Efficient Material Flow in Mixed Model Assembly Lines

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Abstract

This study investigates the material handling system used in mixed model assembly lines which are important to produce diversified product models to satisfy the increasing customer demand. Tugger trains are used to feed by parts the workstations in the assembly lines. These parts are loaded on trains in small containers (bins) from the warehouse or intermediate stores scattered in the factory. These stores are called supermarkets, which are closer to workstations than the main warehouse. In each train tour, several workstations are replenished by bins every a certain time period called train cycle time. This replenishment system is called in-plant milk run which is used to reduce inventory and transportation costs because of its dependence on repetitive just-in-time parts delivery. Besides reducing costs, ergonomic advantages are obtained due to the use of small-sized bins. Safety hazards are also reduced. As an alternative to forklift system, in-plant milk run was used by several industries especially the automotive industry. It is important to investigate this system and to design its parameters to reduce the total material handling and inventory cost. The study divides the general problem to five different problems (systems) based on the situation on the ground. For each system, a certain planning approach is designed to optimize the parameters of the system to minimize its critical costs. There are some similarities and differences between the systems. The methodology is based on genetic algorithm, integer programming, dynamic programming, simulation, and analytical investigation.

The five different systems are classified based on factors such as level of assembly line disturbances, availability of tugger trains, accuracy of expectation of workstations demand for parts, the length of assembly lines and their average demand for parts, and the availability of technical infrastructure such as radio frequency identification (RFID) or bar code technologies. These systems are main warehouse demand-oriented, decentralized supermarket demand-oriented, traditional kanban, electronic kanban, and a hybrid system of e-kanban and demand-oriented systems. The two kanban systems can be applied in both main warehouse and decentralized supermarkets systems. In demand-oriented systems, the exact workstations demand for parts is assumed to be known for the next few shifts based on the predetermined sequencing of product models and needed parts for each product model.

Generally some constraints are considered in all the five systems. These constraints are tugger train capacity, tour time, and the capacity of area beside stations. There are three general problems that must be investigated in the systems. These problems are routing, scheduling, and loading problems. Routing problem is the assignment of trains to different stations. In scheduling problem, the train cycle time and the beginning of the movement of the each train are determined. In loading problem, the type and quantities of bins delivered in each train cycle to each workstation are determined. In the case that there are some peak demand periods in which the total stations demand for parts is more than the tugger trains capacity, some bins are delivered before they are needed. This case is called ‘early loading’. Early loading does not exist in both the traditional and electronic kanban systems. In decentralized supermarket demand-oriented system, the location and number of supermarkets are determined. In traditional kanban system, the number of kanban is determined based on the tradeoff between the average line-side inventory and workstation starvation. In e-kanban, the size of circulating inventory in the system is determined for the same purpose. A new approach namely, adjusted electronic kanban, is presented to accommodate train capacity problems.

The results depend on the systems investigated. The performance of genetic algorithm used in supermarket location problem was tested based on the quality of the results, CPU time, and variability in both of them. Reasonable CPU time and high quality of results were obtained. The performances of e-kanban, adjusted electronic kanban, and traditional kanban were tested using simulation, where the superiority of adjusted electronic kanban was proven especially in the case of limited tugger trains capacity. The inverse relationship between the average line-side inventory and workstation starvation was presented. In the case of demand-oriented system, the effects of using dynamic scheduling, early loading, and the objective of minimizing the number of extra trailers were obvious to reduce the problems of tugger train limited capacity. In the case of using the hybrid system of e-kanban and demand-oriented systems, the dynamic planning approach outperforms the traditional systems to accommodate the line disturbances especially in the case of large workstations demand.

Zusammenfassung

Diese Arbeit untersucht ein Materialflusssystem für Fließlinien zur Fertigung von variantenreichen Produkten. Sogenannte Routenzüge kommen häufig zur Bereitstellung von Teilen an den Arbeitsstationen einer Variantenfließlinien zum Einsatz. Die Teile werden in kleinen Behältern (Kleinladungsträgern) im Zentrallager oder in verteilten Zwischenlagern, sogenannten Supermärkten, auf den Routenzug geladen. Bei jeder Tour des Routenzugs werden mehrere Arbeitsstationen mit Kleinladungsträgern versorgt. Der zeitliche Abstand zwischen zwei Belieferungen definiert die Zugumlaufzeit. Ein derartiges Materialbereitstellungssystem, bezeichnet als In-Plant Milk Run, reduziert Bestands- und Transportkosten, weil es eine regelmäßige Just-in-Time Anlieferung der Materialien realisiert. Außerdem bringt es aufgrund der Nutzung kleiner Behälter ergonomische Vorteile mit sich. Weiterhin sinkt das Unfallrisiko. Deshalb findet das In-plant Milk Run System als Alternative zu Gabelstaplern in vielen Branchen, insbesondere in der Automobilindustrie, zunehmend Verwendung.

Die Untersuchung dieser Systeme und die optimale Auswahl ihrer Parameter sind wichtige Anliegen, um die Transport- und Bestandskosten zu reduzieren. Diese Arbeit unterscheidet bei der Gestaltung von In-plant Milk Run Systemen fünf verschiedene Problemstellungen (Systeme). Für jedes System wird ein bestimmtes Planungsvorgehen zur Minimierung der kritischen Kosten vorgeschlagen. Zwischen den Systemen gibt es sowohl Ähnlichkeiten als auch Unterschiede. Die Methodik verwendet genetische Algorithmen, ganzzahlige und dynamische Programmierung, Simulation und analytische Untersuchung. Die fünf Systeme werden anhand von Kriterien klassifiziert. Als solche werden das Ausmaß von Störungen, die Verfügbarkeit der Routenzüge, die Genauigkeit der Materialbedarfsschätzungen, die Länge der Montagelinien, der mittlerer Teilebedarf und die Verfügbarkeit von technischer Infrastruktur, wie RFID- oder Barcode-Systemen, herangezogen. Unterschieden werden damit das bedarfsorientierte Zentrallager, der dezentrale bedarfsorientierte Supermarkt, das traditionelle Kanban-System, das elektronische Kanban-System und ein hybrides System, bestehend aus bedarfsorientiertem und e-Kanban-System. Dabei kann das Kanban-System sowohl im Zentrallager, als auch im System dezentraler Supermärkte zum Einsatz kommen. In bedarfsorientierten Systemen wird der Materialbedarf der Arbeitsstationen für eine gewisse Anzahl an Schichten aus der Produktionssequenz und den entsprechenden Stücklisten abgeleitet und ist damit exakt bekannt.

In allen Systemen werden einige Restriktionen berücksichtigt. Hierunter fallen die Routenzugkapazität, die Dauer einer Tour und die Kapazität der Lagerflächen direkt an der Montagelinie. In jedem System sind drei Entscheidungsprobleme, das Routing, Scheduling und Loading Problem, zu lösen. Das Routing Problem beinhaltet die Zuordnung von Zügen zu Gruppen von Arbeitsstationen. Im Scheduling Problem werden die Zugumlaufzeit und der Zeitpunkt der ersten Belieferung für jeden Routenzug festgelegt. Die Lösung des Loading Problems erfordert die Determinierung von Art und Menge der in jedem Zyklus und an jede Arbeitsstation ausgelieferten Behälter. Im Falle des Vorhandenseins von Zyklen, in denen der Materialbedarf an einzelnen Arbeitsstationen die Routenzugkapazität übersteigt, werden einige Behälter vorzeitig angeliefert. Dieser Fall wird als „Early Loading“ bezeichnet und tritt in Kanban-Systemen nicht auf. Im System dezentraler bedarfsorientierter Supermärkte ist zusätzlich die Anzahl und der Standort der Supermärkte zu bestimmen („Supermarket Location Problem“). Im traditionellen Kanban-System erfolgt die Festlegung der Kanbanzahl basierend auf dem Zielkonflikt zwischen mittlerem Linienbestand und Fehlbestandswahrscheinlichkeit. Im e-Kanban-System wird der Umfang des zirkulierenden Bestands analog bestimmt. Außerdem wird ein neues Konzept, der sogenannte „Adjusted Electronic Kanban“, zur Behandlung von Kapazitätsengpässen des Routenzugs vorgestellt.

Die Ergebnisse sind abhängig vom betrachteten System. Die Leistungsfähigkeit des genetischen Algorithmus zur Lösung des Supermarket Location Problems wurde anhand der Ergebnisqualität, CPU Zeit und der Variabilität dieser beiden Größen untersucht. Es wurden akzeptable CPU Zeiten und eine hohe Ergebnisqualität erreicht. Die Leistungsfähigkeit der drei Kanban-Systeme wurde unter Verwendung von Simulation getestet. Hierbei wurde die Vorteilhaftigkeit des Adjusted Electronic Kanban insbesondere im Fall begrenzter Routenzugkapazität bewiesen. Der inverse Zusammenhang zwischen mittlerem Linienbestand und Fehlbestandswahrscheinlichkeit konnte aufgezeigt werden. Im Falle der bedarfsorientierten Systeme wurde der Effekt von dynamischer Disposition, Early Loading und Minimierung der Anzahl zusätzlicher Anhänger deutlich gemacht. Bei Verwendung des hybriden Systems aus e-Kanban und bedarfsorientiertem System, liefert die dynamische Disposition in Bezug auf die Verarbeitung von Störungenerheblich bessere Resultate als die Einzelsysteme, insbesondere bei hohem Materialbedarf an den Arbeitsstationen.

Dedication

TO

My mother

My father

My wife

My children

My sisters

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Abbreviations

AEK	Adjusted electronic kanban
AGV	Automated guided vehicle
AS/RS	Automated storage and retrieval system
CONWIP	Constant work in process
CDF or F	Cumulative distribution function
DO	Demand-oriented
DT	Distance traversed
FR	Frequency of routing
IC	Inventory costs
JIS	just-in-sequence
JIT	just in time
KC	kind of conveyor
MC	Manual cart
MIP	Mixed integer programming
MH	Total material handling costs
MMAL	Mixed model assembly line
PDIT	Penalties for deviations of the actual delivery from the ideal feeding time
PFEP	A plan for every part
PK	Pull kanban
pmf	Probability mass function
PoU	Point of use
RFID	Radio frequency identification
RGA	Real genetic algorithm
RP	Routing problem
SL	Parts service level
SP	Scheduling problem
SV	System variability
TCTP	Determining train cycle time
TT	Tow (tugger) train

UW	Utilization of workers
WDM	Weighted distances matrix

Notations

AC_s	The percentage of affected cycles for workstations ‘s’
a_k	*x*-coordinate of supermarket ‘k’
$ALSI_s$	Average line-side inventory for workstation ‘s’
ANG	The average number of generations needed to reach the optimal/best known solution in genetic algorithm
ARL	Average route length
a_s	*x*-Coordinate of station ‘s’
b_k	*y*-Coordinate of supermarket ‘k’
B_s	Bin capacity at workstation ‘s’
b_s	*y*-coordinate of station ‘s’
CAP_K	Capacity of supermarket ‘k’ (in bins unit)
C_k	The cost of used capacity
CP_i	The number of consumed parts of type ‘i’ during the previous disturbance period
CR_{ij}	The feasible range of train cycle times
CV	Coefficient of variance
D	Average cell demand during the train cycle time
D_i	The cell demand in the train cycle ‘i’
d_{ik}	The expected number of parts ‘i’ demanded in station cycle ‘k’ according to a new workpieces sequence.
$dist_{kij}$	The total distance traveled by the train from supermarket k to supply all the stations from station ‘i’ to station ‘j’
d_{ku}	The demand (in bins unit) of station ‘k’ during the station cycle ‘u’
$D_{o/b}$	The average of the difference between the obtained results and the best known ones in genetic algorithm
dp_i	The number of defective parts of type ‘i’ during the previous disturbance period
d_s	The expected demand at station *s* per shift (averaged for a long range)
d_{sC}	Average demand for parts during the time interval from the train departure from workstation ‘s’ in the current cycle and the train departure from the same workstation in the next train cycle.

DS_s	The average number of delayed signals at workstation ‘s’
dS_s	The total station demand during a shift for station ‘s’
d_{st}	Demand of the station ‘s’ for the train cycle ‘t’
Dst_{ij}	The total standard deviation of the demand for parts for all the stations from ‘i’ to ‘j’
d^T	The working time per day
d_{ts}	The number of consumed parts during the time interval t_{ds}
f_{max}	The maximum difference between the numbers of delivered bins and the number of demanded bins in a train cycle at a workstation
H	Inventory holding cost
I_s	Initial inventory near workstation ‘s’
K	Capacity of tugger train
$KL1$	Trailer capacity multiplied by the first maximum train capacity (in trailer unit)
$KL2$	Trailer capacity multiplied by the first maximum train capacity plus 1 trailer
K^{LS}	The capacity of line-side area
L	A very large number
LSC	The total lost sales costs
lw	A very low number
M	Total number of possible locations for supermarkets
$MAXC_{ij}$	The maximum TCT for the cell from station ‘i’ to station ‘j’
MC	The minimum possible TCT minus one (represented in SCT unit) based on the routing time inside the cell and outside it
$MINC_{ij}$	The minimum TCT for the cell from station ‘i’ to station ‘j’
$MLSI_s$	Maximum line-side inventory for station ‘s’
MNC_{ij}	Minimum number of train cycles in the shift for the cell from station ‘i’ to station ‘j’
MNS	Maximum number of supermarkets
MNT	Minimum possible number of trains
MS	Number of supermarkets locations in the solution
N	Number of workstations in the cell
N^*	Maximum possible number of workstations in the cell

NO	Number of handling operators
n_s	Number of kanbans for workstation ‘s’
N^S	The total number of stations supplied by the supermarket
NT	Number of tours
NT	Number of trains
θ	Fixed cost per supermarket
ϖ	Cost of moving one bin one unit distance
$P1$	Penalty value for exceeding the first maximum train capacity
$P2$	Penalty value for exceeding the first maximum train capacity plus the capacity of one more trailer
PD_i	The planned number of delivered parts of type ‘i’ during the previous disturbance period
$Pmax$	The maximum number the f_{max} values appear for the same station at successive train cycles
$P_{o/b}$	The percentage of reaching the optimal/best solution before reaching the roof of 1000 generations
PPi	The price of the product ‘i’
RTI_{ij}	The routing time inside the cell from station ‘i’ to station ‘j’
$RTOC$	Routing time outside the cell
S	The total number of workstations in the assembly line
SCT	Station cycle time
S^T	The total number of workstations in the facility
$TBAD_s$	The average time between arrival of demand for parts for workstation s
TC	Total costs
TCT	Train cycle time
t_d	The time of train departure from the supermarket
$Tdem_{ij}$	Total demand of all the stations from station ‘i’ to station ‘j’
t_{ds}	The time interval between the two time points t_d and t_s
TDS_{ij}	The total cell demand during the shift
t_{lu}	The needed time for loading and unloading in the supermarket plus coming back toward it from the last workstation

t_{lus}	The needed time for workstation loading and unloading plus transportation time from workstation 's-1' to workstation 's'
t_s	The moment of the arrival of the train at the workstation 's'
TSC	Total number of station cycles in the shift
t_{ul}	Time needed for unloading empty bins and loading full bin in the supermarket area
U_{ks}	Utilization based on the capacity of the station
U_s	Utilization for the station 's' (equals 1- δ_s)
$wdis_{kij}$	Total weighted distance in the route from the supermarket k to the cell containing the stations from 'i' to 'j', $wdis_{kij}=Tdem_{ij}\times dist_{kij}$
w_i	The weight of term 'i' in the objective function
x_{st}	The number delivered of bins at station 's' in the train cycle 't'
$y2$	The needed train capacity
Z	Service level for the probability of not exceeding the capacity of the supermarket
α_i	Current size of line-side inventory for parts 'i'
β_i	Ideal safety stock size for parts 'i'
δ	Workstation starvation
ε_{st}	The difference between the actual line-side inventory and β_s
η	Capacity fill rate
$\eta_{EL}(i)$	The fill rate for routes from 1 to 'i'
η_{EL2} (i)	The fill rate for the current and previous routes ('i' and 'i-1') if early loading is used
λ_s	The average demand during protection period for workstation s
μ_s	The average demand for parts per time unit
Γ	The number of the station cycles in the shift

Chapter 1: Introduction

1.1 Background

In the past, the number of different product models presented for the customer was not so high. But with time and after increasing global competition in the market, a lot of different product models are presented to the customer. Theoretically, the number of alternative product models in automotive industry for example can be billions in today’s market. In such a situation, mixed model assembly lines (MMAL) were introduced where the setup time is short and negligible to give the possibility to assemble different models on the same assembly line. However, this environment makes a great challenge for the material flow system due to the dynamic nature of demand for parts and materials. The words “workpiece”, “product model”, and “variant” are usually used in the literature to mean the same thing. Usually there are two directions for material flow: from a station to another, and from the warehouse to stations. This study focuses on the second type of material flow. This type is part of production logistics which is inside facilities. On the other hand, inbound logistics is from suppliers to manufacturers, while outbound logistics is from manufacturers to customers. Production logistics is usually under the control of management (Baudin 2004).

