess per station is simply Z_3/J. Further, if this quotient is divided by the demand forecast, then the average production excess per station is expressed as a percentage of the demand forecast. This quotient is defined as:

$$z_3 = \frac{Z_3}{J \sum_{\ell=1}^{L} D(\ell)}$$

which should be as small as possible. In the numerical experiments, the ideal case, $z_3 = 0\%$, represents a situation of 0 production excess and will receive the maximum satisfaction level of 1. An average production excess per station of 30% or more of the market demand will receive a satisfaction level of 0. Thus, the lower bound is $z_3^\ell = 0\%$ and the upper bound is $z_3^u = 30\%$. Accordingly, the normalization of objective function 3 is as follows:

$$SL_3 = \begin{cases} 1 & \text{if } \frac{Z_3}{J \sum_{\ell=1}^{L} D(\ell)} = z_3^\ell \\ 1 - \frac{\frac{Z_3}{J \sum_{\ell=1}^{L} D(\ell)} - z_3^\ell}{z_3^u - z_3^\ell} & \text{if } z_3^\ell < \frac{Z_3}{J \sum_{\ell=1}^{L} D(\ell)} < z_3^u \\ 0 & \text{if } \frac{Z_3}{J \sum_{\ell=1}^{L} D(\ell)} \geq z_3^u \end{cases} \tag{4.5}$$

Or, more simply:

$$SL_3 = \begin{cases} 1 & \text{if } z_3 = z_3^\ell \\ 1 - \frac{z_3 - z_3^\ell}{z_3^u - z_3^\ell} & \text{if } z_3^\ell < z_3 < z_3^u \\ 0 & \text{if } z_3 \geq z_3^u \end{cases} \tag{4.6}$$

In short, for objective function 3: if the average production waste per station $z_3 = 0$, then $SL_3 = 1$; if the average production waste per station is 30% or more (of the market demand), then $SL_3 = 0$. For any other level of average production excess per station between these two extremes, its corresponding satisfaction level is computed linearly.

Normalization of Z_2

The standard deviation is computed for every working period ℓ, and is then summed for all working periods, $\ell = 0, \ldots, L-1$. On average, the standard deviation of each period is simply $z_2 = Z_2/L$. z_2 should be as small as possible.

A very unbalanced situation is created when the most skillful worker (the worker with the lowest r value and the highest f value) is assigned to the "easiest" station (the station with the highest S^{max} value), the second most skillful worker is assigned to the second easiest station, and so on, until reaching the least skillful worker (the worker with the highest r value and the lowest f value) assigned to the most difficult station (the station with the lowest S^{max} value). z_2 was computed under such situation, and this value was taken as a reference to define the standard deviation value that would receive a SL of 0. A standard deviation of 0 would receive a SL of 1. For any other value of z_2 between these two poles, its corresponding SL is computed linearly, following the same kind of membership function as shown in equations (4.3)–(4.6).

The solution to this multi-objective optimization problem intends to maximize the total satisfaction level.

$$\text{Max } Z = SL_1 + SL_2 + SL_3 \tag{4.7}$$

4.1.3 Incorporation of learning and forgetting effects

We incorporate the formulations of skill improvement and skill deterioration proposed by Azizi et al. [86], which are presented here only for the sake of completeness. Readers are referred to the original work.

On the one hand, when a worker is assigned to a station, his/her skill improves as he/she performs in the same station. A worker's skill improvement may depend on the initial skill (if the worker is assigned by the first time) or the remnant skill (if the worker is re-assigned), the length of the assignment (the elapsed time between the current period, ℓ, and the period on which he/she was assigned, a), and the worker's learning slope. Therefore, skill improvement can be modeled as:

$$S_{jk\ell} = S_j^{max} - \left(S_j^{max} - S_{jka}^{rem}\right) e^{\beta_k(\ell - a)} \tag{4.8}$$

where $S_{jk\ell}$ is the skill level of worker k in station j in period ℓ; S_j^{max} is the theoretical maximum level of skill at station j; S_{jka}^{rem} is the skill level that worker k had in station j when he/she was assigned to that station (in period a). It is the remnant skill; the previously gained skill that has not been affected by forgetting phenomenon. However, at time zero, i.e., $\ell = 0$, the skill level of worker k in station j, S_{jk0}^{rem} corresponds to the worker's initial skill level; so, $S_{jk0} = S_{jk0}^{rem} = S_{jk}^{initial}$. Therefore, in the case that a worker is assigned to a station by the first time, the remnant skill S_{jka}^{rem} in (4.8) should be substituted by $S_{jk}^{initial}$. And β_k is the learning slope of worker k given by $\beta_k = (log\ r_k)/(log\ 2)$, where r_k is the learning coefficient of worker k.

According to Equation (4.8), at infinite time, i.e., $\ell \to \infty$, the skill level of worker k performing in station j reaches the maximum level, $S_{jk\infty} = S_j^{max}$. However, achieving the maximum level of skill in infinite time is unrealistic. Therefore, a notion called *achievable upper level* or *skill upper bound* is introduced. This notion is represented by S_j^{UB}. The relationship between S_j^{max} and S_j^{UB} can be expressed as:

$$S_j^{UB} = S_j^{max} - \delta_j \tag{4.9}$$

where δ_j is the skill upper bound threshold value for station j.

On the other hand, as the worker continues to learn the new skill, his/her previously gained skill decays as a result of the forgetting phenomenon. A worker's skill deterioration may depend on the previous skill level achieved (the worker's skill level at the time of interruption), the length of time that he/she has not been performing (the elapsed time between the current period, ℓ, and the period

d at which the worker's experience with that specific station was last interrupted), and the worker's forgetting slope. Therefore, the corresponding skill deterioration formula is:

$$S_{jk\ell}^{rem} = S_j^{min} + \left(S_{jkd} - S_j^{min}\right) e^{\gamma_k(\ell-d)} \tag{4.10}$$

where $S_{jk\ell}^{rem}$ is the remnant skill of worker k in station j in period ℓ; S_j^{min} is the theoretical minimum level of skill at station j; S_{jkd} is the skill level that worker k had in station j when he/she departed last time (in period d) from that station; and γ_k is the forgetting slope of worker k given by $\gamma_k = (log\ f_k)/(log\ 2)$, where f_k is the forgetting coefficient of worker k.

According to Equation (4.10), at infinite time, i.e., $\ell \to \infty$, the skill level of worker k performing in station j reaches the minimum level, $S_{jk\infty}^{rem} = S_j^{min}$. However, achieving the minimum level of skill in infinite time is unrealistic. Therefore, a notion called *achievable lower level* or *skill lower bound* is introduced. This notion is represented by S_j^{LB}. The relationship between S_j^{min} and S_j^{LB} can be expressed as:

$$S_j^{LB} = S_j^{min} + \epsilon_j \tag{4.11}$$

where ϵ_j is the skill lower bound threshold value for station j.

4.1.4 Constraints

The following set of constraints are related to the number of workers: Constraint (4.12) indicates that in each period, every worker can be assigned, at most, to one station. Constraint (4.13) indicates that in each period, each station receives exactly one worker. Constraint (4.14) indicates that in each period, the sum of workers assigned along the different stations cannot exceed the number of workers available in the factory. Notice that the last period (L) is excluded from these (and other) restrictions because it is not necessary to perform worker allocation and assembly line rebalancing in the last period of the planning horizon. In the DDALRP, the demand of period ℓ is satisfied with the worker assignment solution and the units produced in the previous period, $\ell - 1$. Hence, $D(L)$, the forecast market demand of the last period, is satisfied with the output produced in period $L - 1$.

$$\sum_{j=1}^{J} x_{jk\ell} = 1 \quad \forall\ k \in K,\ \ell = 0, 1, \ldots, L-1 \tag{4.12}$$

$$\sum_{k=1}^{K} x_{jk\ell} = 1 \quad \forall\ j \in J,\ \ell = 0, 1, \ldots, L-1 \tag{4.13}$$

$$\sum_{j=1}^{J}\sum_{k=1}^{K} x_{jk\ell} \leq K \quad \ell = 0, 1, \ldots, L-1 \tag{4.14}$$

Constraint (4.15) links the worker allocation decision to the theoretical number of units produced. The theoretical number of units that can be processed in station j in period ℓ is a function of the worker assigned to station j and his/her respective skill level in period ℓ. Constraint (4.16) shows the binary restriction of the decision variables.

$$P(j, \ell) = \sum_{k=1}^{K} (x_{jk\ell} \cdot S_{jk\ell}) \quad \forall\ j \in J,\ \ell = 0, 1, \ldots, L-1 \tag{4.15}$$

$$x_{jk\ell} \in \{0, 1\} \tag{4.16}$$

The following constraints regulate the actual number of units processed by the stations: Constraint (4.17) indicates that the actual number of units processed by station 1 equals its own theoretical number of units processed. Constraints (4.18) and (4.19) compute the number of units processed by all other stations in period 0 (when there is no WIP inventory), and in subsequent periods (when there may exist some WIP inventory), respectively. Constraint (4.20) stipulates that, in any given period, the actual number of units produced by the last station (J) must satisfy the forecast market demand of the next period.

$$Q(j,\ell) = P(j,\ell) \quad j = 1,\ \ell = 0,1,\dots,L-1 \tag{4.17}$$

$$Q(j,\ell) = min\left\{P(j,\ell), Q(j-1,\ell)\right\} \quad j = 2,3,\dots,J,\ \ell = 0 \tag{4.18}$$

$$Q(j,\ell) = min\left\{P(j,\ell), Q(j-1,\ell) + WIP(j,\ell-1)\right\} \quad j = 2,3,\dots,J,\ \ell = 1,2,\dots,L-1 \tag{4.19}$$

$$Q(J,\ell) \geq D(\ell+1) \quad \ell = 0,1,\dots,L-1 \tag{4.20}$$

The following restrictions control the amount of WIP inventory: Constraint (4.21) computes the WIP inventory that remains at each station at the end of period 0. It is equal to the number of units fed by the upstream (previous) station, minus the number of units processed by the station. Constraint (4.22) calculates the WIP inventory that remains at each station at the end of subsequent periods. It is equal to the WIP inventory remained from the previous period, plus the number of units fed by the previous station, minus the number of units processed by the station. Constraint (4.23) requires the WIP inventory at the stations to be at least the minimum necessary to ensure immediate work at the beginning of each period (i.e., avoid the waiting time of feeding a station). In this way, smooth production flow can be obtained in the line. Period 0 is excluded from this WIP constraint because in period 0 the AL is empty; there is no WIP inventory at all. Again, station 1 is excluded from these three WIP constraints because station 1 is not fed by WIP inventory from a previous station; instead, it is fed by raw materials.

$$WIP(j,\ell) = Q(j-1,\ell) - Q(j,\ell) \quad j = 2,3,\dots,J,\ \ell = 0 \tag{4.21}$$

$$WIP(j,\ell) = WIP(j,\ell-1) + Q(j-1,\ell) - Q(j,\ell) \quad j = 2,3,\dots,J,\ \ell = 1,2,\dots,L-1 \tag{4.22}$$

$$WIP(j,\ell) \geq WIP_{min} \quad j = 2,3,\dots,J,\ \ell = 1,2,\dots,L-1 \tag{4.23}$$

The following restrictions compute the inventory of finished goods (IFG) produced by the last station (J): Constraint (4.24) indicates that the initial IFG in period 0 (i.e., IFG at the beginning of period 0) is 0 units. Constraint (4.25) indicates that the final IFG in period 0 (i.e., IFG at the end of period 0) is the actual number of units produced by the last station in period 0. Constraints (4.26) and (4.27) calculate, respectively, the initial and final IFG for subsequent periods, $1,2,\dots,L$. Constraint (4.26) calculates the initial IFG in period ℓ as the IFG that remained at the end of the previous period, $\ell-1$, minus the demand that must be satisfied (according to the forecast) in period ℓ. If the IFG that remains at the end of the previous period is not enough to satisfy the demand, then the initial IFG in period ℓ is 0. Constraint (4.27) calculates the final IFG on period ℓ as the initial IFG in period ℓ plus the number of units produced by station J in period ℓ.

$$I_i(\ell) = 0 \quad \ell = 0 \tag{4.24}$$

$$I_f(\ell) = Q(J, \ell) \quad \ell = 0 \tag{4.25}$$

$$I_i(\ell) = \max\left\{0, I_f(\ell - 1) - D(\ell)\right\} \quad \ell = 1, 2, \ldots, L \tag{4.26}$$

$$I_f(\ell) = I_i(\ell) + Q(J, \ell) \quad \ell = 1, 2, \ldots, L \tag{4.27}$$

4.2 Numerical experiments

We now present and discuss numerical experiments demonstrating the use of the developed MIP formulation. The assembly line data for these experiments comes from the collection of *simple assembly line balancing problems* (SALBP) that appears in Scholl [87]. All of the cases ran in these experiments were solved using a genetic algorithm implemented in Python NumPy. Both algorithms (for objective A: lost sales and for objective B: back orders) used the same framework and programming language. All cases were launched in the same computer: Intel(R) Xeon(R) with 32 CPUs E5-2667 v3 at 3.20GHz, 125 GB of memory, and SUSE Linux Enterprise Server 12 SP1 operating system.

Next, in sub-section 4.2.1, we describe the methodology and experimental design. Afterwards, in sub-section 4.2.2, we explain the solution procedure via genetic algorithm. In sub-section 4.2.2, we present, analyze, and discuss the results obtained.

4.2.1 Experimental design

The proposed model was tested on 10 problem instances; their main characteristics are shown in Table 4.1.

Table 4.1: Main characteristics of the examined problem instances

Problem instance	Number of tasks	Order strength	Flexibility ratio	Time variability ratio	Degree of divergence	Degree of convergence
1. Jackson	11	58.2	41.8	7.0	0.77	0.77
2. Buxey	29	50.7	49.3	25.0	0.74	0.78
3. Gunter	35	59.5	40.5	40.0	0.78	0.76
4. Kilbrid	45	44.6	55.4	18.3	0.67	0.69
5. Hahn	53	83.8	16.2	44.4	0.63	0.63
6. Tonge	70	59.4	40.6	156.0	0.78	0.73
7. Arcus 1	83	59.1	40.9	15.8	0.73	0.73
8. Mukherjee	94	44.8	55.2	21.4	0.51	0.51
9. Arcus 2	111	40.4	59.6	568.9	0.63	0.63
10. Bartholdi 1	148	25.8	74.2	127.7	0.74	0.72

Preprocessing of the problem instances

These 10 assembly lines were arranged in straight layout. Tasks were assigned to stations respecting their precedence relations. The task times that appear in these data sets were assumed to be the task times that workers are able to execute once they have achieved the theoretical maximum level of skill. Hence, S_j^{max} values were computed based on these task times. For instance, in the Jackson problem, station 1 consists of tasks 1, 2, 4, and 5; making a station load (SL) of 16 minutes.

Therefore, in one working period of available productive time (e.g., 8 hours or 480 minutes), a worker with the theoretical maximum level of skill performing in station 1 should be able to process 480 min $\div$ 16 min/unit = 30 units. S_j^{min} values were all set to 0.

Scenarios and cases for these problems

Each of the 10 problem instances was run under different scenarios, creating a total of 36 cases for each problem instance. The scenarios were created for: (1) learning and forgetting coefficients (optimistic, most-likely, and pessimistic scenarios); (2) initial skill inventory (workers with some initial skill inventory and workers with no initial skill inventory); (3) demand patterns (increasing, seasonally increasing, and erratic demand patterns); and (4) level of difficulty of the demand forecast (easy to achieve, intermediate, and difficult to achieve)

First, optimistic, most-likely, and pessimistic values were defined for learning and forgetting coefficients. In the experiments, learning coefficients of workers ranged from 0.700 to 0.850. (The lower the value, the faster the learning effect.) Optimistic values: [0.700 – 0.750), most-likely values: [0.750 – 0.800), pessimistic values: [0.800 – 0.850). Forgetting coefficients ranged from 0.950 to 0.800. (The higher the value, the slower the forgetting effect.) Optimistic values: [0.950 – 0.900), most-likely values: [0.900 – 0.850), pessimistic values: [0.850 – 0.800). Based on the value of learning and forgetting coefficients, three cases have been developed so far.

Empirical studies for different industries have found that the modal value of the aggregate learning rate is about 81%, whereby very fast learning rates of 56% and very slow learning rates of 95% are observed [88]

It is possible to distinguish between the "best" worker, "average" workers, and the "worst" worker. If workers are sorted in order from the best to the worst, then, the best worker has the lowest r value (fastest learning) and the highest f value (slowest forgetting). Progressively, r values increase and f values decrease, until reaching the worst worker, who has the highest r value (slowest learning) and the lowest f value (fastest forgetting).

Second, in regard to the initial skill inventory, two scenarios were created: (a) workers are experienced, and hence, possess some initial skill inventory ($S^{initial}$ values were obtained randomly following a uniform distribution in some interval approximately between 1/4 and 1/2 of the average S_j^{max} value, e.g., $\sum_{j=1}^{J} S_j^{max}/J$), and (b) workers are new operators or new hires, and hence, do not have any initial skill inventory ($S^{initial} = 0$ for all workers). With this variation, six cases have been generated so far.

Finally, each of these six cases was run under three different scenarios of demand forecast patterns: increasing (cases 1–12), seasonally increasing (cases 13–24), and erratic (cases 25–36); and under two levels of difficulty: attainable and challenging, as illustrated in Table 4.2. In the attainable scenario, workers, at their skill upper bound, are able to produce during the whole planning horizon a total number of units that exceeds by approximately 10% the total demand forecast that needs to be satisfied. In the challenging scenario, workers, at their skill upper bound, are able to satisfy approximately 90% of the total market demand. These different scenarios in the market demand forecast make a total of 36 cases for each problem instance. Since we examined 10 problem instances (Table 4.1), the total number of cases analyzed in these numerical experiments consisted of 360.

4.2.2 Solution implementation

To solve this problem, we implemented a genetic algorithm. According to the survey carried out by Battaïa and Dolgui [15], the implementation of genetic algorithms seems to be the solution method most popularly employed to solve ALBPs. A GA is a powerful metaheuristic technique that is inspired by the process of natural selection, and it is considered a class within the larger category

Table 4.2: Deployment of cases run

Case	Level of difficulty	Skill inventory	r and f parameters
Group 1: Increasing demand pattern			
1	Attainable	Workers have some skill inventory	optimistic values
2			most-likely values
3			pessimistic values
4		$S^{initial} = 0$ for all workers	optimistic values
5			most-likely values
6			pessimistic values
7	Challenging	Workers have some skill inventory	optimistic values
8			most-likely values
9			pessimistic values
10		$S^{initial} = 0$ for all workers	optimistic values
11			most-likely values
12			pessimistic values
Group 2: Seasonally increasing demand pattern			
Case	Level of difficulty	Skill inventory	r and f parameters
13	Attainable	Workers have some skill inventory	optimistic values
14			most-likely values
15			pessimistic values
16		$S^{initial} = 0$ for all workers	optimistic values
17			most-likely values
18			pessimistic values
19	Challenging	Workers have some skill inventory	optimistic values
20			most-likely values
21			pessimistic values
22		$S^{initial} = 0$ for all workers	optimistic values
23			most-likely values
24			pessimistic values
Group 3: Erratic demand pattern			
Case	Level of difficulty	Skill inventory	r and f parameters
25	Attainable	Workers have some skill inventory	optimistic values
26			most-likely values
27			pessimistic values
28		$S^{initial} = 0$ for all workers	optimistic values
29			most-likely values
30			pessimistic values
31	Challenging	Workers have some skill inventory	optimistic values
32			most-likely values
33			pessimistic values
34		$S^{initial} = 0$ for all workers	optimistic values
35			most-likely values
36			pessimistic values

of evolutionary algorithms (EA). GAs were originally developed by Holland [89] in 1975, and today, GAs are widely employed in several research fields because they can provide solutions close to the optimal solution within a reasonable frame of time [90].

It is well known that no optimal settings exist that are feasible for all problems [90]. This fact is the so-called "no-free-lunch problem" (i.e., there is no parameter choice that is optimal for all problems). As a matter of fact, in this research, finding the best possible parameters for the GA was the most time-consuming activity. We undertook a systematical testing of values and, after 200 trial runs, we came up with the parameters that led to the best solutions. The GA was coded according to the following characteristics and parameters:

- Initialization: We randomly generate an initial population of size equivalent to 1% of the total number of all possible allocations. Note that $K!^L$ is the expression that provides the total number of possible allocations. L represents the length of the planning horizon (the number of periods) and K is the number of workers. Note that $K!^L$ is equivalent to $J!^L$ because the number of workers and the number of stations is the same, $K = J$.

- Selection: We select a portion (equivalent to 0.1%) of the existing population to create a new generation. The best solutions are chosen based on the fitness function that was defined in equation (4.7) (total satisfaction level). This expression is employed to measure the quality of the solutions.
- Genetic Operators: We employ *recombination* in order to obtain successive generations. More specifically, a recombination type called *crossover two points* was utilized. We set this parameter at a rate of 0.75. Moreover, we implemented *mutation* to happen randomly and with 0.01 probability of occurrence.
- Heuristics: We did not develop any particular heuristic. We leave the development of specific heuristics that lead to improved solution quality and computation time as a future research plan.
- Termination: Regarding the stopping criterion, our GA is terminated when either, the GA has detected the best possible total satisfaction level that it is able to find (global optimum is not guaranteed), or when the allowable maximum run time of 6 hours is consumed.

A flowchart of the implemented GA is shown in Figure 4.1.

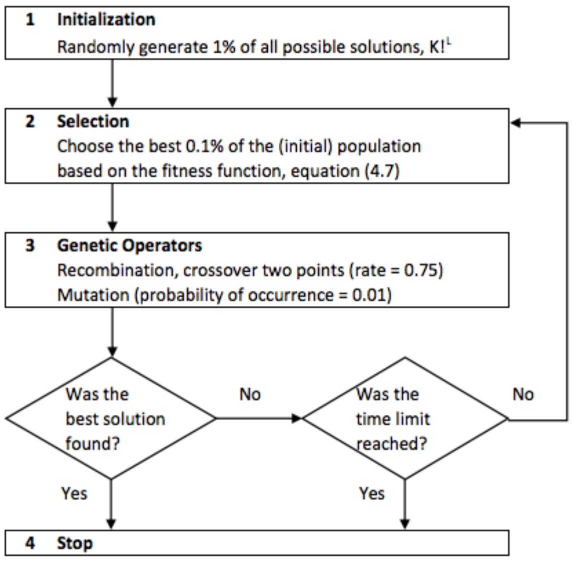


Figure 4.1: Flowchart of the genetic algorithm implemented in this study

4.2.3 Results

Results of the numerical experiments are shown in the next 10 figures (Fig. 4.2 to 4.11). Each figure shows the results on one problem instance under the 36 cases deployed in Table 4.2. The 10 figures embrace the 10 problem instances indicated in Table 4.1, from the Jackson problem (11 tasks) to Bartholdi 1 problem (148 tasks).

The 36 graphs shown on each table are read as follows: The x axis indicates the planning periods (from 0 to 52). The blue trendline shows the demand forecast (from period 1 to 52). The red line indicates the actual output produced by the AL (from period 0 to 51). The stacked column shows the accumulated IFG at the end of each period ℓ (green bar) and lost sales (purple bar). The y axis shows the number of units (forecast, produced, stored as IFG, or lost).

Results of the numerical experiments revealed the following general patterns:

In the optimistic scenario (when workers show faster learning and slower forgetting), it is more likely to observe a higher number of worker reallocation. We measure worker reallocation with the count of the number of times that a worker changed station. In general, "best" workers experience more reallocation than "average" or "worst" workers. Therefore, "best" workers tend to be more multi-skilled; they dominate the work of more stations and tend to process more units (than "average" or "worst" workers).

When workers learn quickly and forget slowly (optimistic scenario), possess some initial skill inventory, and the demand forecast is attainable, then, worker reallocation is likely to occur more frequently. By contrast, the combined scenarios of slower learning and faster forgetting effects, no initial skill inventory, and challenging demand forecasts, require that workers take advantage of learning effects as much as possible, in order to produce as many units as possible. Taking advantage of learning effects implies that workers would remain in a specific station. Consequently, the number of worker reallocation is significantly reduced in presence of these three scenarios.

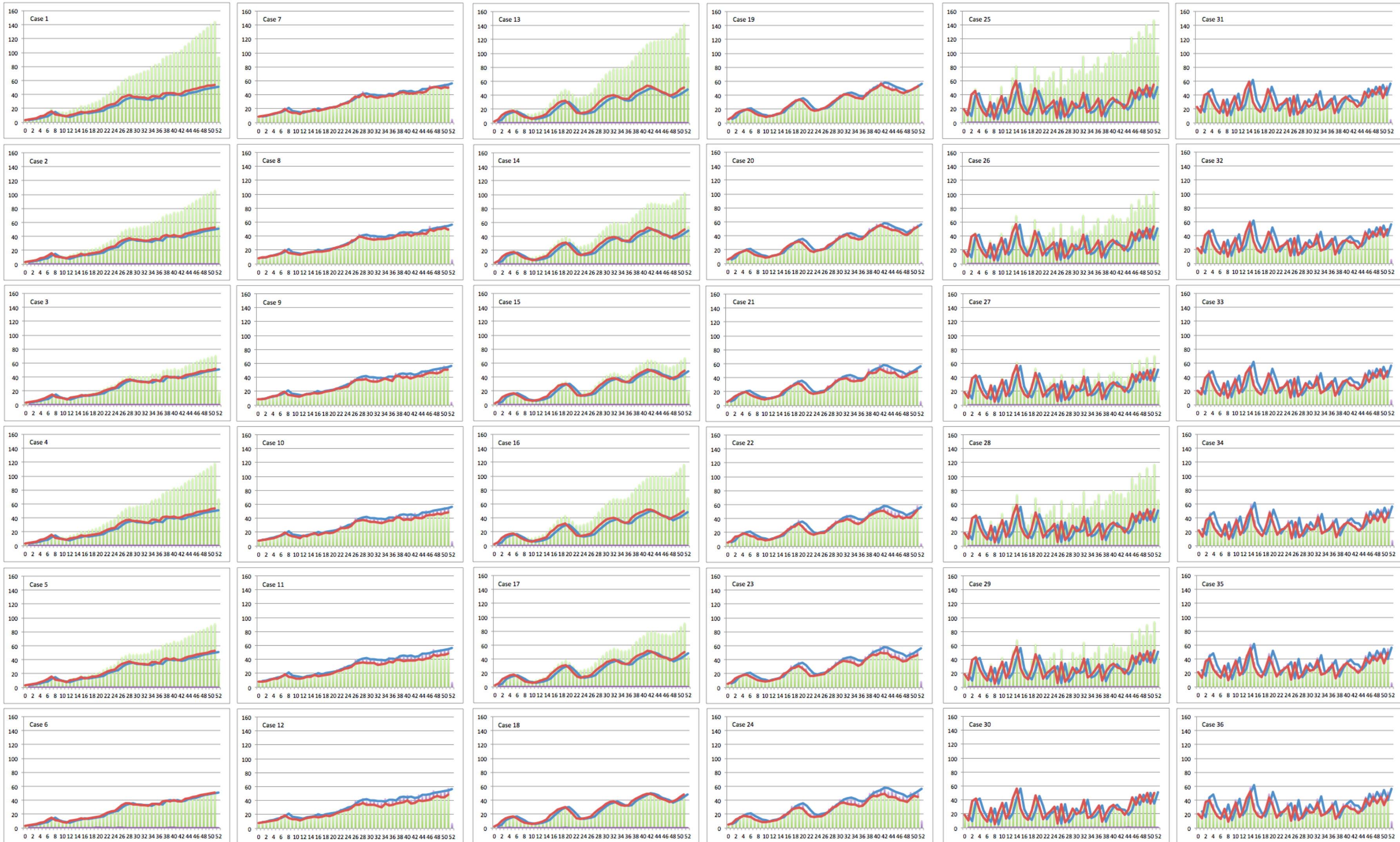
In all scenarios where demand is **attainable**, lost sales were at 0; the assembly line was able to produce the required number of units to satisfy demand. When learning and forgetting coefficients are favorable (optimistic scenario) and when workers have some initial skill, then, more IFG remains at the end of the planning period. Approximately, one more day could be supplied with the IFG that remains at the end. Progressively, in the most-likely scenario, pessimistic scenario, and when workers have no initial skill inventory, the amount of IFG that remains is less and less.

When market demand is attainable, there is more worker reallocation than in the scenario of challenging demand.

In the challenging scenarios (i.e., cases 7–12, 19–24, and 31–36), there are efforts to follow the demand forecast, but the production output always lies behind. In the optimistic scenario and when workers have some initial skill inventory, the actual production output gets closer to the demand forecast, but still remains behind. Although it is possible to accumulate inventory, lost sales take place.