Efficient material flow in MMAL is extremely important. Any delay for parts and materials will stop the assembly line. On the other hand, too early delivered materials can accumulate beside stations, but this area is very scarce and expensive. So just in time (JIT) delivery is very important for MMAL to minimize the system costs. This study investigates this area and designs the material flow system. Usually, forklifts are used to deliver materials and parts in large containers. However, MMAL environment which needs repetitive supply of material in small amounts needs another transportation machine, namely, tugger (tow) train, which has been recently used by a lot of manufacturing facilities especially in automotive industry.

The movement of the train depends on the principle of milk run in which several workstations are supplied by a train from the supermarket or warehouse. Each group of stations fed by the same train in a train cycle is called a *cell*. The train makes its route every certain time, for example one hour. This time is called *train cycle time* (TCT). The supermarket can be at the main warehouse. Also, it can be scattered areas which are intermediate stores inside the facility to be as close as possible to the workstations needing the materials and parts. In this study, supermarket is different from the famous supermarket principle in lean manufacturing. Sometimes, the feeding process of materials and parts depends on kanban to know the exact demand of workstation during the shift. However, in the practice the exact demand of workstation for materials and parts is known at least for the next shift. So in this case, *demand-oriented* system is used. The planning of all these systems is investigated in this study.

1.2 Study motivation

MMALs are very important to respond for the increasing demand for diversified product models. This environment exists in many industries especially the automotive industry. Recently, the milk run system has been used by a lot of factories to replenish materials to the assembly lines. In-plant milk run system presents a lot of potentials to decrease the wastes and costs in the factories such as inventory costs, transportation costs, material handling operators' costs, safety hazards, and ergonomics problems. Compared to its importance, in-plant milk run system was not investigated enough in the literature. Different from forklift system which is flexible and easy to plan, milk run system is complicated and needs deep investigation. There were some tries by some manufacturing facilities to apply the system but these efforts failed to achieve all the capabilities of the system due to the lack of enough planning. In some cases, the application of milk run system resulted in increasing the workforce in material handling and adding new activities such as repackaging. This study tries to smooth the application of milk run by presenting ways to set the best parameters of the systems to minimize its costs. This is done taking into consideration all the possible environments and conditions in the practice.

1.3 Mixed model assembly line

Since the times of the famous Model-T of Henry Ford, the requirements of production systems have changed dramatically. Assembly lines were developed for efficient mass production of a single standardized product. In today's market, the customers can select a lot of options. Theoretically, the manufacturers of the products need to provide product variety which exceeds several billions of models. In this case, traditional production environments are not suitable. In MMALs, different product models are assembled on the same line with negligible setup time and then those models are sequenced in a way that levels the demand for upstream components. MMAL support manufacturing of different products of a common base product in evenly distributed sequences on the same line (Boysen et al. 2009).

Figure 1.1 shows the concept of MMAL. It shows the difference between single model, multi-model and mixed model assembly lines.

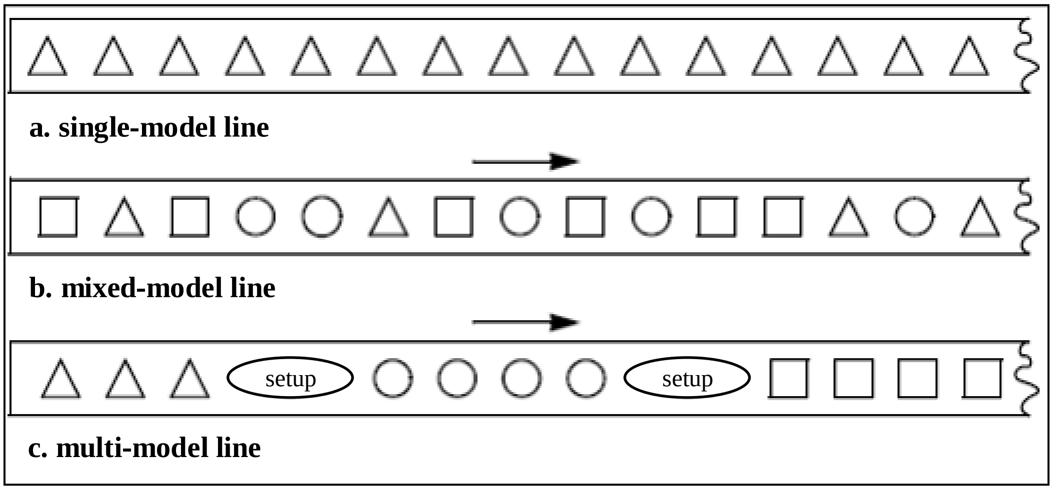


Figure 1.1 Assembly lines for single and multiple products (Becker and Scholl, 2006)

MMALs can quickly respond to unanticipated changes in product demands without keeping so many inventories (Fattahi et al. 2012). The amount of work and materials required to assemble units can vary from model to model, creating an uneven flow of work along the line and dynamic demand for parts. So enough planning is required. This environment was extensively studied in the literature, where the following tasks were investigated in automotive industry (Golz et al. 2012):

- Line balancing: minimizing the total idle time cost at the stations by balancing the work content at the stations over time.
- Master production scheduling: Assign production orders for individual models to production intervals over a short-term planning horizon of several weeks.
- Production sequencing: finding a sequence of different products distributed as evenly as possible
- Re-sequencing: in case of disruptions such as shortage of materials
- Material flow control: on time delivery of materials and parts from suppliers, and on time delivery of these materials and parts at workstations

The focus of this study is on the last task which was not investigated enough in the literature as the other tasks. The study only considers the delivery of materials and parts at workstation.

Material flow control depends on the sequence of models on the assembly line. Some studies in the literature investigated mixed model sequencing to smooth the component demand. This means keeping unfluctuating demand for parts. This step may be important if MMAL uses components fabricated in-house to make the demand for these components uniform over time. However, if this direction of work affects balancing the work on the assembly lines, then other directions of investigation should be accomplished to handle the variable demand over time. This study investigates this direction to accommodate the dynamic nature of demand for different parts using different systematic research tasks.

1.4 Milk run system

Figure 1.2 shows the milk run system and its components. A tugger train delivers the materials from the supermarket to the different workstations. The triangles show the *line-side inventory* which is the inventory beside the stations. This type of inventory is different from the inventory between stations. It is necessary for this inventory not to be so large because the area beside stations is scarce and expensive. The stations supplied by a tugger train can belong to one or more assembly lines. The movement of the train can be subjected to some delays from ‘traffic jam’ of other trains or any objects. The train may have 4 trailers for example or more depending on factors such as safety and facility layout which affects the *turning radius* of the tugger train. The physical design of the train can affect the performance of the system. Design parameters such as train width can affect the possibility of the train to move in narrow aisles. Some train designs are performed to reduce the needed turning radius of the train. These designs provide the possibility to have larger number of trailers and bins in the same train tour. This fact affects the planning process of the system, especially the capacity planning of it. Another factor is the speed by which trailers can be exchanged. This is useful if market attendant is used. Market attendant is the person who is responsible for preparing the bins before the train driver comes to the supermarket area.

In the case that kitting is used, the route of the train can be affected. Kitting systems combine various components into one heterogeneous package according to a future assembly schedule. The kit assembly operation can be performed in a central picking store or in decentralized areas close to the assembly stations.

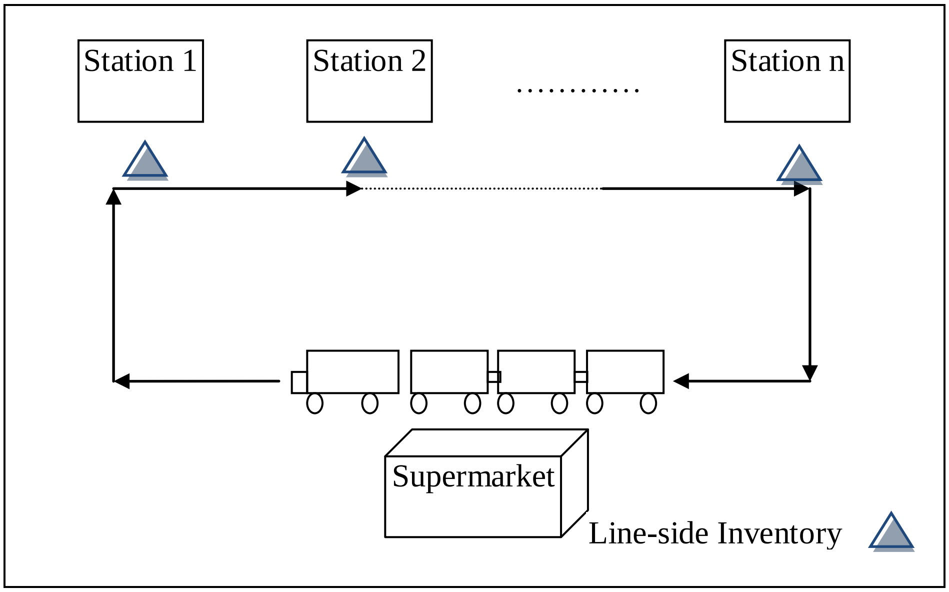


Figure 1.2 In-plant milk run system

Sometimes kitting process cancels the need for milk run concept. Faccio (2014) investigated the use of decentralized supermarket system as an alternative for the line stocking feeding strategy in which relatively large containers are hold in the line storage area. This decentralized system was used to facilitate the use of ‘kanban continuous supply’ which is based on the milk run system, and the use of the ‘kitting system’ in which there is kitting preparation area close to supermarket area. A kit contains all the needed parts by one product model assembled on a group of stations supplied by the same supermarket. This kit is moved to the first station and then moved together with the associated product model. In this case there is no need for the milk run system, but it is needed in the case of kanban continuous supply. According to Faccio (2014), “kitting policy enables the materials required to be determined before product assembly. Thus, if the kit is correctly prepared and scheduled, it is possible to avoid stock-out risks (and so stock-out costs). On the other hand, kanban-based continuous supply has a stock-out risk because of the variability in parts consumption, and this can be reduced only through maintaining a high level of safety stock.” However, kitting process adds kit preparation costs to the system. Faccio (2014) concentrated mainly on the case of moving kit in which the kit moves with the product model. In the case of *stationary kits*, milk run system is used to provide these kits using the tugger train. This second type of kitting is investigated in this study. Actually the knowledge of future stations demand can also be achieved in the case of line stocking where small bins of each type are moved using milk run system. An example for that is the study by Golz et al. (2012) and also in this study. Moreover, in this study, electronic kanban system is investigated to accommodate the stock out cost in the case of continuous supply. Table 1.1 shows the relationship between kitting and milk run system. A special type of kitting will be explained in the next chapter where 'line-integrated supermarket' principle is discussed.

Table 1.1 Milk run, and kitting and line stocking.

System	Kitting	Line stocking
Milk run	• Stationary kits • Demand-oriented	• Kanban or demand-oriented
No need for milk run	• Moving kits • Demand-oriented	• Large containers • Forklift or other machines

1.4.1 Definition

Bozer and Ciemnoczolowski (2013) described milk run systems as "route-based, cyclic material handling systems that are used widely to enable frequent and consistent deliveries of containerized parts on an as-needed basis from a central storage area (the 'supermarket') to multiple line-side deposit points on the factory floor". Material provision is not necessary to be from the main warehouse. Actually multiple supermarkets scattered in the manufacturing area can be used and they have a lot of advantages as will be explained in Chapter 2. The containers used are usually small ones called bins. The small size of these bins has a lot of advantages such as facilitating JIT material provision and ergonomic advantages. As stated by Marchwinski (2009), there are two separate tugger routes — one delivering purchased parts, and the other removing finished goods. The focus of this study is on the first type. There are other types of milk run systems. Milk run operator can move the items to the regular manufacturing stations and from the assembly lines to the testing, repairing, final packaging, and output buffer (Baudin 2004). In milk run, material handling is not necessary to be accomplished using tugger trains. Actually manual carts can also be used depending on the situation on the ground. Choosing the means of transport depends mainly on the distance traveled and the layout of the facility. Generally, for long distances, tugger trains are chosen. On the other hand, sometimes there is no enough space for the tugger trains in narrow aisles. As stated by Baudin (2004), "push carts are not adequate to deliver thousands of items in box quantities at multiple locations every half hour, which is commonly needed in the automobile industry". In the case that tugger trains or manual carts move the materials from one place to another, this in not called milk run. They must supply materials to more than one station in a tour. This fact makes the system complicated because the status of all stations is studied together in parallel. For example, the increase of demand for some stations can affect the capability of the system to supply materials to other stations on time due to the limited capacity of the train.

Table 1.2 Advantages of milk run system

Study	Advantages
Hanson and Finnsgård (2014)	• achieving compact assembly stations with parts presentation that could support efficient assembly. • reducing the work force at the assembly line. • reducing the inventory size beside the workstations. • getting rid of the capacity problems
Rother (2011)	• increasing productivity • enormous cost savings • less empty runs • reducing traffic volume • less amount of resources • saving a huge amount of space • enhancing safety
Finnsgård et al. (2011)	• reducing non-value-adding work • reducing space requirements • enhancing ergonomics • reducing walking distance
Droste and Deuse (2012)	• JIT material provision • enhancing ergonomics
Baudin (2004)	• getting rid of double handling of pallets.
Klenk et al. (2012)	• standardizing supply process • reducing in-plant traffic • avoiding accidents • reducing stock and space at workstations • company strategy • reducing personal costs • increasing security of supply • shortening replenishment lead time

1.4.2 Advantages and disadvantages

Using in-plant milk run system was investigated for work improvement by several studies such as Sihn and Schmitz (2007), Wong and Wong (2011), and Kasperk et al. (2012). Furthermore, milk runs and their tugger trains were recommended by many studies to make improvement inside facilities (Owens 2010; Halim et al. 2012; Hanson and Johansson 2007, Williams et al.

2006). Table 1.2 shows some studies emphasizing some of the advantages of using milk run system. Besides its effects on enhancing ergonomics and safety, using the small-sized bins enhances the material presentation at assembly workstations and reduces the time needed for material handling in workstations. This is important to reduce the needed assembly workforce and enhance the productivity. In the forklift truck system which provides big pallets, the exact time of demand for materials is not easy to estimate. Therefore using small bins enhance the monitoring of consumption of materials. This monitoring achieves better connection between the supermarket area and the workstations, and hence reduces the oversupply of materials and reduces the needed capacity of trains. Moreover, tuggers have been proven to reduce material handling distances within facilities (Owens 2011). Besides supplying full bins to workstations, tugger train returns empty bins to supermarket area. In the forklift truck system, sometimes the demand of workstation for the same part is not high enough to need the full pallet. In this case the forklift must bring back the half-full pallet to supermarket area again. This problem does not exist in the milk run system. Moreover, because the system of milk run depends on supplying several workstations in the same route, it reduces the traffic volume using less number of transporting machines. Klenk et al. (2012) found that the lead time in milk run system is shorter than that time for forklift system especially when the distance between supermarket and workstations is long. This is because forklift transport pallets one by one. So a lot of time is consumed in transportation from the supermarket to workstations.

However, the planning process for transition from traditional system to milk run must take a lot of deep analysis and thinking, because sometimes the costs for this transition are very high. For example, Hanson (2011) presented a case study about “Minomi” which is a unit load where no container is used, and identified the effects of using minomi in the materials supply within an assembly plant. To facilitate using this concept, milk run tugger train was used instead of the traditional forklift system. However, in that case study the parts should be placed and handled in their original steel containers in order for efficient handling and storage to be maintained. With this solution, forklifts were still required for lifting the containers from the storage area onto the tugger train. Therefore, the total number of handling operations increased in the materials supply operations. As a result, there was an increase of 326 percent in the man hour consumption for performing the deliveries. Furthermore, in a case study presented by Hanson and Finnsgård

(2014), the main disadvantage of introducing the milk run system was in adding a new activity which is repacking the pallets coming from the suppliers to the new plastic container size and also the sequenced deliveries which needed additional workers. So applying the principle of in-plant milk run is not always without side effects. As a matter of fact, beside additional work on transferring materials from big containers to smaller bins, milk run systems increase the number of bins in the system and increase the stress on routing operators (Marchwinski 2009).

1.4.3 Milk run in industry

Because milk run system provides material in small lot sizes with high frequency, it is used especially in automotive industry in which the number of unique assembled products on the production line is constantly increasing. Actually, in the automotive industry, a large number of different materials should be delivered to production line. The space for material provision, which is near the assembly line, is not adequate. There are only few bins that can be stored next to the assembly line. As a result, the company has to find a rapid, continual and reliable in-plant supply process to deliver different materials. The in-plant milk run system can satisfy the requirement above. That is the reason, why in-plant milk run system is applied in automotive industry. However, because of its complexity in planning and dimensioning, in-plant milk run system can hardly be applied in other industries (Droste and Deuse 2012). However, there are some other industries in which milk rum can be applied. For example, Satoglu and Sahin (2013) designed a JIT periodic material supply system in a TV assembly plant. This reveals the applicability of milk run system in electronic industry. In automotive industry, some challenges appear when relatively large parts must be delivered. In this case the line-side area may not be enough if new large parts are delivered before the previous parts are consumed. In some cases, the solution is to lift the parts by a special crane in a high position. This solution, however, increases the cost of material handling and complicates the system. Using managerial solution is better. So as will be explained in the next subsection, careful planning must be done.

1.5 Problem complexity

In the forklift truck system, the movement is usually from the supermarket to only one workstation at a time. Then the forklift goes back to the supermarket area to load a new pallet to supply another workstation if there is demand for that. This is a flexible and easy-to-plan system. However, in milk run system, several workstations are replenished by materials in the same tour.

Therefore, the exact demand of all of them must be known. The conditions of some workstations can affect the other workstations because if some workstations have a large demand for materials, the capacity of the train may not be enough to supply all of them on time. Therefore some complicated tasks such as early loading of materials must be accomplished. The planner must take into consideration several factors such as capacity of trains, capacity of line-side area beside stations, the time needed to make a tour to feed a group of stations, the exact demand of the stations, and others. The planner must make the tradeoff between increasing inventory and increasing tugger train capacity keeping the workstations starvation as minimum as possible. Adopting the milk run system may lead to make some changes in the suppliers' selection process. Suppliers who provide materials in bins may be an advantage to avoid the extra material handling such as repackaging of large pallets into small bins. One change that must be done is the suitable design of flow racks to hold small bins in the supermarket area and also the flow racks beside workstations. The tasks of the existing forklift trucks must be redesigned. One of these tasks can be supplying the big pallets from the main warehouse to the repackaging area in the supermarket. Moreover, in some cases automated systems that load full bins and unload empty bins are used. Taking all these factors into consideration makes the planning process of milk run systems not easy. This study is a part of the efforts exerted to facilitate this planning process. Due to the complex nature of the problem it was divided into 5 tasks for each of which a chapter is written.

1.6 Study objectives

The basic objective of this study is the use of mathematical modeling and simulation to design milk run system and optimize its parameters to minimizing the total cost and workstation starvation. The following tasks are investigated to maintain that objective:

1. Determining when to use demand-oriented system and when to use kanban system, and if kanban is used, when to use traditional kanban or electronic kanban (using bar code or radio frequency identification (RFID) system). Also the study investigates designing the parameters of the system such as number of kanbans, circulating inventory, and number of workstations in the cell. Besides that, a new concept namely, adjusted electronic kanban (AEK), is introduced to accommodate tugger train capacity problems. In the three systems of

kanban, workstation starvation, average line-side inventory (ALSI), and maximum line-side inventory (MLSI) are minimized.

2. Determining the optimal number and locations of decentralized supermarkets feeding the MMAL to minimize inventory and transportation costs.
3. Determining the optimal routing of the milk run trains to reduce number of trains, system variability, and inventory costs.
4. Determining the optimal scheduling of the movement of the trains by determining the starting time of the movement and the train cycle time to reduce inventory costs.
5. Determining the optimal bins (containers) loading to reduce loading variability and inventory costs. This is done using early loading in which some bins are delivered before they actually needed to accommodate the train capacity problems in bottleneck periods.
6. Considering capacity planning of the system by using four strategies which are fixed routing, dynamic scheduling, early loading, and minimizing number of extra trailers.
7. Making a plan to respond for assembly line disturbances such as machine breakdown, quality problems, line stoppage, and resequencing. This is done in the study by mixing the e-kanban and demand-oriented systems together. The plan is investigated in terms of routing, scheduling, and loading problems to reduce the deviation from the size of ideal safety stock.

Many of the previous tasks were already investigated in the literature. However, this study makes contributions in each one of them to make it more realistic by introducing new dimensions and also releasing some restrictive assumptions. Other tasks such as introducing AEK, minimizing number of extra trailers, and mixing the e-kanban and demand-oriented systems together are completely new.

1.7 Study outline

During working on the study six papers have been published. Four of them are in journals and two of them are in international conferences. The study is organized in this way: after this introductory chapter, Chapter 2 presents the literature review about MMAL and milk run system. It further presents the theoretical background of the environment considered in this study besides presenting the previous studies related to the same working area, and shows some gaps which were not covered in the literature before. Chapter 3 is about the general scope and methodology of the study. It describes the decisions problems and which costs are minimized by the study. It also presents the tools used, contribution, and inputs and outputs of the study. Chapter 4 discusses the kanban system (traditional and electronic). It also introduces a new concept, namely, AEK to accommodate train capacity problems. It compares between these systems. Giving the workstation starvation probability, the number of kanbans and ALSI are determined using analytical investigation. In the case of electronic kanban, circulating inventory size is determined. The number of stations in each cell and the total cost of the system are presented. Extensive simulation was done to check the effect of the proposed AEK on the MLSI assuming limited capacity of the train. The effect of factors such as station positions and bin size on MLSI was also presented using this simulation. Chapter 5 is about the supermarket location problem and presents how it can be solved using integer programming and genetic algorithm. The performance of the proposed methodology is investigated in terms of CPU time and quality of solution. The variability in this performance was also tested. Chapter 6 investigates the tugger train routing, scheduling, and loading problems together in parallel. New objectives such as minimizing system variability are considered. Constraints such as train capacity, route time, line side area capacity, and time buffer between routes were considered. Analytical investigation and dynamic programming were used. The effect of using time buffers was presented. Chapter 7 presents four strategies to face problems of train capacity considering the capacity of stations line-side space. These strategies are dynamic scheduling, early loading, minimizing number of extra trailers, and the use of market attendant or technical solutions. These strategies were investigated using four integer programming models. Chapter 8 uses a hybrid system by mixing the e-kanban and demand-oriented system to accommodate the line disturbances. The investigation is based on analytical investigation and integer programming to minimize the number of train cycles, the deviation of actual line-side inventory from the ideal safety stock level, and the possibility of early loading to minimize inventory holding costs. The feasibility of fixed routing was presented based on the underutilization of tugger trains. Chapter 9 discusses the conclusion and recommendations for future research.

Chapter 2: Theoretical background and literature review

This chapter further investigates the concepts related to milk run system and the steps needed to design it. The chapter also investigates the lean manufacturing concept related to milk run and the relationship to other planning areas. It also presents the previous studies especially related to the objectives of the study and the gap in research to adequately cover the essential research tasks. The contents of this chapter have been partially published in Alnahhal et al. (2014a).

2.1 Mixed model assembly lines classification and disturbances

The purpose of this section is to investigate the environment in which materials and parts are supplied. The nature of the MMAL affects the nature of demand for parts. So understanding this environment is crucial for successful material flow planning.

2.1.1 MMAL types and concepts

MMAL can be found in industries such as consumer electronic manufacturing, automobile manufacturing, discrete manufacturing, assembly of components on printed circuit boards, and fan manufacturing (Sarker and Pan 2001). MMAL are basically of two distinct types, i.e. *nonmechanical* and *moving belt* lines. Operators on nonmechanical lines are free of any mechanical pacing effect, so buffer stocks of items between stations are used. In contrast, physical buffer stocks of items are rarely practicable on moving belt type lines. The station cycle time (SCT) is the time available for work on an item at a station (Buxey et al. 1973). In the moving belt lines, product models move downstream at a constant speed through each workstation. An operator either walks along or rides on a conveyor to assemble the model (Sarker and Pan 2001).

In an *unpaced line*, the tasks of the work stations can be decoupled from each other. So, each of the work stations operates independently (Smunt and Perkins 1985). In this system, in-process inventory is needed among stations, where it is a design factor (Chakravarty and Shtub 1985). As stated by Battini et al. (2009), “buffers have the function to hold work pieces when the following station is still working on the previous item and is not ready to receive new pieces. Such buffer becomes critical when the assembly activities may take different times per different models, and for this reason, in a mixed model, buffers are normally present”. In contrast to an unpaced line, a *paced* assembly line is one where the job being processed should be finished within certain fixed time at each work station. There is no buffer storage. Thus the paced assembly line is a "conveyer line" type of operation (Smunt and Perkins 1985).

A station may be *closed* or *open* at either side of a station boundary. In a closed station, the operator must work within the boundary limits of the station. In an *open* station, an operator is permitted to move outside his station up to some specific limits (Sarker and Pan, 2001). It is possible for stations to be combinations of the two previous types. For example, a station may be closed to the left and open to the right. This means that the worker is able to cross the downstream boundary of the station, but not the upstream boundary (de Lima Fernandes, 1992). *Work congestion* occurs when the assembly work is done beyond the station downstream limit, while *work deficiency* occurs when the assembly work is done beyond the station upstream limit (Macaskill 1973). Figure 2.1 shows these concepts.

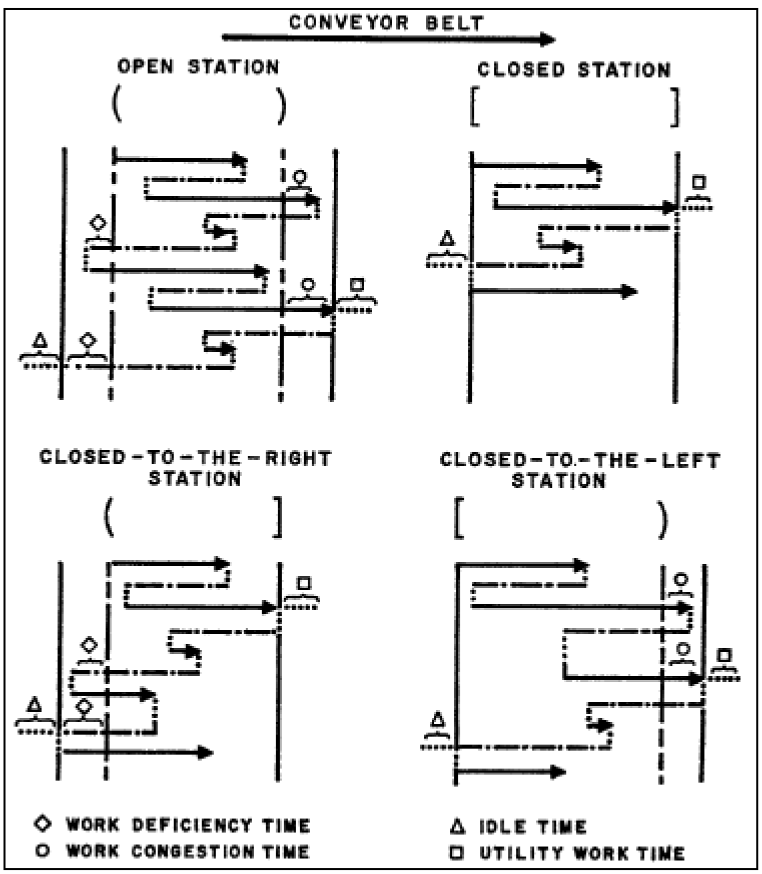


Figure 2.1 Open/closed work stations (Thomopoulos 1967)

Because of the varying assembly time of different models, an operator tends to have an uneven amount of work. As a result, the assembly line is expected to experience *blocking* and *starvation* phenomena. Blocking results in *utility time* (*over load*) which occurs when an operator cannot finish his work on a product model before reaching the workstation boundary downstream and needs additional operator(s) to finish the incomplete product model. *Starvation* results in the *idle time* which occurs when an operator needs to wait for a product model to enter the upstream boundary of his workstation area (Sarker and Pan 2001). There is another type of workstation starvation occurs when there is shortage in the needed materials coming from the warehouse.

Another two concepts are *concurrent work* and *station overlap* where the first one occurs when two operators at adjacent workstations are allowed to work simultaneously on the same unit. Operators should not interfere with each other while working concurrently. *Station overlap occurs* when the operators of each station are allowed to work in an area that is common to both stations (de Lima Fernandes 1992). Another concept is the *launch interval* which is the fixed time interval at which a successive product model is fed into a station. There are fixed rate and variable rate launching. In the variable rate launching, the launching period is the first station's task time of the last product launched; that is, upon completing work on the current product, the first station's operator can immediately begin working on the next product. Fixed rate launching is easier to control.