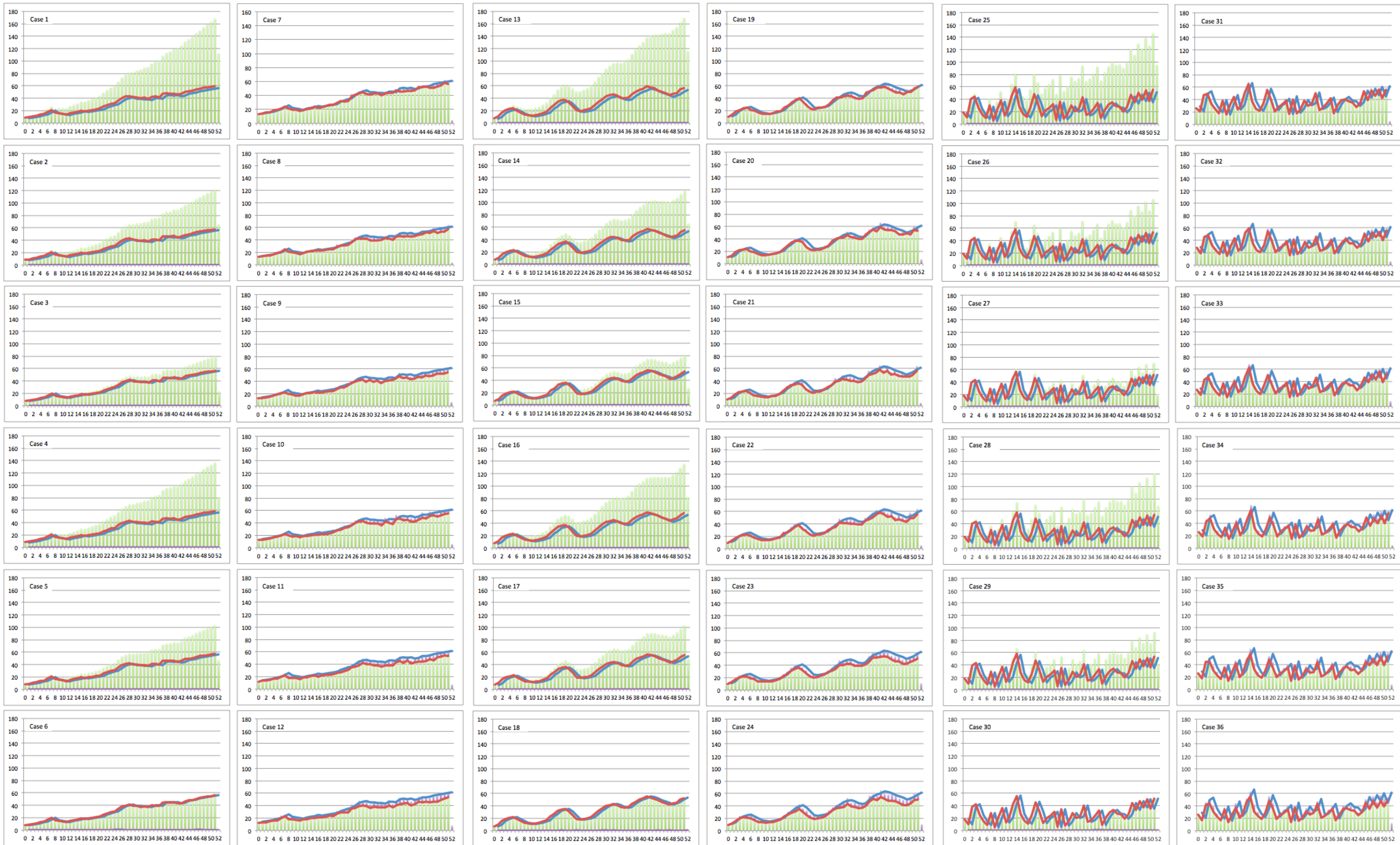
In the scenario of challenging demand, lost sales start to appear and less worker reallocation takes place in order to take advantage of the learning effect.

Figure 4.2: Model A (lost sales): 36 cases of the Jackson problem



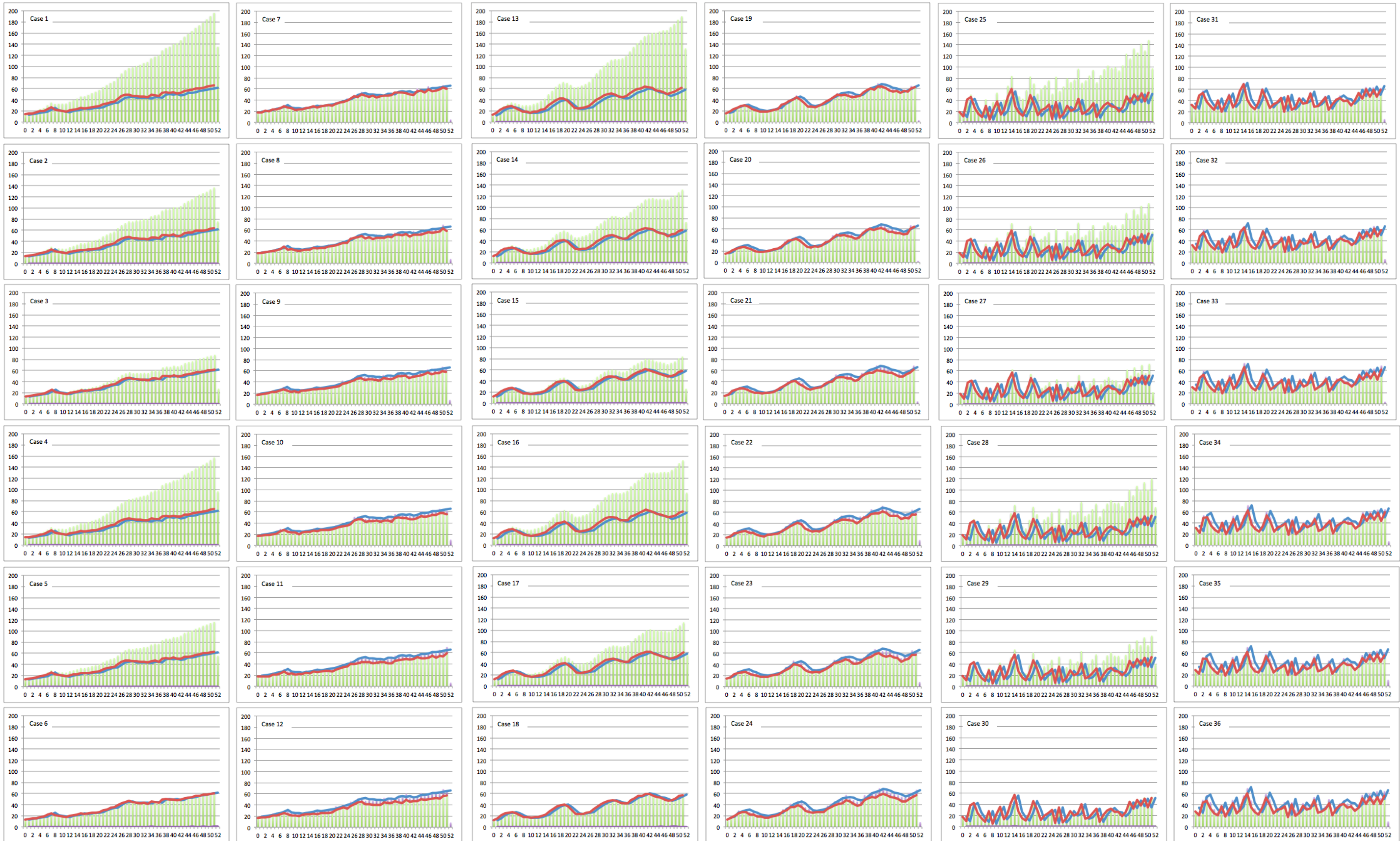
Legend: blue trendline: demand forecast; red line: actual output of the assembly line; green bar: inventory of finished goods accumulated at the end of each period; purple bar: lost sales.
Axis: x axis: units; y axis: periods.

Figure 4.3: Model A (lost sales): 36 cases of the Buxey problem



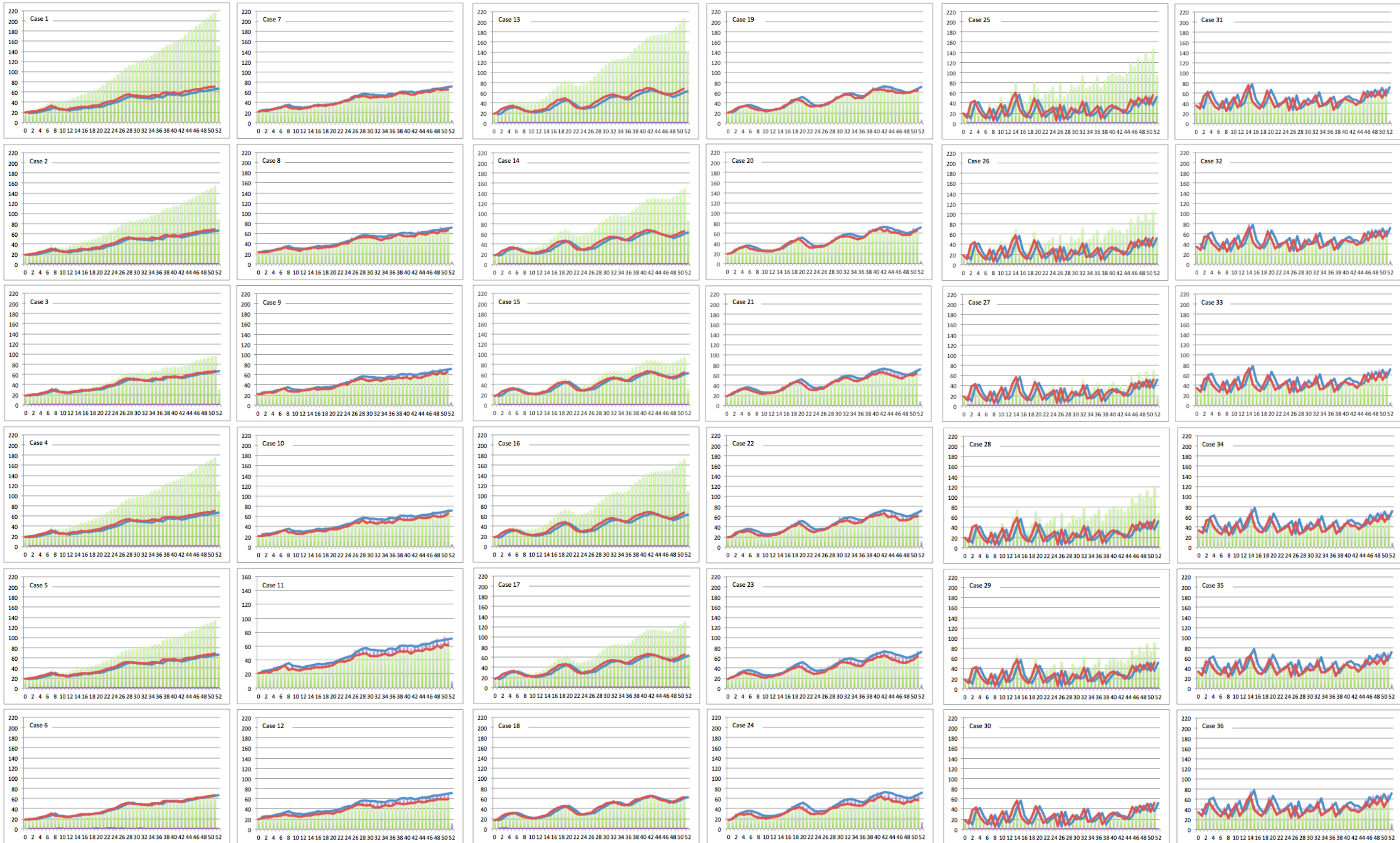
Legend: blue trendline: demand forecast; red line: actual output of the assembly line; green bar: inventory of finished goods accumulated at the end of each period; purple bar: lost sales. Axis: x axis: units; y axis: periods.

Figure 4.4: Model A (lost sales): 36 cases of the Gunter problem



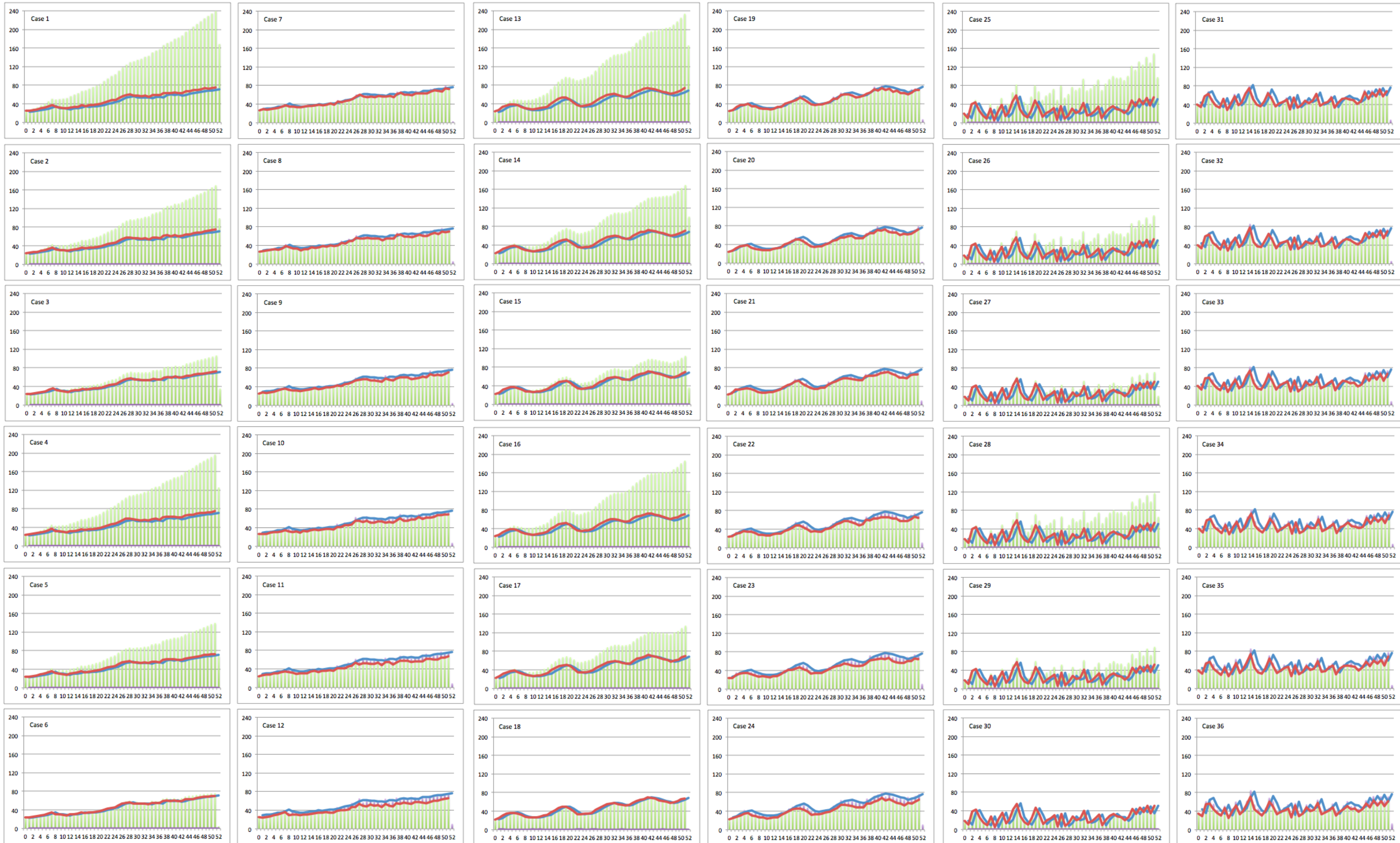
Legend: blue trendline: demand forecast; red line: actual output of the assembly line; green bar: inventory of finished goods accumulated at the end of each period; purple bar: lost sales.
Axis: x axis: units; y axis: periods.