Al-Zuheri et al. (2014) presented a special type of manual MMAL which is walking worker assembly line. In this system, each cross-trained worker travels along the line to carry out all required tasks specifically designed to respond to the fluctuating nature of market demands. This system is with fewer workers than workstations on the line. This system is to enhance the flexibility of the system but it is more complex in comparison with single fixed worker assembly lines.

2.1.2 MMAL disturbances

Disturbances in the line affect the pattern of demand for parts coming from the warehouse, and that means that these disturbances affect the planning process of milk run system. For example, the starting time of each task affects the exact time of demand for parts. Beside starvation and blocking there are other types of disturbances that affect the work of MMAL. Some of these disturbances come from the failure of some machines, different processing times for different product models, and fluctuations and changes in customer demand. Different product models need different processing times on the same station. If several work intensive models follow each other at the same station, the cycle time of the station might be exceeded and an overload occurs, which needs to be compensated by some kind of reaction (line stoppage, utility workers, off-line repair or higher local production speed). To avoid that, the sequence of the models is found where those models which cause high station times alternate with less work-intensive ones at each station (Boysen et al. 2008). The sequencing problem decides on the succession of product models launched down the line. However, if unforeseen disturbances like machine breakdowns or material shortages occur, a resequencing of a given production sequence often becomes equally essential (Boysen et al. 2012).

Disturbances in MMAL were considered in the literature. For example, Bock et al. (2006) proposed an approach for an adaptive real-time control of assembly lines that takes into consideration the mapping of consequences of possible disturbance scenarios such as the loss of a worker, a material bottleneck or a machine breakdown. The controlling methodology reacts instantly to a disturbance by adapting the current plan in a very short time. Sarker and Pan (2001) investigated designing a mixed-model, open-station assembly line using mixed-integer programming. The problem minimizes the total cost of the idle and utility times. Moreover, Zhao et al. (2007) considered overload times that refer to uncompleted operations for operators within their work zones. They established a method to analyze the expected overload times for MMALs with stochastic operation times. Furthermore, Boysen et al. (2011) and Cano-Belmán et al. (2010) investigated the same problem to minimize the number of work overload situations. To reduce the variation in the assembly times, Tamura et al. (1999) investigated installing a bypass subline which processes a portion of assembly operations of products with relatively longer assembly times.

In an assembly line of a JIT production system, workers have the power and the responsibility to stop the line when they fail to complete their operations within their work zones. Xiaobo and Ohno (1994; 2000) investigated a sequencing problem for the mixed-model assembly conveyor line in the JIT production system to minimize the total line stoppage time. Moreover, Okamura and Yamashina (1979) presented a mixed-model sequencing model to minimize the risk of stopping the conveyor under the circumstances of system variability. Furthermore, Tsai (1995) investigated sequencing problem to minimize utility work and the risk of conveyor stoppage.

Gujjula and Günther (2009) investigated the alterations to a scheduled sequence. These alterations lead to blockings of workpieces which are removed from the sequence and rescheduled in later production periods. Adding formerly blocked workpieces to a sequence can heavily increase utility work. Therefore, formerly blocked workpieces should be integrated into a given sequence in a way that makes the amount of utility work caused by the final sequence to be minimized. For more details about resequencing, the reader can refer to Boysen et al. (2012) who reviewed existing research on resequencing in a MMAL line context.

2.2 Storage types

The supermarket area from which the workstations in the assembly line are replenished by materials can be one central place, or can be several scattered places in the facility. Figure 2.2 shows the two cases where the upper part of the figure represents the centralized system and the lower part represents the decentralized system in which two or more supermarkets can be used. Each supermarket can feed a group of stations in the same assembly line or one or more assembly lines. The principle of decentralizing some facilities was proven to have some advantages over the centralized ones. For example, Yano et al. (1998) investigated the decentralized receiving to facilitate JIT principle. Decentralized inventory principle was also widely used in the literature (Wanke and Zinn 2004). According to Emde and Boysen (2012b) decentralized supermarkets are “decentralized storage areas scattered throughout the shop floor which serve as an intermediate store for parts required by nearby line segments. Some of the advantages of decentralized supermarket system are shorter delivery times by being closer to the consumer (i.e., the assembly line), freight consolidation by being supplied by industrial trucks, and faster turnover by stocking and delivering parts just as needed. On the downside, supermarkets consume space on the factory floor, which is scant and expensive”. The supermarket concept has been recently applied in industry, and discussed in some recent studies due to its benefits.

There is, however, a new novel supermarket type called ‘line-integrated supermarket’ introduced by Boysen and Emde (2014). In this type of supermarket, the part containers transported by forklifts are stored beside stations. Then a logistic operator is responsible for kit preparation in this small supermarket to provide just-in-sequence (JIS) kits near the station according to the expected parts demand. This is to unify the advantages of kitting and line stocking. In this system, there is no need for tugger trains. However, the major disadvantage of the system is the space requirement at the line which exceed the requirement for both the line stocking and traditional milk run kitting type.

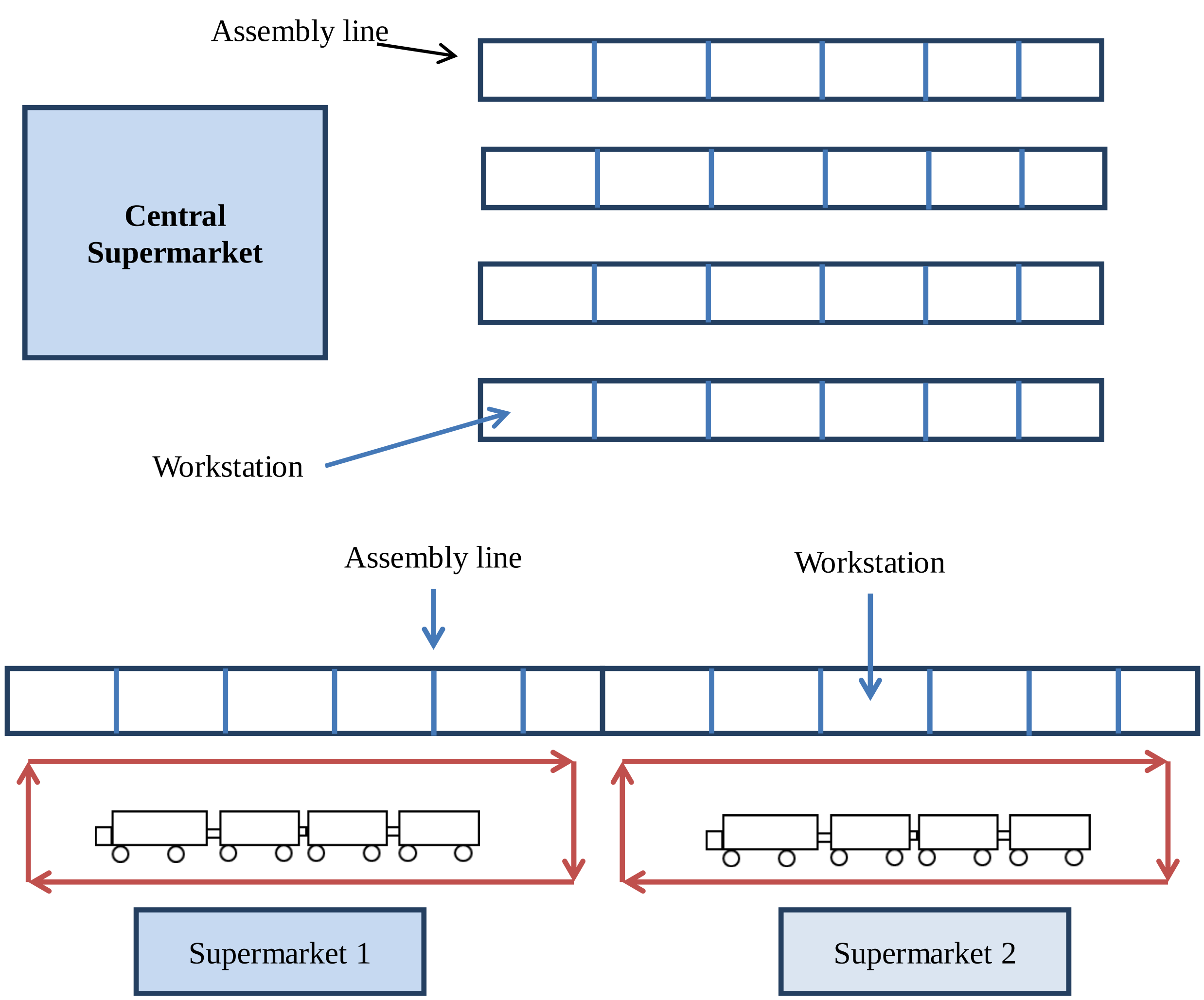


Figure 2.2 Supermarket types

Boysen and Emde (2014) make a comparison between the three systems which are line stocking, kitting, and line-integrated supermarket. Figure 2.3 shows this caparison. As stated before, the milk run system can be used in the case of kitting or line stocking. For the milk run concept to be possible kitting must be stationary and demand-oriented system must be used. In the case of line stocking, container size should be small and kanban system should be used. However, there are cases in which kitting or line stocking systems do not need the milk run concept. In these cases large containers are loaded on the forklift in the case of line stocking, and moving kits are used in the case of kitting. Figure 2.3 shows the superiority of milk run concept most of the time.

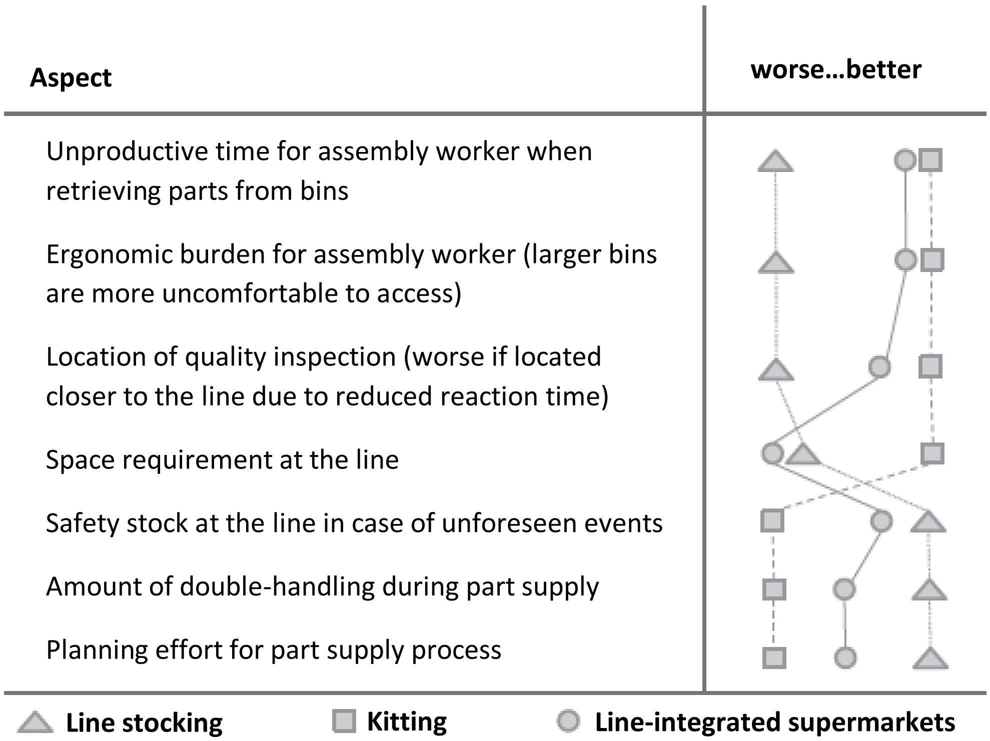


Figure 2.3 Comparison of the three part supply processes (Boysen and Emde 2014)

2.3 Part feeding problem and milk run classifications

The part feed problem has been widely studied in the literature. For example, Caputo and Pelagagge (2011) investigated the part feeding policy where their analysis focused on three basic policies, namely kitting, just in time kanban-based continuous supply and line storage. Some guidelines and decision tools were provided to assist production managers in the selection of proper policies for components delivery to assembly systems. The research methodology was based on developing theory-based quantitative planning models associated with an empirical approach to assign candidate delivery methods to specific components groups. Moreover, Battini et al. (2015) presented an approach for the part feeding for assembly systems in which supermarket storage is adopted and coupled with an automated transportation system. They made a conceptual framework for the design of the system. The supermarket type can be fish bone, single line, or multi line. The transportation mode can be shuttle/conveyor, AGV/LGV, or tow train. The line side presentation can be load unit, station kit, and traveling kit. A decision support matrix was presented where the tow train, AGV, and shuttles are compared based on certain criteria. In most of the cases the tow train was found to be the best option. The transportation system choice was found to be strongly affected by four key parameters: the number of meters traveled during the feeding process, the assembly line dimension (i.e. the number of stations), the assembly line takt time and the number of part bins demanded by stations per takt.

The forklift system was investigated by several studies. For example, considering Assembly to Order (ATO) or Make to Order (MTO) mixed model assembly lines systems, Battini et al. (2009) investigated both the inventory centralization/decentralization problem and the line feeding policy in a general framework. They considered three feeding policies which are pallet to workstation, trolley to workstation, and kit to assembly line. So they concentrated on three different transport devices (forklift, hand truck or trolley, assembly kit). They ignored investigating the use of tugger trains in their feeding policy. A multi-factorial analysis has been carried out and an industrial application of the introduced framework was illustrated. Boysen and Bock (2011) considered the feeding of parts using forklifts from a central warehouse. They presented a case study for a company manufacturing cars. In this company the mixed model assembly line is located in the second floor. So a hoist system is used to get the parts to the second floor where forklifts are ready to take parts and deliver them to the workstations. Part distribution by the forklift is a bottleneck. Therefore, a suitable sequence of given material boxes has to be found. Furthermore, a direct comparison with a simple two-bin kanban system was provided.

Classification of decisions of milk run design was investigated in previous studies. For example, Droste and Deuse (2012) defined four design alternatives the decision maker should focus on when he wants to use milk run system, these alternatives are material control, warehouse, means of transport, and Point of Use (PoU). In material control, the planner can decide between just in time, just in sequence, and also between kanban and constant work in process (CONWIP) systems. In the warehouse, there is direct and parallel picking from flow rack, pallet rack, shelf, etc. In means of transport, the planner can consider the types of conveyor, manually operated cart or propelled towing train. In PoU, the planner can consider provision directly to stations in flow rack or provision on a spot close to station.

Moreover and based on the observations in real manufacturing environment and limited literature, milk-run distribution problem was categorized and explained in a study by Kilic et al. (2012). Their classification was related to the routes and their time periods (TCTs). There are three categories of problems: general assignment problem, dedicated assignment problem, and determined time periods assignment problem. In “general assignment problem”, the routes and TCTs are not known. “Dedicated assignment problem” is the second category where the routes are known but the problem is to determine the TCTs of the vehicles on the related routes. The last category is “determined time periods assignment problem” in which time periods are known but the routes are not known. In chapter 6, the first type is investigated while chapter 7 and 8 investigates the second type. Figure 2.4 shows the classification in detail.