Figure 4.5: Model A (lost sales): 36 cases of the Kilbrid problem



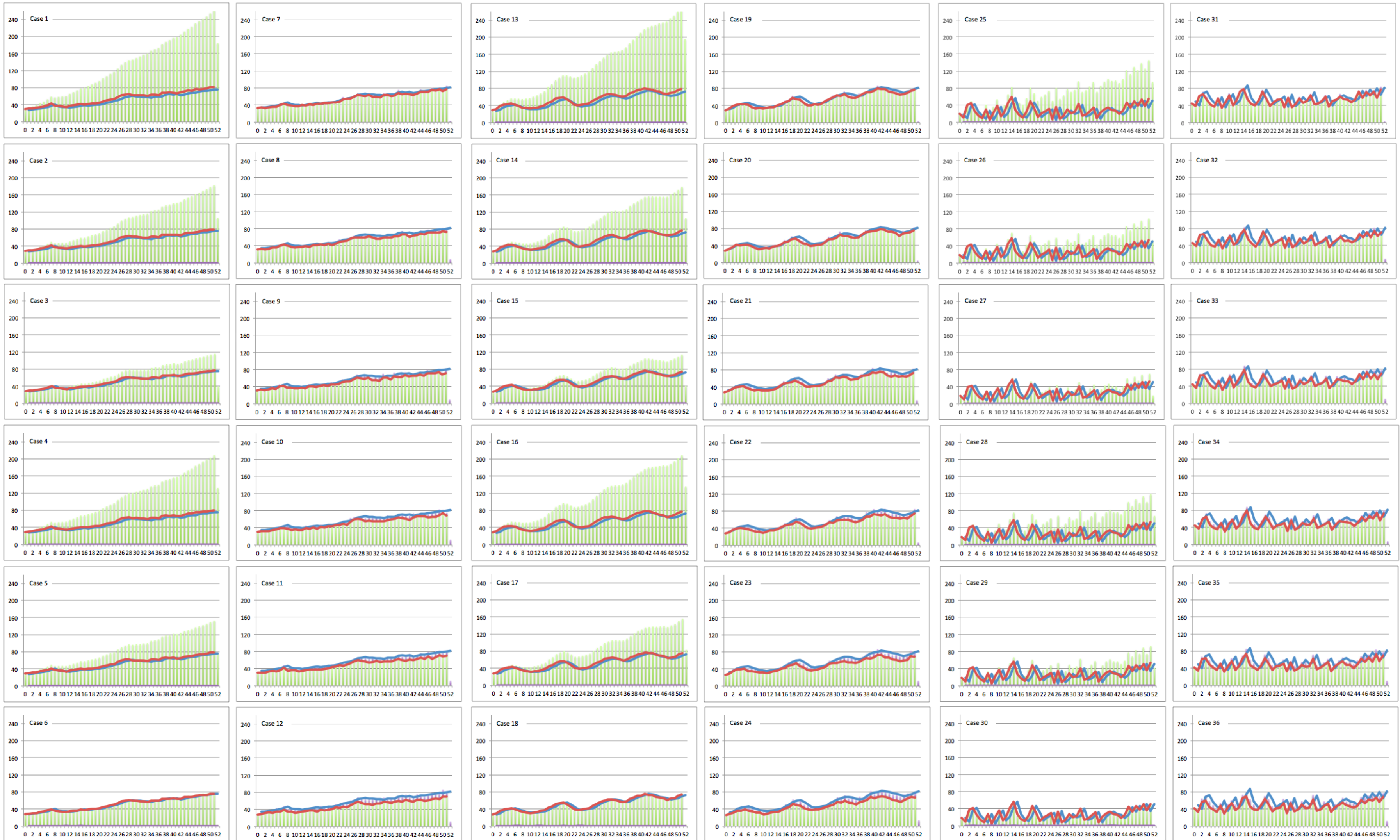
Legend: blue trendline: demand forecast; red line: actual output of the assembly line; green bar: inventory of finished goods accumulated at the end of each period; purple bar: lost sales. Axis: x axis: units; y axis: periods.

Figure 4.6: Model A (lost sales): 36 cases of the Hahn problem



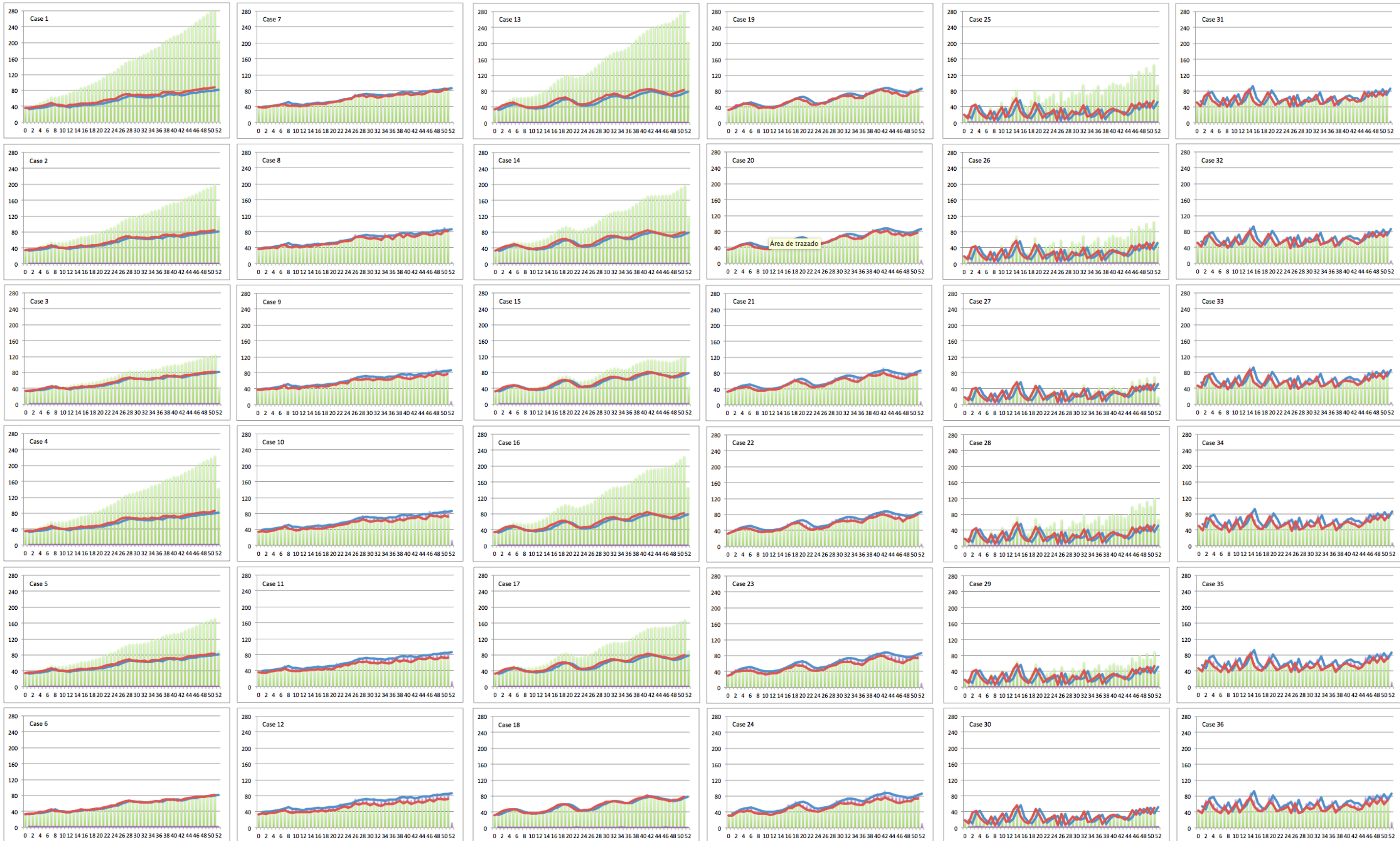
Legend: blue trendline: demand forecast; red line: actual output of the assembly line; green bar: inventory of finished goods accumulated at the end of each period; purple bar: lost sales. Axis: x axis: units; y axis: periods.

Figure 4.7: Model A (lost sales): 36 cases of the Tonge problem



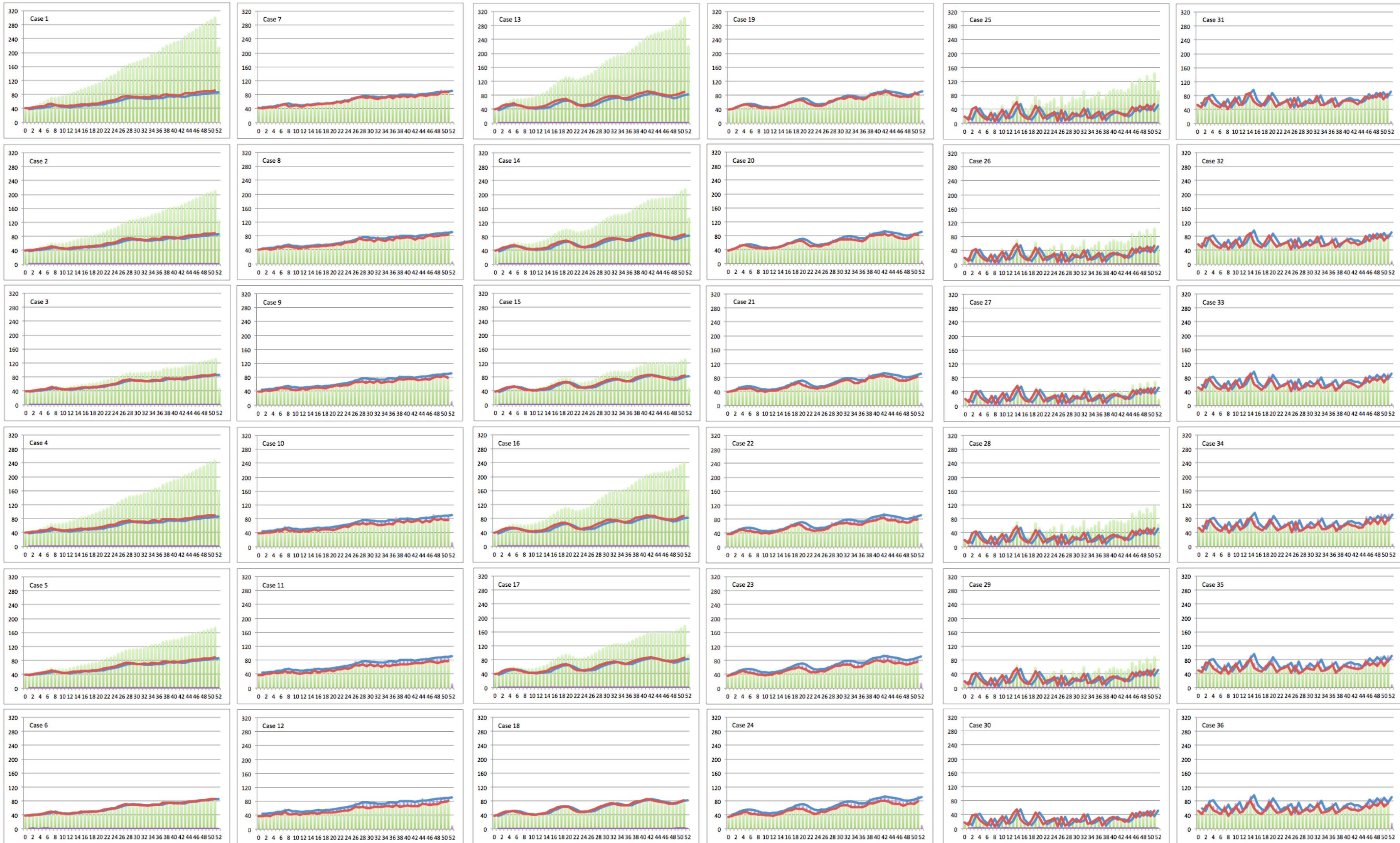
Legend: blue trendline: demand forecast; red line: actual output of the assembly line; green bar: inventory of finished goods accumulated at the end of each period; purple bar: lost sales. Axis: x axis: units; y axis: periods.

Figure 4.8: Model A (lost sales): 36 cases of the Arcus 1 problem



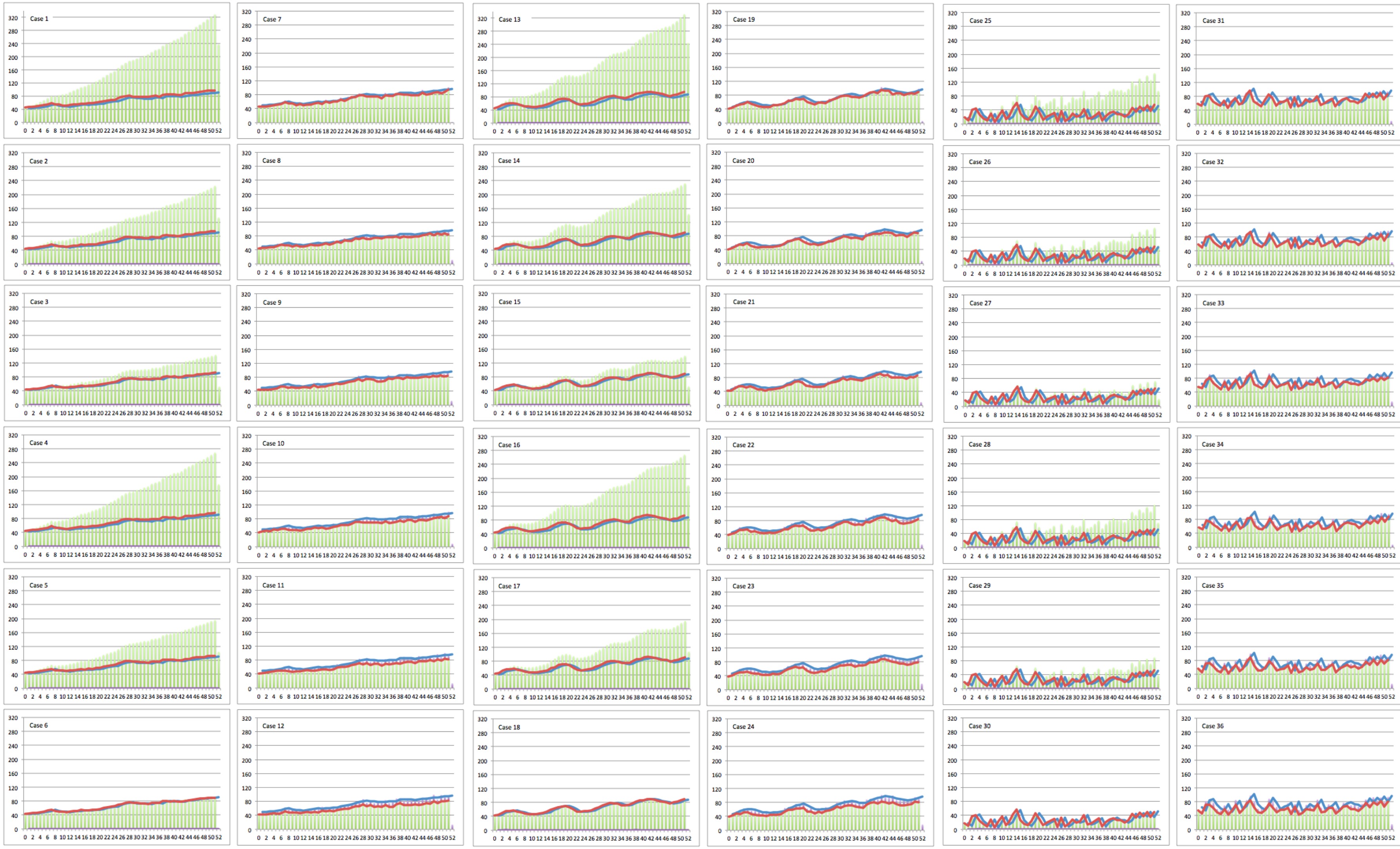
Legend: blue trendline: demand forecast; red line: actual output of the assembly line; green bar: inventory of finished goods accumulated at the end of each period; purple bar: lost sales. Axis: x axis: units; y axis: periods.