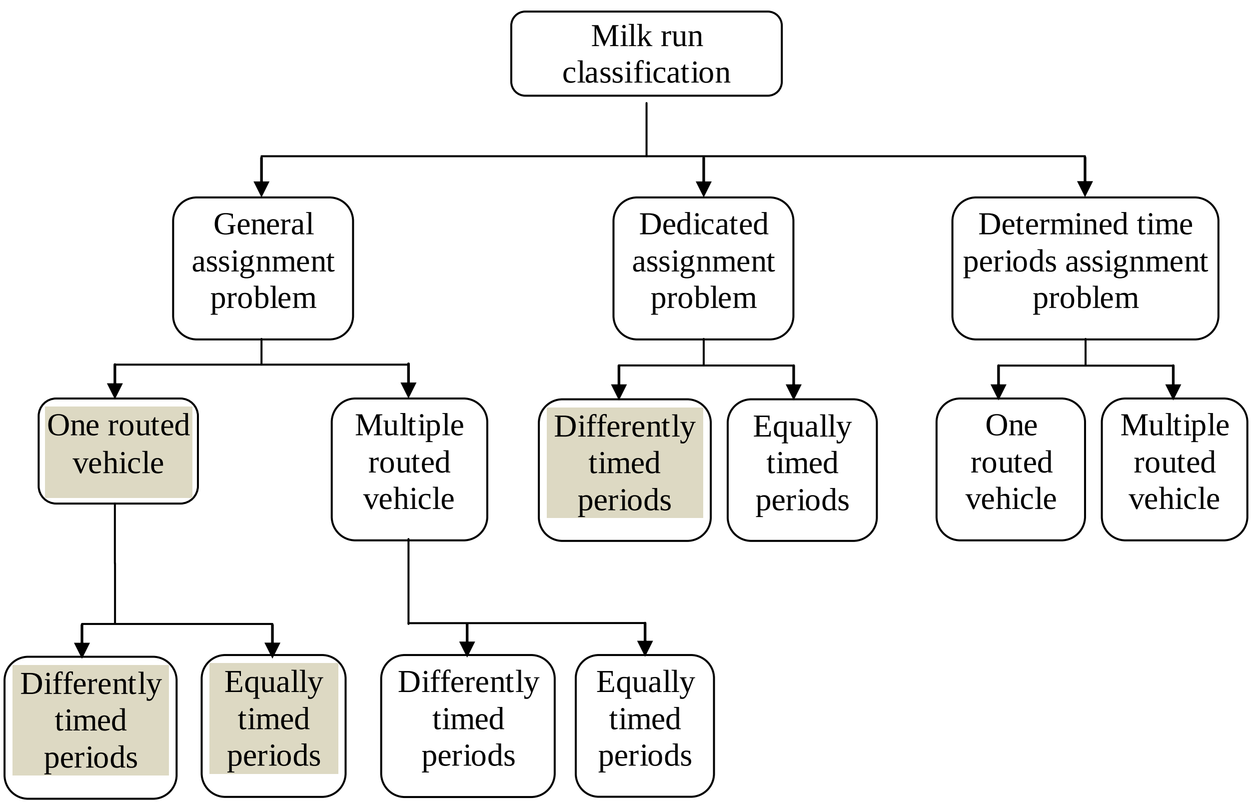


Figure 2.4 Classification of the milk-run distribution problem (Kilic et al. 2012)

For one routed milk-run trains, the tugger train has only one route and travels on that route in specific time periods. This is good from the side of standardization. However in this case, the idle time of the vehicle can be very high. Multiple routed milk-run trains have more than one route, and in specific time periods, they travel on the related routes. They provide effective usage of milk-run trains by minimizing idle time and the number of vehicles. Domingo et al. (2007), for example, defined different routings for different hours in the day, since it is not necessary to visit each job with a high frequency. In this study, one routed vehicle is assumed. The shaded areas in figure 2.4 shows the categories investigated in the study. This classification does not include all the cases. In one routed vehicle, the routes change from a shift to another. So the routing is fixed during the shift, but variable from one shift to another. In this study, *fixed routing* means that routing is always fixed for several shifts. The fixed routing is investigated in chapter 7 and chapter 8.

Another classification can be considered. In chapter 3, the problems are classified in the following different areas:

a. Demand-oriented:
    1. Centralized supermarket
    2. Decentralized supermarket
b. Kanban
    1. Traditional kanban
    2. Electronic kanban

As will be seen later, there are some similarities and differences among these four systems. For example there is no decision for number of kanban in the first two systems, but routing and scheduling of tugger trains must be done in all the four systems.

Moreover, Klenk et al. (2012) presented 21 milk run concepts of major automotive companies and suppliers as well as companies from related industries. The concepts were classified using the following criteria:

- Material source: automated storage system, manual storage system, production supermarket, buffer area
- Handling unit: small load carrier, large load carrier, pallets, special carrier (e.g. for sequenced provision), mixed carriers

- Replenishment principle: kanban, reorder level, sequenced orders, demand-oriented
- Route: fixed route, dynamically planned route, flexible route
- Assignment of vehicle to route: fixed assignment, flexible assignment
- Milk-run control principle: tact / fixed schedule, workload-oriented, permanent, on demand
- Integration of loading process: as part of tour, separate loading, buffering of loaded trailers
- Integration of empty bins process: 1:1-exchange, pick-up on demand, no integration

Klenk et al. (2012) found that most concepts share some similarities:

- Almost all concepts are operating on fixed routes.
- Vehicles are assigned to one single route.
- Most small bin processes operate on a fixed schedule; large bin processes run permanently.
- The empty bin process is usually integrated into the milk run.

2.4 Milk run steps

Harris and Harris (2004) defined 5 major steps for the transition from traditional material flow to the lean material flow using the milk run systems:

1. Develop a plan for every part (PFEP).
2. Build the purchased-parts market
3. Design delivery routes
4. Implement pull signals
5. Continuously improve the system

During doing these five steps, most of the decisions can be made. For more information about applying these steps, the reader may refer to Marchwinski (2009) who presented a case study about that. At first, enough information should be available for every part in the system in the first step. In the second step, the major steps in designing the market are figuring the maximum inventory level for each part, and establishing rules for operating the market. After determining the maximum inventory level, the maximum space level for the inventory should be determined. In the third step, decisions such as choosing the transporter type, routing, scheduling, design of racks, and number of containers in the racks can be made. In the fourth step, the configuration of the kanban system can be determined such as the number of kanbans based on the type of routes, coupled or decoupled (will be explained later). Different standardized procedures should be followed to continuously improve the work.

The work is not necessary to be done in this way. For example, in a lot of cases in the literature, kanban was not used at all where demand-oriented system was used. In this case the exact schedule of different product models for the next few shifts must be previously known. Using bills of material for each unique product model, the detailed demand for parts is obtained and loading problem is accomplished.

2.5 Milk run decisions

The planning of designing milk run systems was investigated in the literature. Abele and Brungs (2009) formulated fundamental concepts to optimally design and develop milk runs. In a study by Alizon et al. (2009), milk run trains and forklift system were used in the same time to feed the same assembly workshop. Michael and Claudia (2009) presented several characteristics of milk run and showed that a higher delivery frequency has a positive effect on a marked reduction of inventory volume at the production stations. Furthermore, they presented approaches regarding demand requirements, supply, and transport control that must be considered in the system so that efficient and ecologically beneficial delivery system can be implemented.

Table 2.1 shows different studies with the decisions investigated, objectives, type of transporter (tow train (TT) or manual cart (MC)), and the feeding system used (pull kanban (PK) or demand-oriented (DO)). The study by Choi and Lee (2002) does not require using tugger trains. Actually AGV can be used. However, tugger trains can also be used. DO means working based on certain and known stations demand for just short periods. As can be seen from the table, there are some studies which used demand-oriented system in milk run. These studies investigated assembly lines in automotive industry. Difficulties come in the case of high variant mixed model assembly when the demand of stations changes every day because of the ever changing daily production sequences. What makes it even harder is the fact that materials must be there when they are needed to avoid disruptions in the assembly process. So in this case, demand-oriented system performs superior to the popular kanban systems (Golz et al. 2012). In this demand-oriented system, using small frequent deliveries of raw materials facilitates using the JIT principle, and “forecasting” the demand of stations is only for three or four days. This could be better than waiting to be ‘‘surprised’’ by low stocks, which may make it very necessary to make necessitate emergency deliveries if the next scheduled stopover at the station is too far off (Emde and Boysen, 2012a). As obvious in table 2.1, most of the researches concentrated on the case of using tow trains. The only decision about manual carts was just to determine to choose them or to choose the tow trains instead. The decisions can be summarized as follows:

- Choosing kind of conveyor (KC)
- Choosing demand-oriented or kanban systems
- The number of kanban required in the system (n)
- Determining minimum number of trains (MNT)
- Number of handling operators (NO)
- Routing problem (RP)
- Scheduling problem (SP)
- Determining TCT (TCTP)
- Loading problem (LP)
- Frequency of routing (FR)
- Parts service level (SL)

Decisions introduced by Droste and Deuse (2012) which were mentioned in the previous section can be added to the list. In table 2.1, the study by Battini et al. (2013) is a conceptual one reviewing the previous researches investigating the decision problems in the case of using decentralized supermarket system. The number of trains is a decision variable and an objective in the same time where the objective of course is to reduce it. The time periods (TCT_S) in scheduling can also be fixed or variable. Emde and Boysen (2012b) showed that the variable periods are optimal for reducing inventory costs. However and from the point of view of lean manufacturing, it is better to standardize the system by stabilizing the periods. Some studies even considered fixed periods as a must to call the system as milk run such as Bozer and Ciemnoczolowski (2013). Moreover, Hanson and Finnsgård (2014) presented a real case study in which the time period of the tugger train was constant. Another aspect to consider is that the routing and scheduling are related to each other. Some studies assumed that routing is input and they investigated the scheduling problem. On the other hand, some studies assumed that the periods are input, and they investigated the routing problem. However, other studies such as Emde and Boysen (2012b) studied the routing and scheduling together.

In the case that for some periods of time the demand is more than the capacity of the trains, loading problem will be necessary. In loading problem some parts are loaded in previous non bottleneck periods. Therefore, the decision here is about determining for each route which parts type and quantity should be loaded on the train to minimize the total inventory. This was in the demand-oriented system formulated by Emde et al. (2012). However in the pull kanban system, there is another decision problem which control the precise times and quantities of parts delivered to stations. It is important to precisely control the number of kanbans circulating in the system.

Table 2.1 In-plant milk run studies: decisions and objectives

Study	PK	DO	TT	MC	Decisions	Objectives
Álvarez et al. (2009)	X			X	KC, FR, RP	IC, UW
Battini et al. (2013)		X	X		RP, SP, LP	IC
Choi and Lee (2002)		X	X		RP, SP, LP	PD
Ciemnoczolowski and Bozer (2013)	X		X		n	δ
Costa et al. (2008)	X		X		MNT	MNT
Domingo et al. (2007)	X			X	KC, FR, RP	IC, UW
Emde and Boysen (2012b)		X	X		RP, SP	IC
Emde et al. (2012)		X	X		LP	IC
Faccio et al. (2013a)	X		X		MNT, n	UW
Faccio et al. (2013b)	X		X		n, NO, SL	IC
Fathi et al. (2014)		X	X		SP, LP	IC, NT
Golz et al. (2012)		X	X		RP, SP	MNT
Kilic et. al. (2012)	X		X		RP, TCTP	MNT, DT
Satoglu and Sahin (2013).	X		X		RP, TCTP	MH, IC

The first step is to determine how frequently to deliver material to stations, and whether the route is "coupled" or "decoupled." In a coupled route, the tugger driver loads carts in the market and drives them to the stations, and delivers them to the point of use. In a decoupled route, the work is divided between a market attendant who loads parts, and the driver who delivers them. Decoupled routes require two sets of carts but they improve labor utilization, so routes can be longer and have more carts (Hanson and Johansson, 2007). Ciemnoczolowski and Bozer (2013) determined the number of kanbans and considered the effects of the number of kanban, the physical capacity of the tugger, and the cycle time on *workstation starvation* defined as the fraction of available time a workstation is idle due to lack of parts.

The objectives contain minimizing inventory costs (IC), system variability (SV), MNT, starvation probability (δ), distance traversed (DT), total material handling costs (MH), penalties for deviations of the actual delivery from the ideal feeding time (PD), number of tours (NT) which is the number of train cycles; and increasing utilization of workers (UW). Besides the decisions and objective, a very important aspect about in-plant milk run system is its constraints. There are restrictive dimensions of in-plant milk run systems which are time, capacity and ergonomics and have to be considered properly in order to achieve an efficient in-plant milk run system (Droste and Deuse 2012). Obviously, the necessary handling and transportation time of a milk run has to be less than or equal to the milk run cycle time in order to maintain the planned material provision takt. The capacity of the tow train must be considered. The physical strain on the material handlers must also be considered. Beside these restrictions, different restrictions were found in the literature such as starvation introduced by Bozer and Ciemnoczolowski (2013) and Ciemnoczolowski and Bozer (2013) where they took into consideration determining the level of workstations starvation for given system parameters. Other studies such as Emde and Boysen (2012b) assumed in their model that the part shortage must be zero.

2.6 Relation to lean manufacturing

In-plant milk run system supports lean manufacturing philosophy in which seven wastes are reduced (Rother et al. 1999; Womack et al. 2010). These wastes are

- Waste from producing defects
- Waste in transportation
- Waste from inventory
- Waste from overproduction
- Waste of waiting time
- Waste in processing
- Waste of motion

The second waste is the focus of our study. If material is delivered just in time, another type of waste, namely, inventory cost, is decreased. The advantages previously mentioned such as reducing inventory costs, workforce requirements, the space required for materials, non-value-adding work, and walking distance coincide with the principle of lean which is about minimizing wastes. Moreover, introducing milk run help in organizing the shop floor, and this coincides with the 5S principle. 5S is the name of a workplace organization method that uses a list of five words which are sort, set in order, shine, standardize, and sustain.

The basic principle of in-plant milk run is providing small and repetitive amounts of materials for the workstations. This is done according to the JIT principle to minimize inventory costs, and this coincides with the lean manufacturing philosophy. In many cases, the pull system using kanbans is used in the milk run systems. However, in some cases as stated before, the demand-oriented system is also used to predict the demand only for few days which does not contradict severely with the JIT principle. In JIT, only the needed parts, at the right time, in the right quantities are delivered, and in addition, the stock on hand is held down to a minimum. JIT is able to shorten the lead time from the entry of materials to the completion of job. It also discloses existence of surplus equipment and workers (Sugimori et at. 1977)

Another tool of lean manufacturing is value stream mapping (Rother et al. 1999). External milk runs were extensively used in the literature in value stream mapping. However, only few studies considered using in-plant milk runs in this tool such as the study by Álvarez et al. (2009) which used in-plant milk run inside the value stream mapping for redesigning an assembly line. According to the same study, using kanban alone without internal milk run is not enough for reducing the total inventory.

One of the most important tools of lean manufacturing is standardized work. The effect of this tool is very obvious in stabilizing the TCT_s and the routes themselves. The TCT should be the same even if this is not optimal, because changing the TCT for every route is very confusing for material handlers. The same is also for standardizing the trains' routes. This standardization in routing and scheduling was emphasized by several studies such as Abele and Brungs (2009).

Some studies such as Emde et al. (2012), Emde and Boysen (2012a), Emde and Boysen (2012b) assumed using "shooter racks" in tow train systems. The special gravity flow racks are used to automatically load bins on the wagons using elastic springs. These racks reduce the length of a stopover to a few seconds. However, not all the automotive companies use this system. From the point of view of lean manufacturing which makes more emphasis on managerial (not technological) enhancements, consideration should be more for manual loading and unloading.

2.7 Other related decisions

In-plant milk run system does not stand alone. There are many decisions that are related to this system. Some of them can be considered as inputs to the milk run system and others can be considered as outputs. The in-plant milk run was considered in a study by Kovács (2011) as input for the storage assignment problem which involves the placement of a set of items in a warehouse in such a way that some performance measures are optimal. In that case, the most important input from the milk run is routing. In another study by Alizon et al. (2009), in which the assembly work shop was fed by tow trains and forklifts in the same time, the assignment problem was performed. However, the major concern of that study was the delivery of components performed by forklifts, so it was assumed that the routes followed by trains are fixed. The problem is then to optimize forklift delivery loops by including congestion caused by loading/unloading in a potential blocking aisle.

On the other hand, according to Ramesh et al. (2009), a good layout can lead to an effective implementation of milk run concept for the smooth flow of in-process material. Another important input decision that can be investigated is storage centralization/decentralization decision. For example, Battini et al. (2010) considered investigating this decision where they studied the usage of supermarkets. Furthermore, a cost model was presented in a study by Sargent et al. (1995) where the model can be used to determine if further consideration should be given to decentralized storage in a facility currently utilizing centralized storage. The cost model consists of examining the trade-off between the savings in material handling flow costs due to moving from centralized to decentralized storage and the additional costs associated with implementing and utilizing decentralized storage for a designated period of time. Satoglu et al. (2006) evaluated the conversion from central storage to decentralized storages in cellular manufacturing environments using activity-based costing. Furthermore, Alizon et al. (2009) studied the flow of materials from several internal warehouses to supply the same assembly workshop. Moreover, in a study by Hanson and Finnsgård (2014), a case study was explained in which the material feeding was organized by using three drop zones which were close to three assembly lines. These drop zones get the material from the automated storage and retrieval system (AS/RS). Then material was transported from the drop zones to the different stations in the assembly lines. One the other hand, in a study by Marchwinski (2009), a case study was presented about a company which had 4 storage areas feeding the assembly lines using the traditional forklift system. Then when the company wanted to use milk run tugger train, it used one central supermarket and considered that as an advantage to reduce the inventory costs. Besides, its location near the receiving dock permits quick delivery from receiving to storage racks.

So if the decentralization decision has been made, another decision also must be made which is the location problem of the decentralized supermarkets. Warehouses location problem was extensively studied (Melo et al. 2009). In warehouses location problem, decisions such as the optimal number of warehouses, locations of warehouses, and allocation of these warehouses to different customers are determined. However that type of studies isn’t exactly the same as the problem in this study which concentrates on the location of internal decentralized inventory (supermarket) supplying stations with milk run system inside the facility. Little literature was made regarding this decision problem in the internal environment. Supermarket location problem was investigated by Emde and Boysen (2012a). In this problem, the decisions such as the optimal number of supermarkets, the positions of these supermarkets, and the allocation of the supermarkets to different workstations are determined. This means that at first, a decision has to be made about using centralized or decentralized supermarkets. If the decision is to use the decentralized supermarket, the location problem is a must. After that, other milk run decisions can be studied. For example, Emde and Boysen (2012b) studied the scheduling and routing problem of the tow trains, and Emde et al. (2012) studied the loading problem. However, if the decision is to use the centralized system, there is no need for the supermarket location problem such as the way in the study by Golz et al. (2012). The general framework of these decisions can be shown in figure 2.5.

There are also other decisions that interact with the decisions in the milk run systems such as line stocking and kitting which are two alternative material supply systems that are common in assembly systems. Line-stocking systems supply components to the assembly line in homogeneous individual component containers stored close to the assembly workstations at the border of the line. On the other hand, kitting systems combine various components into one heterogeneous package according to a future assembly schedule. The required quantity of components is stored in kit containers at the border of the line (Limère et al. 2012).

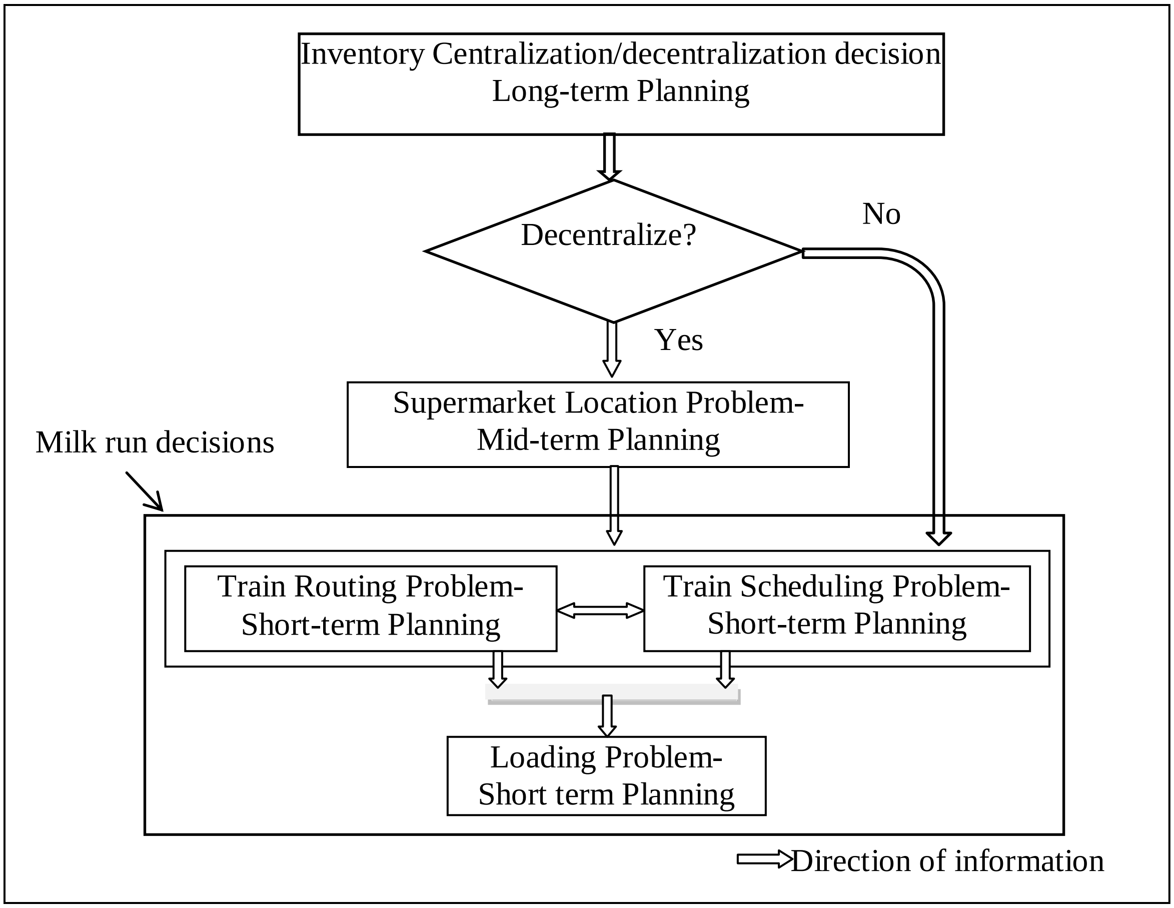


Figure 2.5 General Framework of the milk run system found in the literature in the case of demand-oriented system.

The kit assembly operation can be performed in a central picking store or in decentralized areas close to the assembly stations. In the case of using central picking store, the parts are transported to this store from the central warehouse using the tow train or the forklifts. So besides its working in the milk run tours, the tow train can also be used for handling material from the central warehouse to the central picking store of kitting. In this case, the milk run route feeding different stations does not start from the central warehouse but from central picking store. Figure 2.6 summarizes the input and output decisions related to milk run system found in the literature.

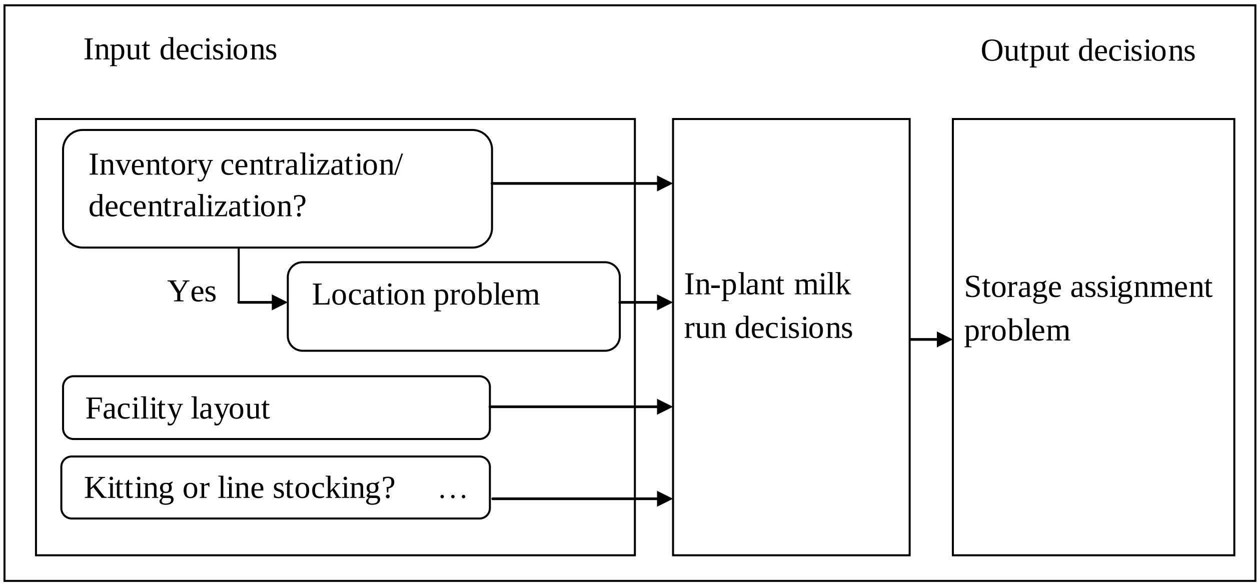


Figure 2.6 Input and output decisions, found in the literature, related to milk run

2.8 Research gaps in the literature

Most of the literature about milk run systems investigated inbound or outbound logistics. Maybe one reason for that is that external milk runs are more complicated to set up than in-plant milk runs (Baudin 2004). Brar and Saini (2011) reviewed the literature on milk run logistics outside the manufacturing plant especially in automotive industry. Milk run system still needs a lot of research since the size of research is still low and the system is not so easy to plan. The following gaps were found:

- There are some situations found in the practice that have not been covered at all.
- Sometimes the investigation does not consider all the sides of the problem.
- Sometimes the assumptions in the literature are restrictive.

A new direction in research is the electronic kanban system in milk run, which was not investigated at all in the literature. Chapter 4 presents and compares it to the traditional kanban and introduced the AEK system. The investigation is based on analytical investigation of the traditional and electronic kanban systems. Bozer and ciemnoczolowski (2013) and Ciemnoczolowski and Bozer (2013) investigated the traditional kanban system where they determined the number of kanbans assuming a given workstation starvation level. Before that they presented the distribution of demand for bins assuming that the demand is always one or two bins for each workstation. In this study, the two kanban systems (traditinal and electronic) are investigated without any assumption about the maximum number of bins. Also a new concept which is AEK is presented to accomdate capacity problems of line-side space and tugger trains. Traditinal kanban system was also investigated by other studies. A study by Faccio et al. (2013b) used simulation to analyze the system. In another study by Faccio et al. (2013a), a cost model has been proposed using analytical approach. They concentrated on the special attributes of such a system and they provided an innovative procedure to optimally set all decision variables related to such a material supply system. However, in this thesis, a cost model distinguishes between the circulating inventory in the system and ALSI, where emphasis was put on the later one due to the fact that the area beside workstations is very expensive and scarce. Compared to line-side area, the inventory holding cost of bins in supermarket area is low. A study by Faccio (2014) also investigated the milk run kanban system and compared it to kitting system in the case of using decentralized supermarket. The comparison was based on the impact of production mix variability and of the models variety (i.e. the assembled product's bill of materials diversity). However, that study ignored the case in which kits are stationary and supplied by milk run system. This type of kitting is investigated in the demand-oriented system.

An important aspect of material flow in MMAL is the supermarket location problem. In this problem, the number and locations of supermarkets are determined to minimize supermarket installation and transportation costs. It was investigated by Emde and Boysen (2012a), where it was assumed that supermarkets can be located in any place beside the stations. However, some areas may be occupied by other things and hence it is not possible to have supermarkets in these areas. Chapter 5 investigates this problem and releases this assumption. Besides that, the capacity of supermarkets was also considered.

The studies in the literature ignored integrating the loading problem in the routing and scheduling problems. For example, Emde et al. (2012) studied the loading problem assuming that the results of routing and scheduling are inputs for the loading problem. Moreover, Emde and Boysen (2012b) studied the routing and scheduling together in parallel to minimize inventory holding costs. Furthermore, Fathi et al. (2014) investigated the scheduling and loading problems together in parallel where they used a mixed integer linear programing (MILP) model to minimize inventory level and number of tours. Choi and Lee (2002) studied the feeding process.

Besides routing probelm, they investigated the loading problem in which the parts to be fed and the feeding amounts are indentified. However, the loading problem in the study by Choi and Lee (2002) did not take into consideration peak demand periods in which the shuttles capacities are exceeded. This means that their study does not contain early loading. Chapter 6 investigates all the three problems together in parallel to further decrease inventory costs and introduce new objectives such as minimizing the variability in the system.

It was found in the practice that sometimes the routing decision is made independently from the scheduling problem where certain colors are used to distinguish different routes. This system simplifies the tasks for the material handler but complicates the planning process due to the dynamic nature of workstations demand for parts. This variable demand creates bottleneck periods in which the capacity of the trains is not enough to handle the situation. Chapter 7 will present four strategies to accommodate the capacity problem. These strategies are dynamic scheduling, early loading, minimizing number of extra trailers, and using market attendant or automation in loading and unloading. The objective of scheduling defined in Emde and Boysen (2012b) and also Satoglu and Sahin (2013) was to minimize inventory holding cost. However, in this study, the dynamic scheduling is to minimize the needed number of trailers and MLSI to accomdate capacity problems. Moreover, the study by Golz et al (2012) assumed that routing and scheduling are investigated together in parallel to minimize the number of trains. However, in chapter 7 routing is assumed to be fixed and is input for the scheduling process. Furthermore, early loading was studied by Emde et al. (2012) to minimize the inventory holding costs. However, in chapter 7, early loading is integrated to dynamic scheduling and minimizing the number of extra trailers, where the result of dynamic scheduling is input for early loading. Early loading results are input for minimizing the number of extra trailers. Furthermore, MLSI was considered as a constraint in early loading. The effect of using market attendant and automatic loading and unloading was explained.