Figure 4.9: Model A (lost sales): 36 cases of the Mukherjee problem



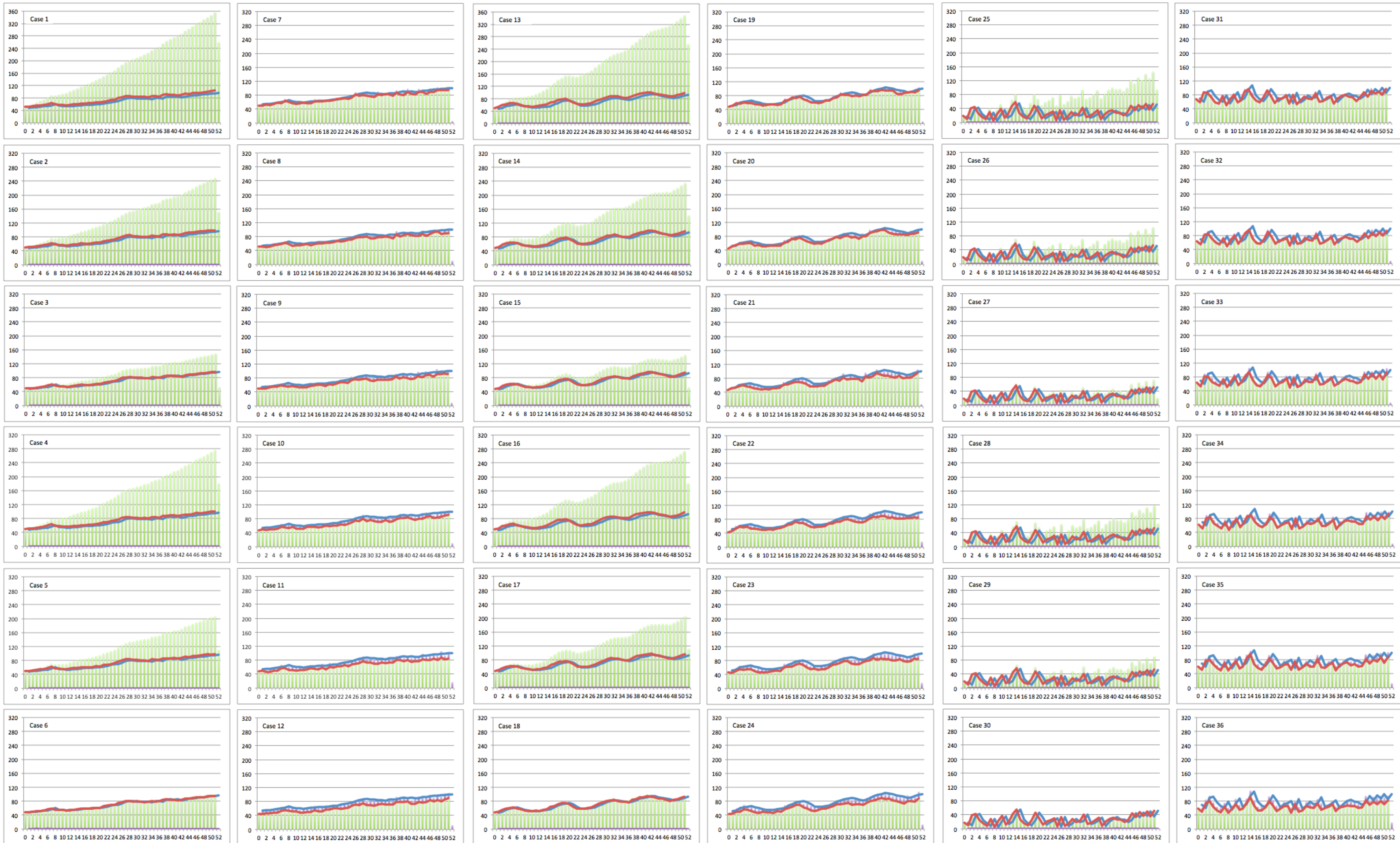
Legend: blue trendline: demand forecast; red line: actual output of the assembly line; green bar: inventory of finished goods accumulated at the end of each period; purple bar: lost sales.
Axis: x axis: units; y axis: periods.

Figure 4.10: Model A (lost sales): 36 cases of the Arcus 2 problem



Legend: blue trendline: demand forecast; red line: actual output of the assembly line; green bar: inventory of finished goods accumulated at the end of each period; purple bar: lost sales. Axis: x axis: units; y axis: periods.

Figure 4.11: Model A (lost sales): 36 cases of the Bartholdi 1 problem



Legend: blue trendline: demand forecast; red line: actual output of the assembly line; green bar: inventory of finished goods accumulated at the end of each period; purple bar: lost sales.
Axis: x axis: units; y axis: periods.

Chapter 5

A Demand-Driven Model to Minimize Back Orders

In some situations, when there is a commitment regarding the delivery of finished products to the customer, the unmet demand, rather than being treated as a lost sale (as treated in the previous Chapter), should be treated as a backlog or back order. A backlog or back order is demand pending to be met; it is demand that should have been met in the past, but due to unavoidable circumstances, the demand remained unmet and the pending items must be delivered some time later, but as soon as possible. This treatment of unmet demand as a backlog or back order is considered in this Chapter.

First we address the mathematical formulation of this model. Many of the equations to be employed in this model are identical to equations already introduced in Chapters 3 and 4. Therefore, we will focus our attention on the new or revised equations, only.

Then, we proceed to explain and analyze the numerical experiments.

5.1 Proposed model

5.1.1 Objective functions and normalization procedure

In this model, the first objective function is B-I (Equation 3.6), introduced in Chapter 3. The normalization procedure is as follows: Let z_1 be the number of back orders expressed as a percentage of the forecast demand.

$$z_1 = \frac{Z_1}{\sum_{\ell=1}^{L} D(\ell)}$$

z_1 should be as small as possible. In the numerical experiments, the ideal case, $z_1 = 0\%$, represents a situation where demand is fully satisfied on time, and hence, there are no units supplied behind schedule; this ideal case will receive the maximum satisfaction level of 1. On the other hand, a backlog level of 30% or more of the market demand will receive a satisfaction level of 0. Thus, the lower bound is $z_1^\ell = 0\%$ and the upper bound is $z_1^u = 30\%$. Accordingly, the normalization of this objective function is as follows:

$$SL_1 = \begin{cases} 1 & \text{if } \frac{Z_1}{\sum_{\ell=1}^{L} D(\ell)} = z_1^\ell \\ 1 - \frac{\frac{Z_1}{\sum_{\ell=1}^{L} D(\ell)} - z_1^\ell}{z_1^u - z_1^\ell} & \text{if } z_1^\ell < \frac{Z_1}{\sum_{\ell=1}^{L} D(\ell)} < z_1^u \\ 0 & \text{if } \frac{Z_1}{\sum_{\ell=1}^{L} D(\ell)} \geq z_1^u \end{cases} \tag{5.1}$$

Or, more simply:

$$SL_1 = \begin{cases} 1 & \text{if } z_1 = z_1^\ell \\ 1 - \frac{z_1 - z_1^\ell}{z_1^u - z_1^\ell} & \text{if } z_1^\ell < z_1 < z_1^u \\ 0 & \text{if } z_1 \geq z_1^u \end{cases} \tag{5.2}$$

In short, for this objective function: if backlog is 0, then $SL_1 = 1$; if backlog is 30% or more (of the market demand), then $SL_1 = 0$. For any other amount of backlog between these two poles, its corresponding satisfaction level is computed linearly.

Objective functions 2 (minimize the standard deviation of the number of units processed among all stations during the whole planning horizon) and 3 (minimize total overproduction or production excess) are also part of this "backlog" model. Objective functions 2 and 3 are used exactly as introduced in Chapter 4, and their normalization is made exactly as explained in the previous chapter. Hence, this demand-driven model to minimize back orders also consists of three objective functions that need to be minimized, and are combined in a single maximization function that aims for the highest overall satisfaction level (Equation 4.7).

5.1.2 Constraints and learning and forgetting effects

Learning and forgetting curves are implemented in the same way as explained in the previous Chapter. However, in regard to constraints, when running this model to minimize back orders, constraint (4.26) must be replaced by the following constraint (5.3), as it reveals the real dynamic of the IFG at the beginning of each period:

$$I_i(\ell) = \max \left\{ 0, \sum_{\ell'=0}^{\ell-1} Q(J, \ell) - \sum_{\ell'=1}^{\ell} D(\ell) \right\} \quad \ell = 1, 2, \ldots, L \tag{5.3}$$

According to constraint (5.3), any accumulated unmet demand is satisfied as soon as new inventory is built up.

In short, the modifications made to the mathematical model were:

- Objective function A-I (Equation 3.1) was replaced by objective function B-I (Equation 3.6).
- The normalization of objective function B-I was made according to Equation (5.1) or (5.2).
- Constraint (4.26) was replaced by constraint (5.3).

5.2 Numerical experiments

5.2.1 Experimental design

The demand-driven model to minimize back orders was tested on the 36 cases detailed in the previous chapter, and on the same 10 problem instances. Therefore, a second set of 360 cases was run and analyzed.

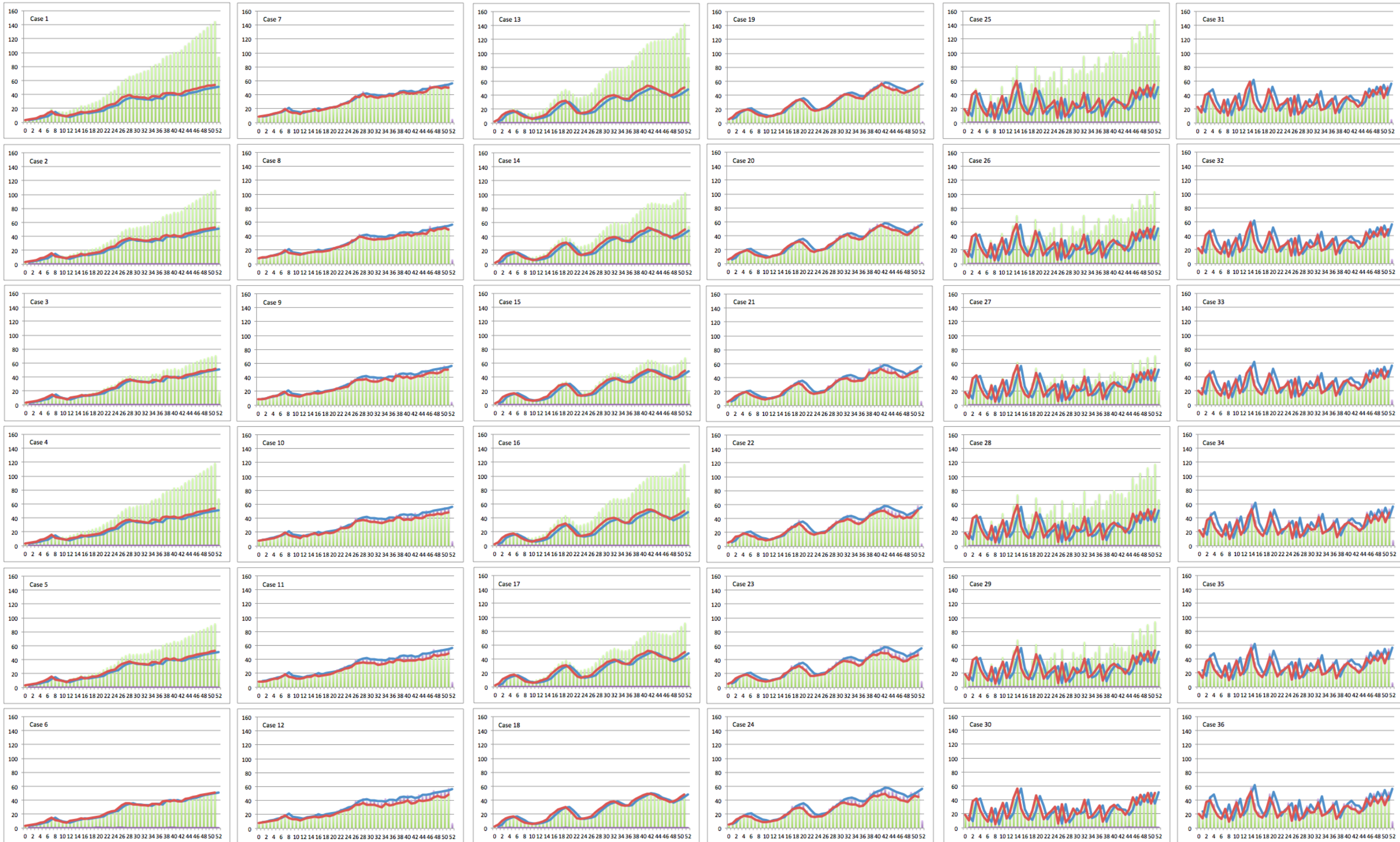
5.2.2 Results

Again, we observe that when demand is attainable, (1) backlog remains at 0, (2) more worker reallocation takes place, and (3) workers become more multi-skilled as a consequence of more worker reallocation.

The green bar on any period is the IFG accumulated at the end of that period. Those are the units used to satisfy the market demand of the next period. In the challenging scenarios, the amount of IFG accumulated is not enough to satisfy the market demand, thus, generating a small portion (shown in purple) which represents the accumulated backlog. In the challenging scenario, we can see that the backlog tends to be higher in the pessimistic scenario (slow learning, fast forgetting, workers without initial skill inventory).

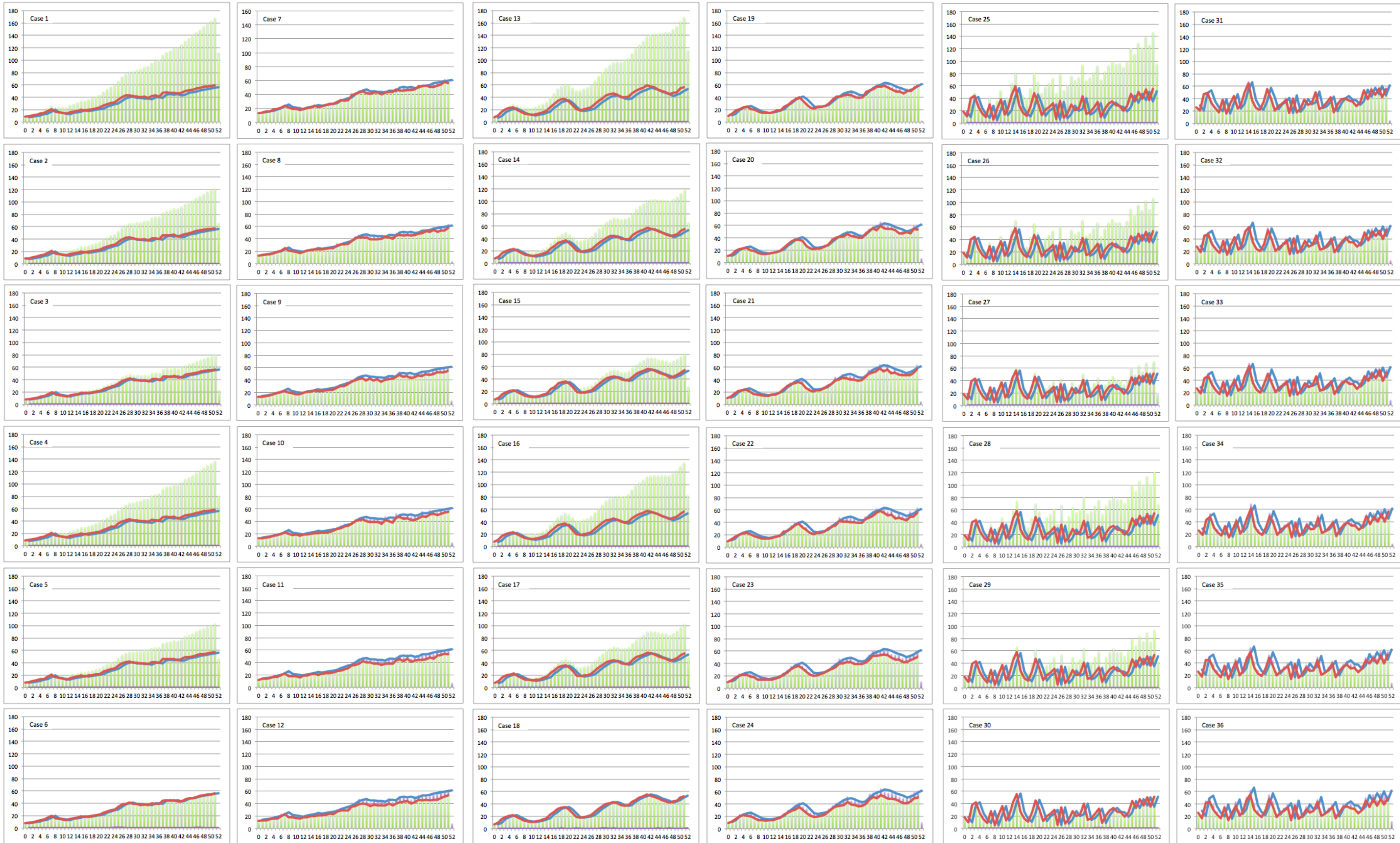
We speculate that a major difference between the *lost sale* model and the *back order* model can be seen when evaluating cost (Type II). Due to the economic loss of a sale, it may be preferable to build inventory in advance, anticipating a rise in demand. Holding inventory might be preferable than losing a sale. Hence, in the *lost sale* model it would be more likely to see that IFG accumulates. By contrast, in the *back order* model, since unsatisfied demand can be met later, it might be less likely to see inventory build up.