Dynamic planning for material replenishment was investigated by Choi and Lee (2002) who studied the feeding process in an automotive plant. The sequencing of product models was assumed to be dynamic. The exact demand for parts can not be known for the complete shift because the sequence can be changed any time. Therefore, Choi and Lee (2002) proposed a methodolgy to react for the resequencing problem. At first, they investigated the loading problem in which the parts to be fed and the feeding amounts are indentified. Then the feeding orders to feeders are assigned and routes are formed. This is based on the objective of minimizing the deviation of actual delivery time from the ideal one, where a certain safety stock level should be kept. However, the loading problem in the study by Choi and Lee (2002) did not take into consideration peak demand periods in which the shuttles capacities are exceeded, so their study does not contain early loading in which some bins are loaded before they are needed. Furthermore, they only considered the case of resequencing. According to the best of the knowledge of the author, the study by Choi and Lee (2002) was the only one which concentrated on dynamic planning of the feeding system. Chapter 8 investigates this dynamic planning process in terms of routing, scheduling, and loading problems and considers the peak demand periods. The system proposed is able to deal with resequencing based on disturbances or customer needs, quality problems, line stoppage caused by machine breakdown or inability of worker to finish his work on time. To do that, a mix between the demand-oriented and e-kanban was investigated. Fixed routing problem was studied. Then scheduling and loading problems were investigated to accomdate the special needs of that system where the deviation from ideal size of safety stock was minimized. There are still several research directions that were not investigated. They are presented in the last chapter of conclusion and recommendations for future research.

Chapter 3: Study general framework

3.1 Introduction

This chapter defines the general scope, methodology, and the main contribution of the study. The main purpose of the study is to design the milk run system and set its parameters to minimize its costs. The decisions made depend on the type of the system. Figure 3.1 shows the main types and their decisions. Figure 3.1a represents the demand-oriented system in which the exact demand is known at least for the next shift. So the planning is based on that knowledge of demand. In this system, there are two cases, namely, decentralized supermarket system, and main warehouse system. In this study, 'main warehouse' and 'centralized supermarket' are used interchangeably. In figure 3.1b is the kanban system which can be classified as traditional kanban and electronic kanban. Each one of the kanban systems can be applied in main warehouse and decentralized supermarket environments. In the case of disturbances such as machine breakdown, line stoppage, defective parts, and resequencing, a mix between the e-kanban and demand-oriented systems was used. This hybrid system is important to get the continuous feedback about the status of the assembly line using e-kanban and also to utilize the knowledge about the expected stations demand after disturbance in the recovery period. So in this case a dynamic planning approach is needed. This approach is in figure 3.1c.

Figure 3.1 defines the scope of the work containing the shown decisions. In the decentralized supermarket system, the three decisions, routing, scheduling, and loading problems are investigated in parallel. Therefore, they are considered as one item. The routes are assumed to be fixed during the shift but variable from a shift to another. If the routes are assumed to be fixed over several shifts as it was found in the practice in some cases, fixed routing decisions are investigated. These decisions can be applied in the two demand-oriented systems: centralized and decentralized supermarket systems. This is the reason for putting the rectangle of fixed routing decisions in figure 3.1a in the places of the two systems. These problems are studies step by step. So the way of investigation is different from the investigation way for problems in decentralized demand-oriented decisions. There are main decisions that are common in the four different systems such as routing and scheduling. Routing in traditional kanban system used in the study is very straightforward. Because of that, it was not considered in the figure 3.1.

Decentralized supermarket	**Main warehouse**
1. Supermarket location problem (Ch. 5) 2. Train routing, scheduling, and loading problems (Ch. 6) Objectives: min MNT*, transportation costs, inventory costs, fixed supermarket installation costs, and system variability	Fixed routing (Ch. 7) **: 1. Train fixed routing 2. Train dynamic scheduling 3. Early loading 4. Minimizing number of extra trailers Objectives: min MNT, MLSI, average number of extra trailers.

* MNT is minimum number of trains
** These decisions can be applied in the two systems (main warehouse and decentralized supermarkets)

a. Demand-oriented system

Traditional kanban (Ch. 4)	**Electronic kanban** (Ch. 4)
1. Number of kanban 2. Cycle time Objectives: min MNT, ALSI and workstation starvation	1. Circulating inventory 2. Cycle time 3. AEK 4. Train routing Objectives: min MNT, ALSI and workstation starvation

b. Kanban system

A mix between demand-oriented and e-kanban (Ch. 8)

1. Train fixed routing***
2. Train scheduling
3. Train loading

Objectives: min MNT, number of train cycles, probability of early loading, deviation from ideal safety stock size

*** Fixed routing in the mix system is similar to that found in demand-oriented system

c. Dynamic planning

Figure 3.1 Milk run system classification and decisions problems

On the other hand, supermarket location problem is necessary only if decentralized supermarket demand-oriented system is used. Moreover, determining the number of kanbans is needed only if traditional kanban system is assumed. The fixed routing problem in figure 3.1a and 3.1c is the same. It was assumed in this study that in the case of assembly line disturbances the best strategy is to use fixed routing to provide some stability in the system. Figure 3.1 also shows the assignment of the problems to different chapters in the study. For the four fixed routing tasks found in demand-oriented system, only three of them are presented in chapter 7. The fixed routing problem is only presented in chapter 8 because this routing problem in chapter 7 and chapter 8 is the same.

The scope of the study does not contain all the cases of milk run. In the case that variable routing (one routed vehicle) is used in the centralized supermarket system, the reader can refer to Golz et al. (2012). Moreover, the study does not consider the case of multiple routed vehicles. Furthermore, the following main assumptions are made in the study:

1. In kanban systems and also in fixed routing, the demand of stations was assumed to be represented by Poisson distribution.
2. In the case of demand-oriented system, the time unit used was SCT. For example, the loading and unloading time plus movement from one station to another can be represented by integer number of SCT.

Besides the previous assumptions, there are several assumptions in each chapter. These assumptions limit the scope of the study. Figure 3.1 contains the types of costs the study tries to minimize or eliminate according to the systems previously defined. The objectives shown in the figure are only for the work done by the author. Other objectives were studied in the literature. However, this study contains most of the objectives.

3.2 Study contribution

Each type of the five systems has its contribution. Figure 3.2 shows the contributions where some of them are the same. The size of contribution in electronic kanban is larger than that for traditional kanban because the first one did not get the attention from the researchers. There are some items that are in the two kanban systems because of the similarities in the two systems. For example, analytical investigation was done at first for electronic kanban. Then the formulas were altered to fit traditional kanban as will be seen in chapter 4.

Decentralized supermarket

a. Supermarket location problem:
   1. Considering the availability of areas beside workstations for possible supermarkets
   2. Considering the capacity of supermarkets

b. Routing, scheduling, and loading problems:
   1. Studying the three problems together
   2. Considering minimizing system variability
   3. Further decreasing the total inventory holding costs

Main warehouse

Fixed routing:

1. Considering fixed routing problem
2. Considering minimizing the number of trailers
3. Accommodate capacity problems using a systematic way of four strategies

a. Demand-oriented system

Traditional Kanban

a. Analytically studying the system to find the relationship between starvation and number of kanban/ circulating inventory size
b. Finding ALSI.
c. Investigating if market attendant or automatic loading should be used

Electronic kanban

a. Introducing a new concept, namely, AEK, to face capacity problems
b. Introducing a cost model
c. Routing problem: simplified way based on average demand.

b. Kanban system

A mix between demand-oriented and e-kanban

1. Dynamic material flow planning approach that considers peak demand periods
2. Accommodating disturbances such as defective parts, line stoppage, machine breakdown, and resequencing
3. Considering the current line-side inventory size in scheduling and loading problems

c. Dynamic planning

Figure 3.2 Study contribution

3.3 Tools used in the study

The study depends mainly on operations research, analytical investigation, and simulation. Figure 3.3 shows the assignment of the tools used for each system. Some numerical examples similar to that found in the literature were used. As in figure 3.3, there are some similarities between some systems due to the similarity of general conditions. Compared to that in traditional kanban, the analytical investigation done in electronic kanban have some similarities but also some new dimensions.

Decentralized supermarket	**Main warehouse**
a. Supermarket location problem: 1. Genetic algorithm b. Routing, scheduling, and loading problems: 1. Analytical investigation 2. Integer programming 3. Dynamic programming	Fixed routing: 1. Integer programming 2. Dynamic programming 3. Analytical investigation.

a. Demand-oriented system

Traditional kanban	**Electronic kanban**
a. Analytical investigation b. Simulation	

b. Kanban system

A mix between demand-oriented and e-kanban

a. Analytical investigation
b. Integer programming

d. Dynamic planning

Figure 3.3 Tools used in the study

Table 3.1 study inputs and outputs

Inputs	Outputs
1. Type of material control system used: – Demand-oriented (centralized and decentralized) – Traditional kanban – Electronic kanban – Dynamic planning 2. Type of inventory system: – Centralized warehouse – Decentralized supermarket • Available areas for supermarkets and (x, y) locations 3. Stations: – Demand (averaged and detailed if possible) – Exact location (x, y) – Loading and unloading needed times – Path of flow for product models – Maximum line-side capacity for inventory – Idea safety stock size 4. Costs: – Unit inventory holding costs – Product model price – Tugger train investment cost – Material operator cost – Material handling cost per unit distance per bin – Installation cost of decentralized supermarket 5. Trains – Capacity (number of bins, number of trailers, number of bins per trailer) – Speed (average) – Loading and unloading time at supermarket – Number available 6. Decisions that may be enforced by management – Cycle time – Maximum allowed starvation percentage.	1. Supermarket best locations and number (if any) 2. Routing (trains assignment to stations) 3. Needed number of trains and trailers per train 4. Cycle time and the starting time of each route (scheduling). 5. Loading (bins types and quantities to be loaded in each route). 6. Optimal number of kanban (if any) 7. Optimal circulating inventory size (in the case of e-kanban) 8. Workstation starvation (in the case of using kanban) 9. ALSI for each station 10. Total system costs 11. Number of extra trailers

3.4 Study inputs and outputs

To utilize all the capabilities of the study, the needed input of information and the output results are in table 3.1. To design the milk run system and define its parameters, a lot of information is needed. Some information is raw data such as locations of workstations. However, some information is the results of decisions of management such as maximum allowed workstation starvation percentage. In the case of fixed routing, the average expected workstation demand for the long range is required. So forecasting must be done. Some information needs some judgment by the decision maker such as the fixed cost of using decentralized supermarkets.

3.5 Summary

This chapter defines the general scope of the study where five different milk run systems were considered. It also defines the types of cost the study tries to minimize, the contribution in the different systems, tools used, and inputs and outputs of the study. The situation on the ground defines which system to use. E-kanban for example needs technical support in the form of bar code or RFID. The accuracy of expecting the demand for parts by each station is the motive to use demand-oriented system. If there are some disturbances that need fast reaction, then a hybrid system which combines the advantages of e-kanban and demand-oriented systems is needed. There are some similarities and differences in the planning tasks between the five systems. This chapter is important to understand the general concept of the thesis.

Chapter 4: Kanban in milk run system

This chapter investigates the kanban system. The principle of e-kanban will be used again in chapter 8 in a proposed system that utilizes both the demand-oriented and e-kanban system to accommodate line disturbances. The current chapter analyzes analytically the e-kanban system used in in-plant milk run, and shows the relationship between the workstation starvation and inventory level in the system. Workstation starvation and ALSI are derived based on the number of kanbans or circulating inventory. Moreover, it analyzes the traditional kanban system with no restrictions on the number of bins demanded by a station in one cycle. It also presents a cost model for the system. The cost model distinguishes two types of inventory which are the circulating inventory in the system and ALSI, where emphasis was put on the later one due to the fact that the area beside workstations is very expensive and scarce. Moreover, the chapter also presents a new concept, namely, adjusted electronic kanban (AEK), which is used to reduce the needed number of trains as much as possible while keeping workstation starvation below a certain level. Besides analytical investigation, simulation was used to check the effect of using AEK on the performance of the system. The impacts of factors such as circulating inventory, bin capacity, and distance between supermarket and workstations were investigated. Furthermore, a cost model which takes into account the inventory holding cost, workstation starvation, and number of trains has been introduced. The contents of this chapter have been partially published in Alnahhal et al. (2014b).

4.1 Kanban system

The *workstation cycle demand* is the demand of that workstation during the time period from the departure of a train from the workstation in the current train cycle to the next departure in the next train cycle. In kanban system the tugger train starts a cycle j at the supermarket and that cycle ends when that tugger train returns to the supermarket. In traditional kanban system, just before the beginning of cycle j the driver of the tugger train had delivered to the supermarket the kanbans that were picked up during the previous cycle j-1, and respective materials for those kanbans are delivered in the cycle j. At specific times the tugger train departs from the supermarket area after loading the required materials in bins and starts a particular delivery route. Along that delivery route, the tugger driver stops beside the workstations needing parts and unloads the respective bins (containers) and loads the empty bins. TCT can be considered as the time interval between train departures from the supermarket/a workstation until the next departure from the supermarket/that workstation.

The problem of traditional kanban system is that in some routes the total number of kanbans (number of bins) is more than the capacity of the train. Suppose that there are five stations as a part of the route of the train. Each station has a demand of 1 or 2 bins during the cycle time. In this case, the total number of needed bins is fluctuating over time from 5 to 10. But what if the capacity of the train is just 7 bins for example? In a study by (Ciemnoczolowski and Bozer 2013), it is assumed that if the capacity is not enough for some periods, the kanban for the first stations should be satisfied, and the rest of kanbans will have the priority in the next cycle. This strategy was found to be accepted if the average of demand is less than or equal to K which represents the capacity of the tugger train. However if this average is higher than K, then a new strategy will be needed. But even in the first case, the starvation probabilities of the stations at the end of the train route are a little bit higher than other stations at the beginning of the route.

In e-kanban system, signals are sent electronically using radio frequency identification (RFID) or bar code technology. Usually, RFID tag or bar code is put on each bin. So the consumption of a bin by a workstation is detected even after the departure of the train from the area of that workstation. Therefore, the feedback about the consumption is sent to supermarket area or warehouse until the last possible moment. This means that the time interval between sending the signal and receiving it is shorter. This short response period is important to reduce the average size of line-side inventory. As stated before, the TCT can be the time interval between two successive train departures from the supermarket area or departures from a workstation. In e-kanban system, the critical TCT is from the departure of the train from the supermarket to the next departure from the supermarket. This is because any signals for demand after the departure of the train from the supermarket area are not fulfilled in the current train cycle. In traditional kanban, the critical TCT is the one started in the moment of departure from the workstation. This is because any kanban put in the kanban post after the departure of the train from the workstation cannot be fulfilled in the next train cycle. The critical TCT in e-kanban is always fixed. This characteristic is an advantage to decrease uncertainty in the system. In traditional kanban, on average, the critical TCT is the same. However for any workstation, each individual TCT is variable over the shift depending on the number of loaded and unloaded bins in the previous workstations in the train route. For example, if there are a lot of loaded and unloaded bins in the previous workstations, some delay will occur. This delay leads to longer critical TCT in the current cycle. The following assumptions are made in this chapter:

1. The workstation cycle demand for parts can be represented by Poisson distribution.
2. For e-kanban, if it is possible, the exact time of every part consumption can be known. If this is not possible, the time of the consumption of the first part in each bin is known. In the second case which is the cheaper one, bar codes or RFID tags are attached not to individual parts but to bins.
3. The variability of loading and unloading time of bins at a workstation is negligible. So this time for a workstation is assumed to be constant during the shift.
4. In the case of traditional kanban, the kanbans that were collected in the previous train cycle are delivered with full bins in the next train cycle.
5. In e-kanban, any demand signal that arrives at the supermarket area just before the departure of a train can be satisfied in that train cycle if there is enough capacity for it on that train.
6. There is always enough inventory of each material in the supermarket area.
7. Standardized bins or containers are used at each workstation. As parts are likely to have different dimensions at each workstation, the maximum number of parts per bin at workstation s is denoted as B_s.