Figure 5.1: Model B (back orders): 36 cases of the Jackson problem



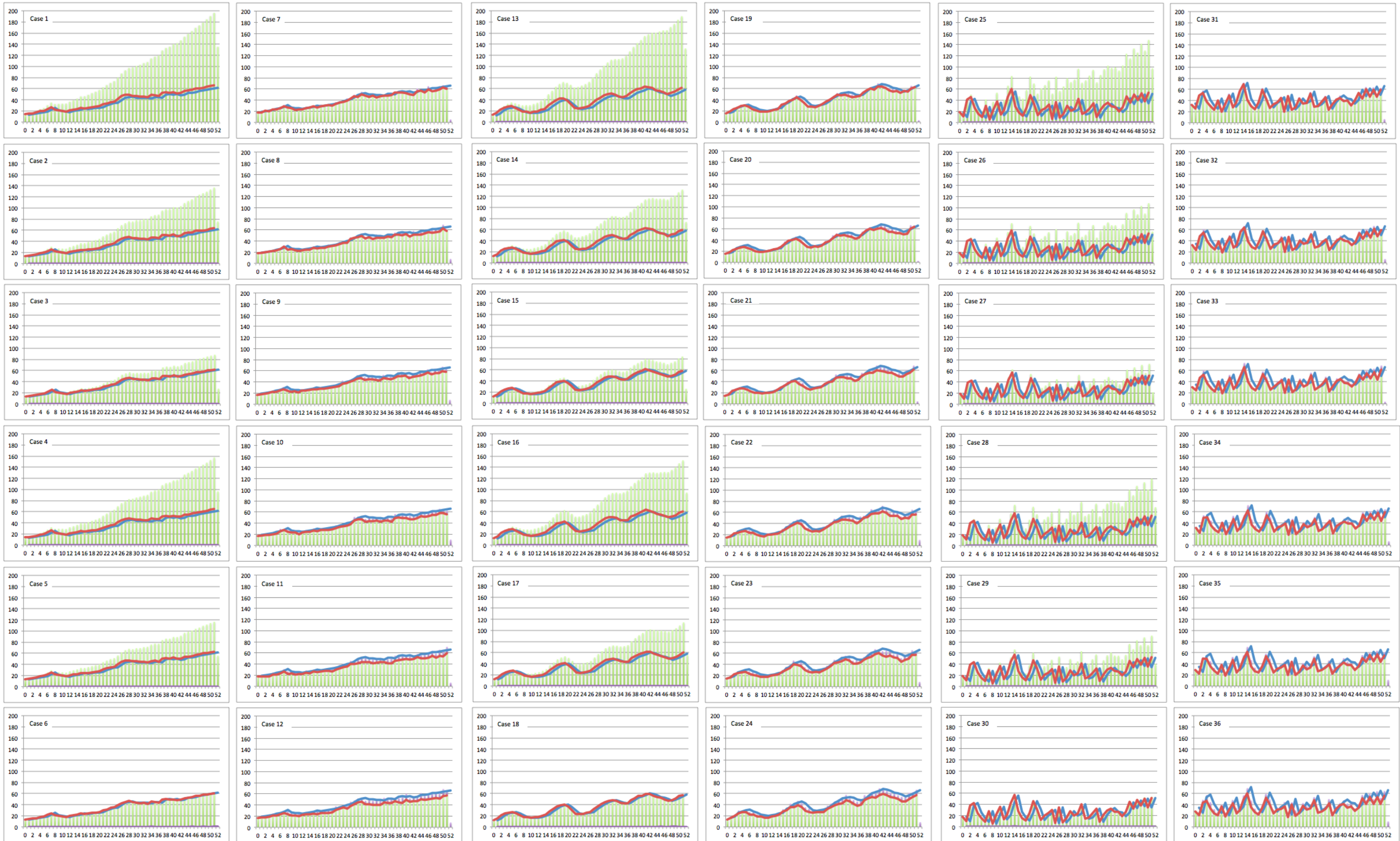
Legend: blue trendline: demand forecast; red line: actual output of the assembly line; green bar: inventory of finished goods accumulated at the end of each period; purple line: backlog. Axis: x axis: units; y axis: periods.

Figure 5.2: Model B (back orders): 36 cases of the Buxey problem



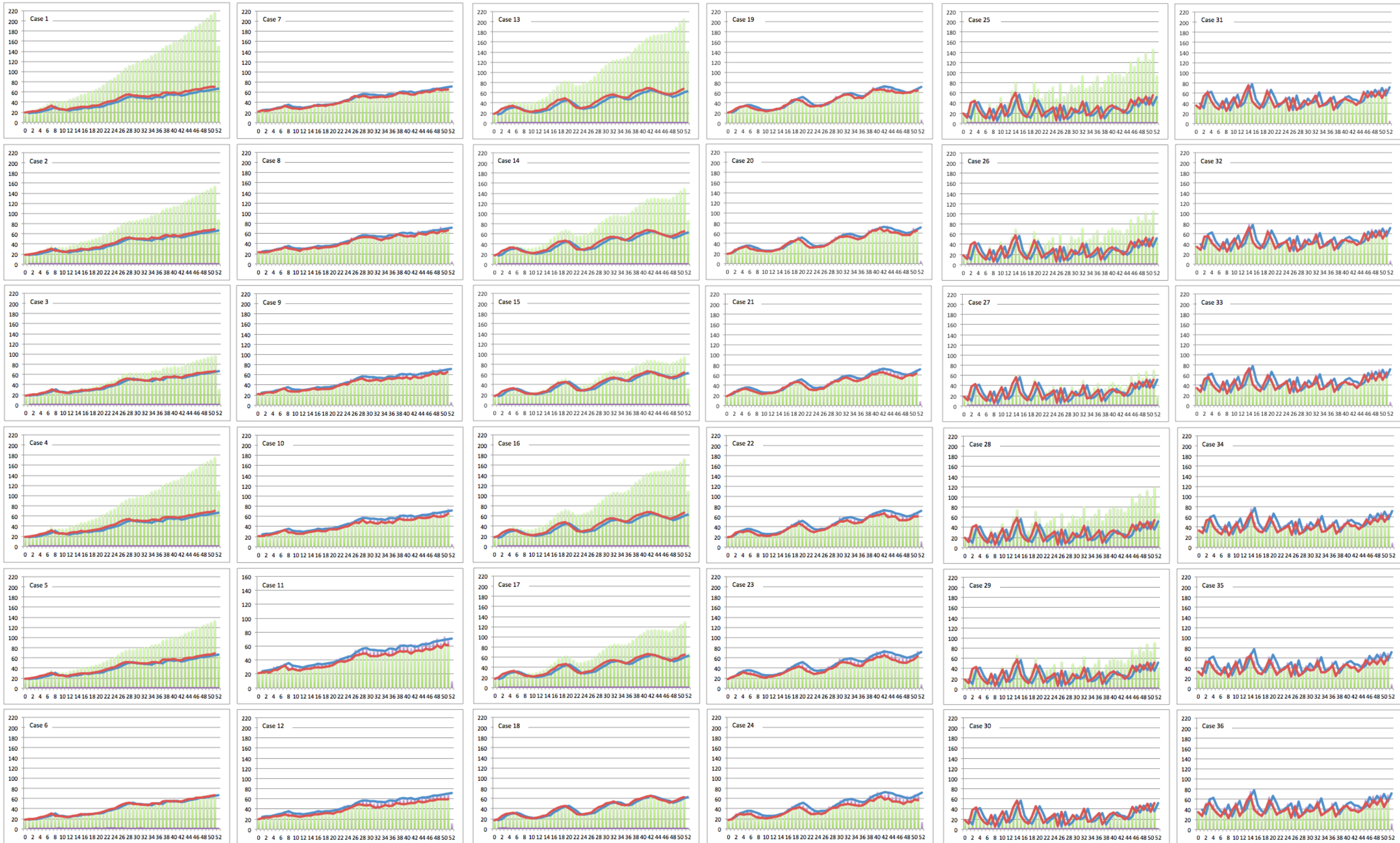
Legend: blue trendline: demand forecast; red line: actual output of the assembly line; green bar: inventory of finished goods accumulated at the end of each period; purple line: backlog.
Axis: x axis: units; y axis: periods.

Figure 5.3: Model B (back orders): 36 cases of the Gunter problem



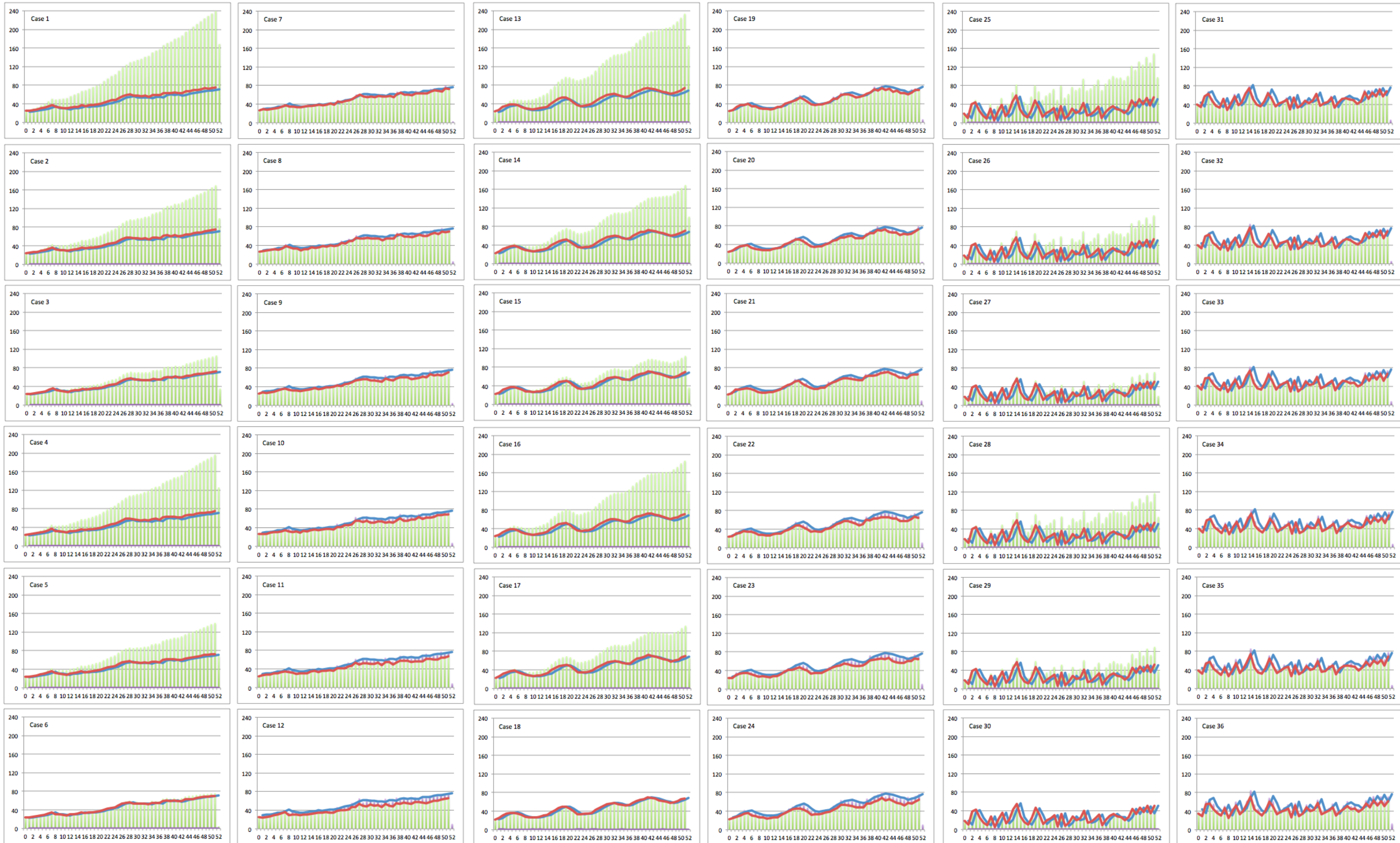
Legend: blue trendline: demand forecast; red line: actual output of the assembly line; green bar: inventory of finished goods accumulated at the end of each period; purple line: backlog. Axis: x axis: units; y axis: periods.

Figure 5.4: Model B (back orders): 36 cases of the Kilbrid problem



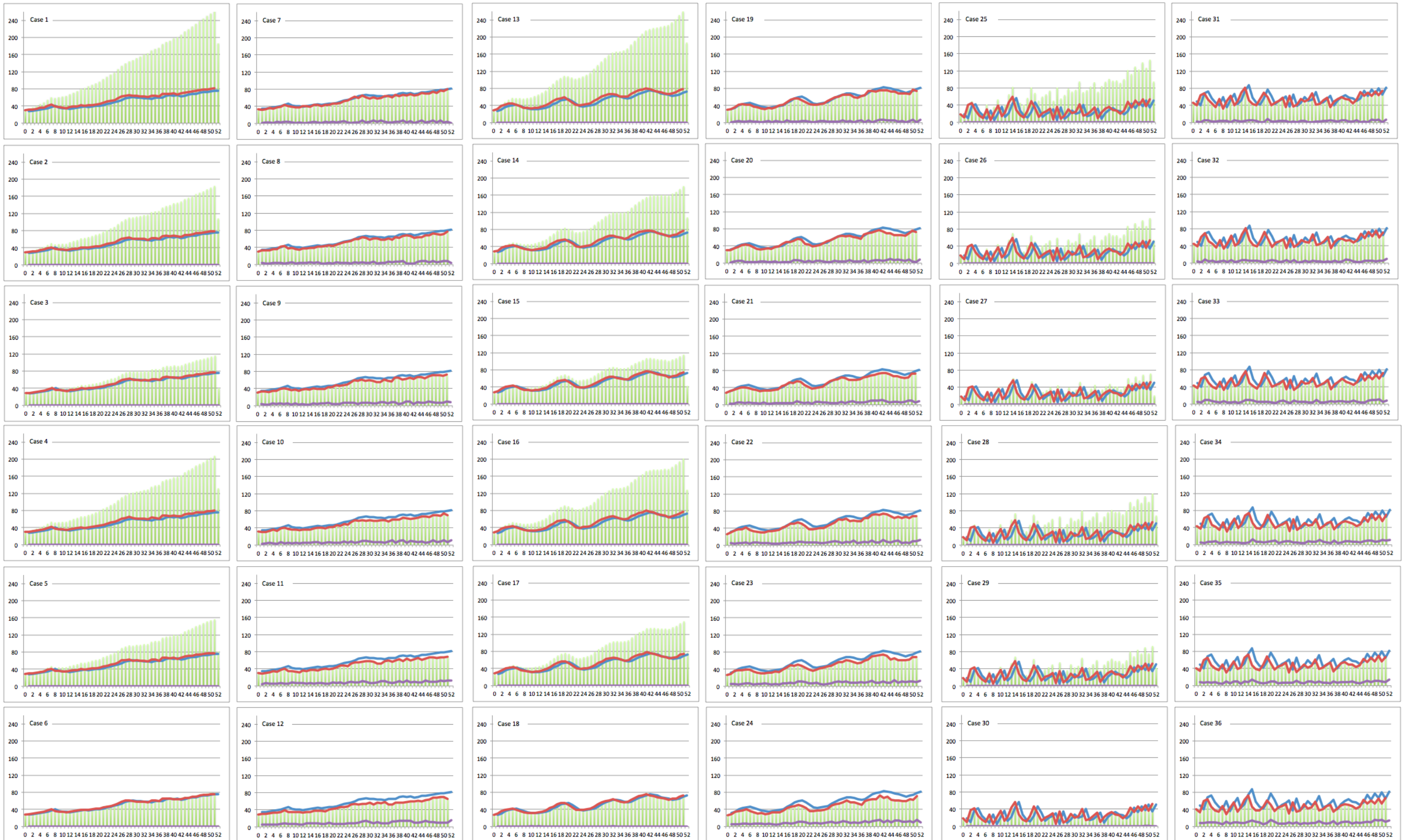
Legend: blue trendline: demand forecast; red line: actual output of the assembly line; green bar: inventory of finished goods accumulated at the end of each period; purple line: backlog.
Axis: x axis: units; y axis: periods.

Figure 5.5: Model B (back orders): 36 cases of the Hahn problem



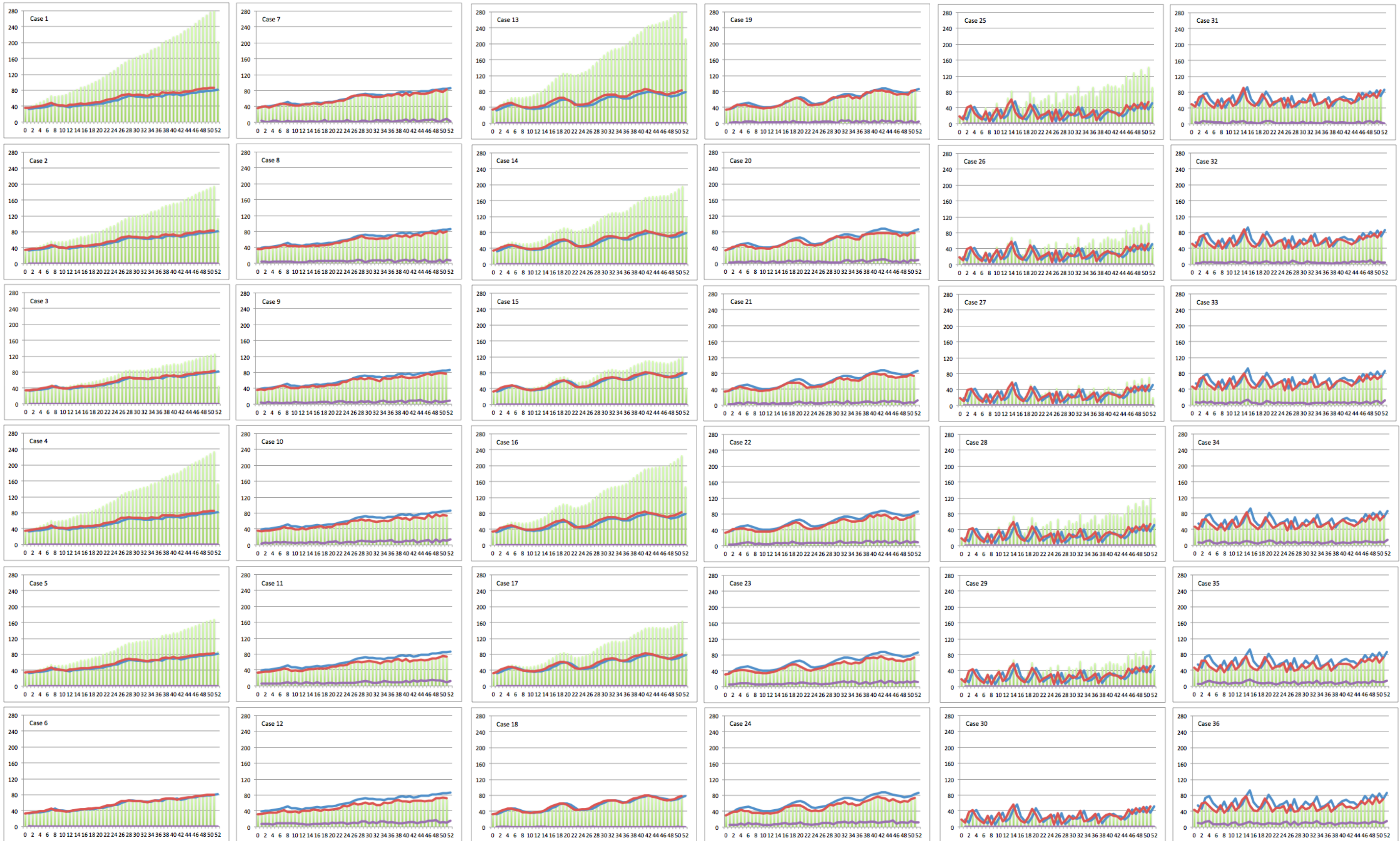
Legend: blue trendline: demand forecast; red line: actual output of the assembly line; green bar: inventory of finished goods accumulated at the end of each period; purple line: backlog. Axis: x axis: units; y axis: periods.

Figure 5.6: Model B (back orders): 36 cases of the Tonge problem



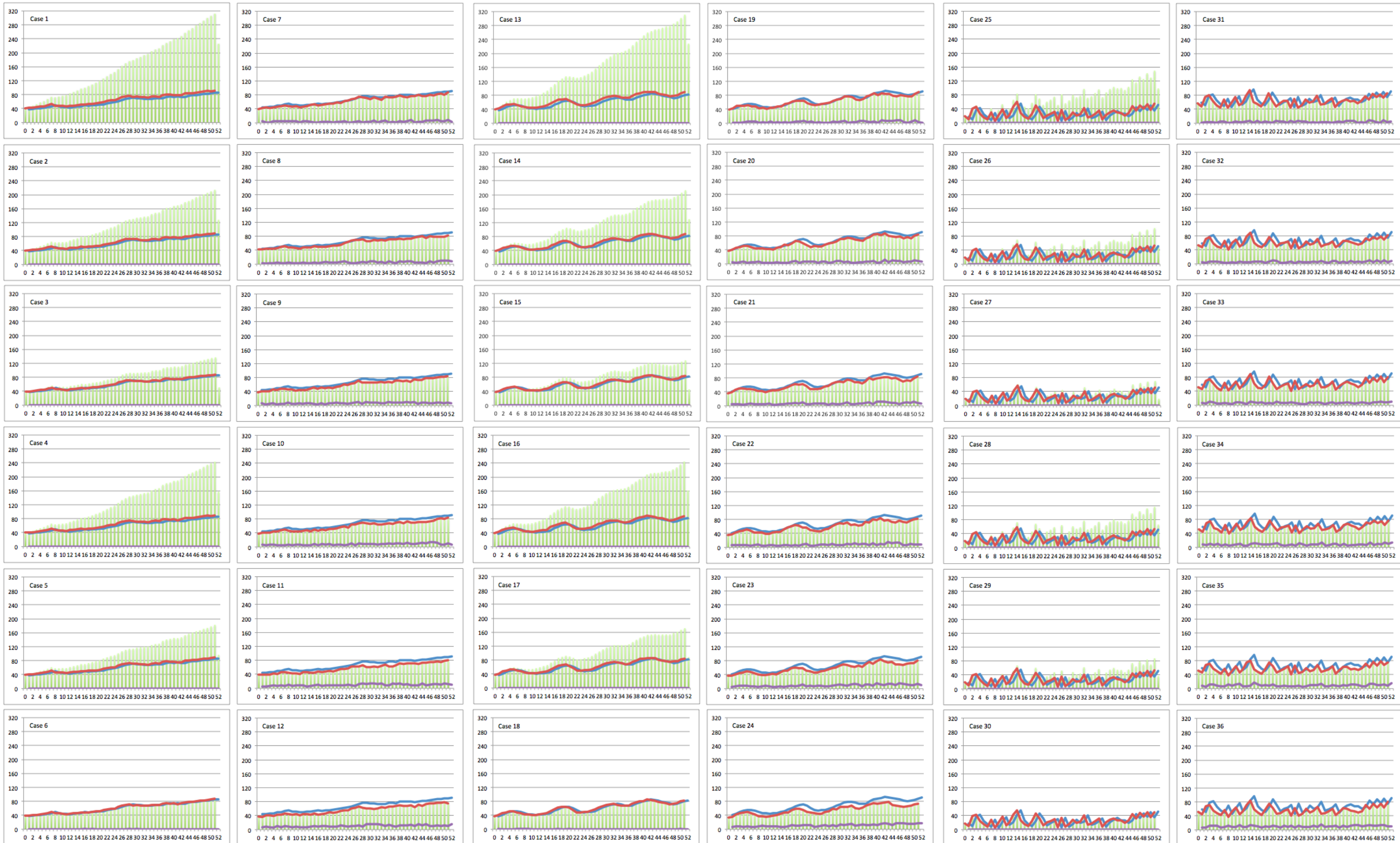
Legend: blue trendline: demand forecast; red line: actual output of the assembly line; green bar: inventory of finished goods accumulated at the end of each period; purple line: backlog. Axis: x axis: units; y axis: periods.

Figure 5.7: Model B (back orders): 36 cases of the Arcus 1 problem



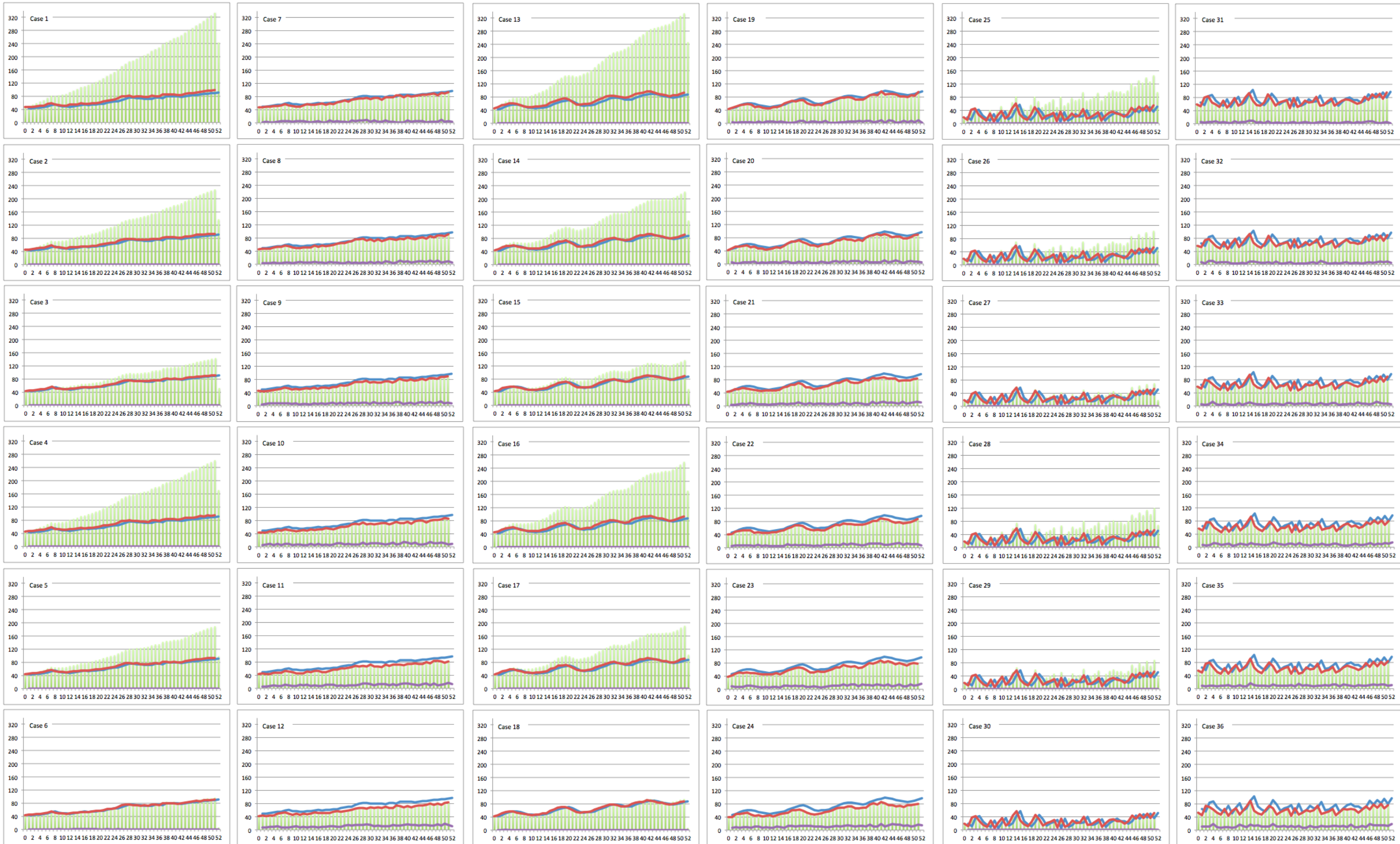
Legend: blue trendline: demand forecast; red line: actual output of the assembly line; green bar: inventory of finished goods accumulated at the end of each period; purple line: backlog. Axis: x axis: units; y axis: periods.

Figure 5.8: Model B (back orders): 36 cases of the Mukherjee problem



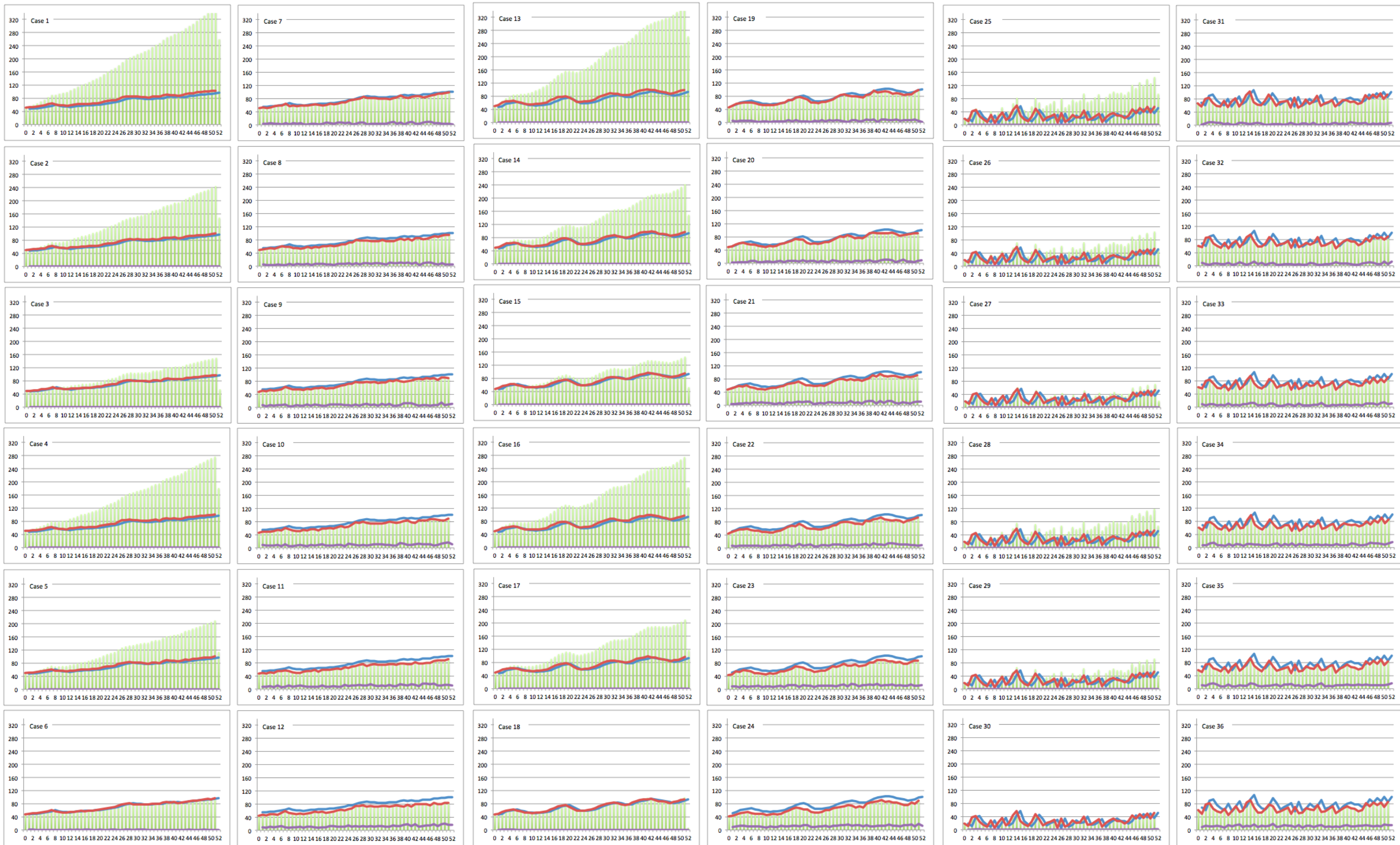
Legend: blue trendline: demand forecast; red line: actual output of the assembly line; green bar: inventory of finished goods accumulated at the end of each period; purple line: backlog. Axis: x axis: units; y axis: periods.

Figure 5.9: Model B (back orders): 36 cases of the Arcus 2 problem



Legend: blue trendline: demand forecast; red line: actual output of the assembly line; green bar: inventory of finished goods accumulated at the end of each period; purple line: backlog. Axis: x axis: units; y axis: periods.

Figure 5.10: Model B (back orders): 36 cases of the Bartholdi 1 problem



Legend: blue trendline: demand forecast; red line: actual output of the assembly line; green bar: inventory of finished goods accumulated at the end of each period; purple line: backlog.
Axis: x axis: units; y axis: periods.

Chapter 6

Concluding Remarks

6.1 Conclusions

Different from other methods, which focus on maximizing the efficiency of the lines without regard to their role within the extended supply chain they belong to, this research aimed at balancing the assembly line in such a way that the production output of the line meets a given market demand forecast. In particular, the research presented in this dissertation:

1. Introduced the *demand-driven assembly line rebalancing problem* (DDALRP);
2. Proposed a framework for the DDALRP based on two objectives (A: minimize lost sales, B: minimize back orders) and two measures of interest (I: units, II: cost), thus, defining four types of DDALRPs (A-I, A-II, B-I, B-II);
3. Proposed two formulations for the DDALRP: one for A-I (a demand-driven model to minimize lost sales in terms of units) and one for B-I (a demand-driven model to minimize back orders in terms of units);
4. Undertook an extensive computational study to evaluate the behavior of the proposed models under different scenarios: (a) optimistic, most-likely, and pessimistic learning and forgetting coefficients; (b) workers with and without initial skill inventory; (c) increasing, seasonally increasing, and erratic demand patterns; and (d) attainable and challenging demand forecasts; and
5. Obtained conclusions and a general understanding of the dynamic of the reallocation of workers.

In fact, the purpose of the numerical experiments was to study the behavior of the proposed models for different instance sizes and considering diverse scenarios. The followings were the main insights of about the dynamic of worker reallocation:

- More worker reallocation takes place under an optimistic scenario (fast learning, slow forgetting, workers have some initial skill inventory). As learning occurs slower, or forgetting occurs faster, or the initial skill inventory of workers is lower, then, less worker reallocation takes place.
- More worker reallocation takes place when the market demand is attainable. As the level of difficulty of the demand forecast increases (i.e., higher the demand forecast), less worker reallocation occurs.
- "Best" workers experience more number of reallocations than "average" workers. "Average" workers experience more reallocation than "worst" workers.

The followings were the main insights of about the dynamic of IFG, lost sales, and back orders:

- More IFG accumulates when market demand is attainable and in presence of an optimistic scenario. When demand is attainable and the scenario is "most likely" or "pessimistic", IFG also accumulates, but less than in presence of an "optimistic scenario".
- Less back orders or lost sales occur under an optimistic scenario. When the scenario is "most-likely" or "pessimistic" there may be an increased number of lost sales or back orders.
- Less back orders or lost sales occur when market demand is attainable. As the forecast demand increases (i.e., as the forecast demand becomes more challenging or more difficult to attain), then, more back orders or lost sales are observed.

6.2 Contributions

We proposed a new, useful, and practical model to balance an assembly line via worker reallocation, adapting, as much as possible, the production output of an AL to a demand forecast, and aiming to minimize lost sales or back orders. *New*: while the extensive literature has focused on maximizing line efficiency, we tackled an ALBP where the aim is to achieve a production output that varies according to some demand forecast. *Useful*: to reduce the gap between industry needs and the status of research findings. *Practical*: the models are applicable to any manufacturing plant involving human labor in their assembly systems arranged in I-shaped structure (also known as straight layout or serial configuration).

6.2.1 Practical implications

We created two mathematical models to tackle the problem of balancing an assembly while at the same time adjusting the production output of the line to a given demand forecast. The models are:
1. Demand-driven model to minimize lost sales
2. Demand-driven model to minimize back orders

The proposed models in this dissertation support plant engineers and production managers in the analysis of their production lines, in the tracking of their workers' skill inventory, and their decision making process in regard to worker reallocation to balance ALs and match a demand forecast.

Some positive, practical implications and additional advantages of worker reallocation are: (a) more job variety, (b) more motivation and less boredom, and (c) multi-skilled workers.

6.2.2 Academic implications

This research presents a new family of assembly line balancing problems that we have denominated: *demand-driven assembly line rebalancing problem* (DDALRP). The DDALRP itself is a contribution to the body of knowledge of the field of *Assembly Line Balancing* (ALB). As a reference, other problems introduced by other researchers over the last few years include:
- Assembly line worker assignment and balancing problem (ALWABP) [36]
- Assembly line worker integration and balancing problem (ALWIBP) [45]
- Time and space constrained assembly line balancing problem (TSALBP) [78]
- Accessibility windows assembly line balancing problem (AWALBP) [47]
- Traveling worker assembly line (re)balancing problem (TWALBP) [49]

To add a new item to the list above, the DDALRP presented in this dissertation is a new contribution to the ALB / ALR body of knowledge.

In addition, it is worthy to note that the classical ALBP faces the problem with the traditional task precedence constraints, considers deterministic task times, aims at one single objective (usually minimize the cycle time or the number of stations), and the balancing task is a one-time endeavor (i.e., does not require re-balancing). Therefore, from an academic point of view, it is worth to contrast that, in contrast, we have addressed the ALBP considering simultaneously: (1) dynamic processing times of tasks (learning and forgetting effects), (2) a demand forecast, (3) multi-period balancing (i.e., rebalancing over a planning horizon), and (4) multi-objective formulation.

6.2.3 Contribution to Knowledge Science

From the Knowledge Science point of view, we have applied *conceptual combination*, a fundamental cognitive process by which two or more existing basic concepts are mentally synthesized to generate a composite, higher-order concept [91], e.g., the *demand-driven assembly line rebalancing problem.* The DDALRP is a fascinating problem that combines:

- Multi-objective optimization: three objective functions were combined: two intended to achieve high efficiency, and one intended to adapt the production output of the assembly line to some forecast.
- Multi-period analysis: we balance and re-balance the assembly line over a planning horizon.
- Worker reallocation: we balance and re-balance the assembly line by performing allocation and re-allocation of workers.
- Dynamic times: learning and forgetting effects were taking into consideration.
- Demand forecast

The combination of these elements conform a real industry scenario that has critical importance in manufacturing facilities and production plants. We named it DDALRP and we created two mathematical models to tackles this problem (demand-driven model to minimize lost sales and demand-driven model to minimize back orders), contributing, thus, to the body of knowledge in the ALB research area.

From the Knowledge Science point of view, the definition of the DDALRP and its framework proposed (Chapter 3) is an example of *knowledge creation.* As mentioned in my personal motivation, the DDALRP emerged from a real industry situation that I experienced in my workplace. Citing the words of Tenenbaum: *"A concept is an abstraction or generalization from observable examples or a transformation of existing ideas. New concepts never come out of nowhere. Past experiences support the learning of new concepts by showing the learner what matters for generalization."* [92] Further, as a new knowledge created, the appearance of the DDALRP into the body of knowledge in the field of ALB could be modeled in a SECI spiral (cfr. [93]).

Finally, we highlight transformation of data into information, and transformation of information into knowledge. **Data** includes learning and forgetting coefficients, a demand forecast, and other input parameters. These data were processed and transformed to generate **information.** For instance: Based on the learning parameters, how many units can workers produce? Given the demand forecast, to which station should workers be allocated? **Knowledge:** management of industrial knowledge: How to properly manage organizational resources (e.g., workers) to efficiently balance assembly lines? How to balance assembly lines in order to minimize lost sales or back orders, and to sustain competitive advantage? These questions are answered under the framework (DDALRP) and tool (non-linear, multi-objective, combinatorial optimization model) presented in this study.

6.3 Directions for future research

The models proposed in this research were applicable to the straight AL. Thinking in terms of *generalization* (of models), a possible direction for future research is the exploration of a generalized model capable of being applicable to assembly systems having different layouts or configurations. Regardless of the physical flow of the line (straight, U-shaped, S-shaped, carousel, etc.), the presence of some parallel stations or parallelization of the whole line, or the presence of feeder lines (sub-assembly operations), a production system is comprised of J stations, which, independently of their physical location within the factory, configuration, or layout arrangement, the production system should be balanced in such a way so as to achieve smooth production flow, and match as much as possible the forecast market demand.

Additionally, in our numerical experiments, we assumed a "well-aligned" set of workers that can be sorted from "best" to "worst" based on progressively increasing (decreasing) learning (forgetting) coefficients. In reality, a worker may show fast learning in certain tasks, and slower learning in other tasks. Similarly, the forgetting coefficient of a worker may be different depending on the kind of task that he/she will perform. More complex dynamics of worker reallocation might be seen when learning and forgetting values are completely shuffle or random. Thus, investigating the dynamics of worker reallocation under such scenario may constitute a further step.

Further comments

Contrary to the well-known principle "divide and conquer", conquering new research frontiers in ALB is about doing exactly the opposite: it is about (a) simultaneously considering branches that are connected to the problem, and (b) about considering more reality.

In regard to the first item, this research has already considered the demand forecast in the ALBP. (The demand forecast his is only one connecting branch.) Recently, Sternatz [94] introduced the *joint line balancing and material supply problem*. (Materials supply to the assembly line is another connecting branch.) Roy and Khan [95] developed an integrated model for line balancing with work-station inventory management. (Inventory management is another branch associated with ALB.) Che [96] proposed a multi-objective optimization algorithm for solving the supplier selection problem with assembly sequence planning and assembly line balancing. (Further, the supplier selection problem is also related to operations management issues of the assembly line.)

Therefore, it seems that a new trend in this research field is, in general terms, connecting nearby issues surrounding the ALBP, and in particular, connecting inbound and outbound logistics issues to the ALBP. In the past, materials requirement planning (MRP), inventory management problems, the supplier selection problem, the ALBP, and other problems had been addressed separately. Probably, the reason that may explain the new trend to formulate a bigger problem is the fact that addressing the problem as a whole yields a better solution, closer to optimum, than dividing the problem into sub-problems and solving them separately and independently. In this regard, future research efforts should be addressed to holistically optimize the work system. (Will we visualize in the future one single, "all-mighty" model capable of solving "the factory management problem"?)

Another possible way to extend the research frontier in this field is by considering additional reality in order to improve the accuracy of the models. For instance, the processing rate at which workers process units in a station is affected not only by learning-forgetting effects. There are other elements present. Fatigue-recovery and motivation-boredom are realities that certainly affect the processing time of a job or workpiece. Simultaneously considering these realities would lead to a more complex model that more accurately computes the time it would take a worker to process a unit, crucial data for solving the ALBP.

Jaber et al. [97] incorporated human fatigue and recovery into the learning-forgetting process and presented the "learning-forgetting-fatigue-recovery model" (LFFRM). Givi et al. [98] considered fatigue-recovery and learning-forgetting parameters to develop a mathematical model that estimates the human error rate when performing an assembly job. In addition to estimating the error rate, it would be desirable to estimate the processing time, as well. Azizi et al. [86] developed motivation-boredom formulations and skill improvement-deterioration formulations to model job rotation in a manufacturing system. Corominas et al. [99] addressed an important element of reality: if task A and task B are related or are similar, then, when a worker performs task A, he/she also gains experience on task B –even though he/she had not performed task B before.

Moreover, linked to our demand-driven models, it would be interesting to study the actual effect of higher frequency of reallocation experienced by the "best" and "average" workers. Would a higher frequency of reallocation lead to the development of more stress, fatigue, and a possible sick leave? Or would it contribute to job variety, motivation, and development of more skills? In short, as more elements and more realities are considered, (and as the real consequences of more reallocation are understood), the more accurate the models will be.

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