4.1.1 Traditional kanban

At the moment the train departs from a workstation, any demand for a new bin by that workstation has to wait until the next train arrival which is after one train cycle time. After that, kanban is transported with the driver and will not be satisfied until the next train cycle. So the *protection period* here equals two cycles which implies that there must be adequate inventory of parts at each workstation for two train cycles. Figure 4.1 represents the system of traditional kanban. The following notations are important:

n_s number of kanbans for workstation s

C cycle time. TCT and C are used in this study interchangeably, but C is usually used in equations.

d_{sC} average demand for parts during the time interval from the train departure from workstation 's' in the current cycle and the train departure from the same workstation in the next train cycle. This time interval equals C but must start from the train departure from the workstation s. Moreover, $d_{sC}= \mu_s C$.

μ_s the average demand for parts per time unit, where $\mu_s = 1/TBAD_s$ where $TBAD_s$ is the average Time Between Arrival of Demand for parts.

$2d_{sC}$ average demand for parts during the protection period for workstation 's'.

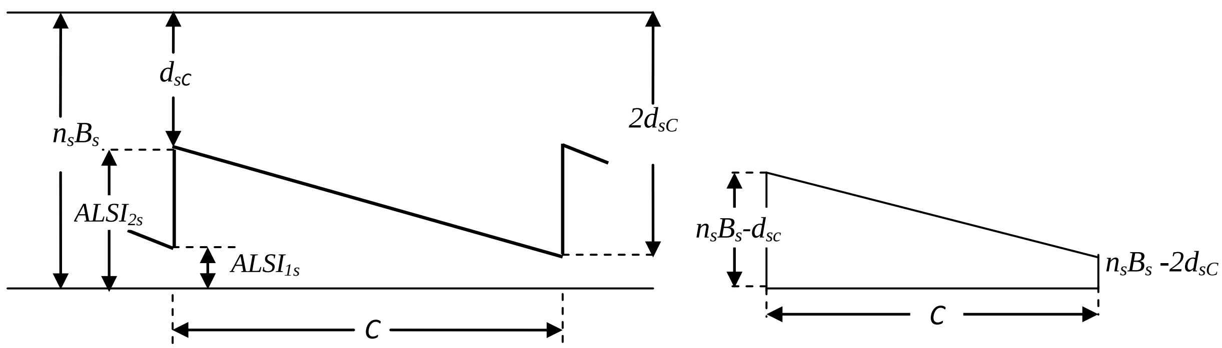


Figure 4.1 ALSI in traditional kanban system

The thick solid line at the left-hand side of the sketch represents the level of line-side inventory at workstation's'. The upper line represents the number of kanbans multiplied by the bin capacity. At the time of arrival of the train there are three types of kanbans:

1. Kanban in kanban post corresponding to the inventory that has been consumed during cycle which is d_{sC}. The number of these kanbans will be $d_{sC}/B_s = n_s - (ALSI_{2s}/B_s)$, where $ALSI_{2s}$ is the average line-side inventory just before the arrival of train to the workstation s.
2. Kanbans corresponding to the arriving material quantity, which on average is also d_{sC}. The number of these kanbans will be d_{sC}/B_s.
3. The kanban attached to the residual inventory representing the safety stock which is represented by $ALSI_{1s}$, where $ALSI_{1s} = n_s B_s - 2d_{sC}$

To estimate average line-side inventory over the shift for workstation s ($ALSI_s$) in parts unit, use the triangle at the right side of the figure 4.1 where the upper line represents the size of inventory over time. The area of the figure can be determined using equation (4.1).

$$Area = \frac{n_s B_s - d_{sC} + n_s B_s - 2d_{sC}}{2} C = \frac{2n_s B_s - 3d_{sC}}{2} C \quad (4.1)$$

$ALSI_s$ can be determined by dividing this area by C. Moreover, n_s is multiplied by B_s to find $ALSI_s$ in parts unit. So generally $ALSI_s$ can be estimated using equation (4.2)

$$ALSI_s = \frac{2n_sB - 3d_{sC}}{2} \tag{4.2}$$

B is used instead of B_s because it will be assumed starting from here that the bin size is the same for all types of materials. To add the rest of parts in the bin from which some parts have been consumed, (B-1)/2 is added to the previous term. The added term is not B/2 but (B-1)/2, because at the beginning of consumption of parts of a bin one part is on process and not inside the bin. So the final equation is

$$ALSI_s = \frac{2n_sB - 3d_{sC}}{2} + \frac{(B-1)}{2} \tag{4.3}$$

This system is similar to the famous *periodic review system* of inventory management (see Krajewski et al. (2007)) with some main differences:

1. The lead time is equal to the time between orders which is the TCT in milk run system. So the protection period here equals $2C$. Lead time means the time between sending the signal (kanban card) by a workstation and receiving the associated bins by the same workstation.
2. The target inventory position (in bin unit) is equal to the total number of kanbans.
3. Parts and materials are supplied in bins unit.

4.1.2 Electronic kanban

In the electronic kanban, an automatic identification system monitors the inventory level at each workstation and sends kanban signals to the supermarket via the internal communication network. Therefore the receipt of e-kanban signals at the supermarket does not depend on the current position of tugger train. The signals are sent instantaneously to the supermarket. This is usually done using bar codes or RFID technology to track inventory level. The kanban signals that are received at the supermarket after the departure of the train cannot be satisfied in the current train cycle but will be fulfilled in the next one. So the protection period in this case equals C plus the time from the departure of the train from the supermarket to the time of arrival at the workstation. It is not necessary to prepare bins when the kanban signal is received by the supermarket. Actually the advantage of e-kanban is sending the demand information to the supermarket until the last possible moment.

One important aspect to consider is the initial inventory near each station. As will be seen later, it was found using simulation that initial inventory should be not only full bins but also some parts plus the full bins to decrease MLSI. The electronic signal should go to the warehouse or supermarket when the consumed parts equal the bin capacity. For example, suppose that B= 30 parts and initial inventory beside workstation s (I_s) = 45 parts. The signal must be sent when the station consumes the first part and also the 31st part in the line-side inventory (16th part in the bin). To do so, in electronic kanban, we may use RFID tag with each part. Another cheaper strategy is to estimate the part consumption. So the tag is only for the container (bin) and the time of the 16th part is estimated based on the average consumption rate. We will call the first system as *part-based electronic kanban*, and the second one *time-based electronic kanban*. For the previous example if the full bin is consumed in about 30 minutes, the signal is sent to the warehouse 15 minutes after consuming the first part in the bin. This system increases MLSI just a little bit more than that for part-based electronic kanban. In traditional kanban system it is not easy to use parts plus full bins in initial inventory.

As found using simulation, there are several factors affecting MLSI which are:

- Type of material flow control: traditional kanban causes higher levels of MLSI than that for electronic kanban
- Station position (in electronic kanban): the longer the distance (in time unit) between the warehouse and the station, the higher the MLSI is
- Electronic kanban type: time-based electronic kanban causes higher levels of MLSI than that for part-based electronic kanban.
- Bin capacity: larger bin capacities causes larger MLSI
- Material demand: larger demand causes larger MLSI

The ideal situation for the minimum possible level of MLSI is when part-based electronic kanban is applied for a station that is very close to the warehouse when the bin capacity is one and assuming unlimited capacity of the train. In this case the MLSI which appears each time the train arrives at the station is the same for all the routes for the same station. This is because any consumption level in the material will be compensated by the exact level in the next time the train arrives at the station. So in this case, utilization (U_s) for the station s can be estimated using equation (4.4) assuming that arrival rate of parts demand follows Poisson distribution.

$$U_s = \frac{C - \sum_{i=1}^{\infty} \frac{iC}{MLSI + i} f(MLSI + i, C\mu_s)}{C} \tag{4.4}$$

Where f(k, λ) = P(X=k) is the probability mass function (pmf). The term $C\mu_s$ represents the average demand during the cycle if δ_s= 0, where δ_s is the workstation starvation probability and U_s =1- δ_s. If the total station demand in a cycle is more than MLSI, station starvation occurs. In this case, the term C/(MLSI+i) represents the real average of $TBAD_s$ in that cycle. Equation (4.4) uses very simple logic: finding the probability that the actual demand is more than MLSI by i parts multiplied by the time these i parts take. This value is then summed over all possible values of i. The summation represents average time of starvation per cycle. Only the first few values of i are important because the probability of having MLSI+i will almost be zero when i is large.

Figure 4.2 shows the behavior of the e-kanban system. In traditional kanban system the number of kanbans is the factor that defines the size of the inventory circulating in the system. In e-kanban, this circulating inventory (I_s) can be controlled by the available amount of materials beside workstations before the starting of the shift plus the amount of materials delivered in the first train cycle, where the train makes the delivery in this cycle without any feedback (signals). The train just delivers the needed material required to obtain I_s level of inventory. Moreover, t_d represents the time of train departure from the supermarket, while t_s represents the moment of the arrival of the train at the workstation s and the delivery of parts to that workstation. During the time interval between the two time points (t_{ds}), the number of consumed parts is estimated to be d_{ts}, where d_{ts}= $\mu_s t_{ds}$. From figure 4.2, there are three important levels of ALSI:

$ALSI_{1s}= I_s - d_{sC}$

$ALSI_{2s}= ALSI_{1s} - d_{ts} = I_s - (d_{sC} + d_{ts})$

$ALSI_{3s}= I_s - d_{ts}$

The term $d_{sC} + d_{ts}$ represents the demand during the protection period which is $C + t_{ds}$. Figure 4.2 just shows the average inventory values over time. The individual cycles inventory over time looks like figure 4.3

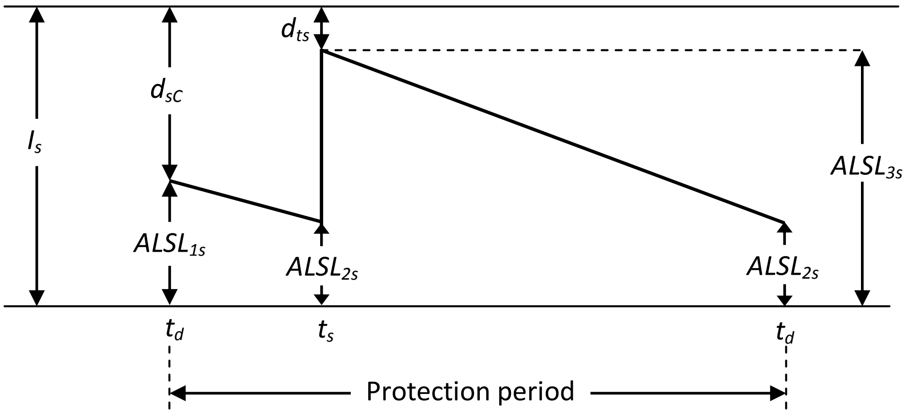


Figure 4.2 ALSI in e-kanban system

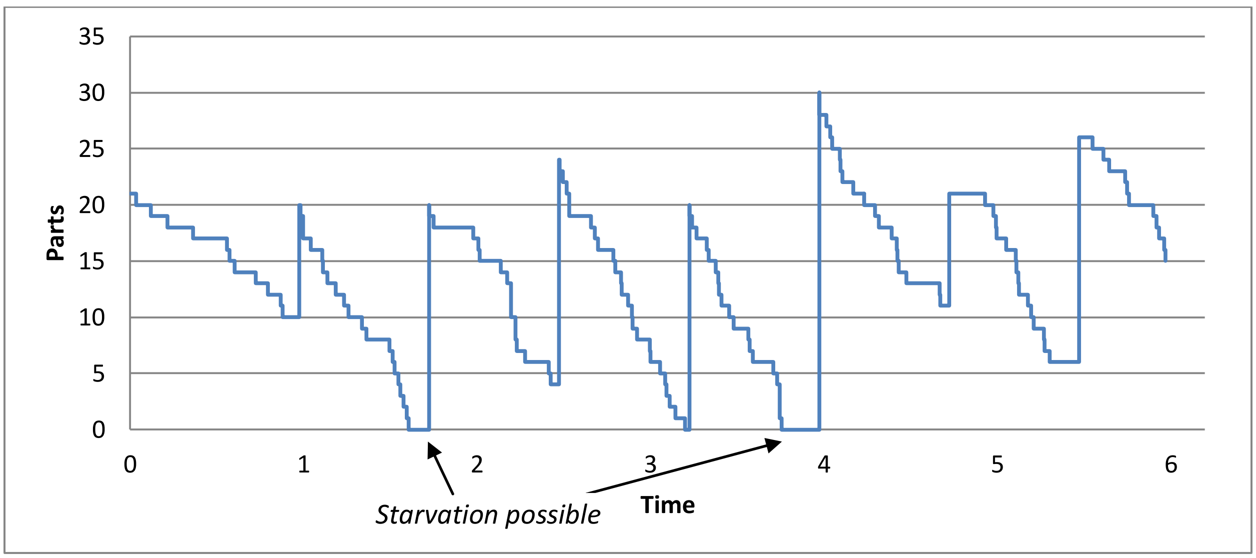


Figure 4.3 Line-side inventory in e-kanban system

There are some advantages for e-kanban compared to traditional kanban:

1. Fixed critical TCT in e-kanban to reduce uncertainty in the system.
2. Protection period is shorter; therefore, the line-side inventory is lower.
3. The initial inventory is assumed to be with any size (not necessary to be integer number of containers) to have full control over the level of inventory. This will reduce the needed line-side inventory. For example if the initial inventory is an integer number of bins plus a half of a bin, then a signal will be triggered every time the line-side inventory contains exactly a half of a bin plus any other integer. This can be possible if RFID tag is attached to each part, or if the consumption of a half of bin can be expected with high accuracy.

This is not possible in the case of traditional kanban because there is no way to estimate the time of consumption of half of a bin for example.

To estimate the value of $ALSI_s$, figure 4.2 is used to get equation (4.5) by computing the area under the solid line and dividing it by the protection period $C + t_{ds}$. This is done assuming that the effect of starvation on $ALSI_s$ can be negligible.

$$ALSI_s = \frac{2I_sC - (2t_{ds} + C)d_{sC}}{2C} + \frac{(B-1)}{2} \tag{4.5}$$

Because $d_{ts}= \mu_s t_{ds}= (d_{sC}/C)\, t_{ds}$, equation (4.5) can be rewritten as:

$$ALSI_s = I_s - d_{ts} + \frac{B - d_{sC} - 1}{2} \tag{4.6}$$

Materials and parts in the system can be classified into three categories: line-side inventory, bins loaded currently on tugger trains, and bins in supermarket area. The study concentrates on the first category because it is the most critical one where the area beside stations is very scarce and expensive. Later this type of inventory will be used in the cost model.

4.1.3 Estimating the effect of circulating inventory level

At first, the circulating inventory level for the case of e-kanban is estimated, and then the formula is generalized to estimate the number of kanbans in the case of using traditional kanban system. The percentage of affected cycles (AC_s), which is the probability of having a cycle with some starvation, is estimated using equation (4.7)

$$AC_s = 1 - F\left(J_s = I_s + 0.5B\ \frac{C}{(C + t_{ds})}, \lambda_s\right) \tag{4.7}$$

Where λ_s is the average demand during protection period for workstation s, and F(X, λ) is the cumulative distribution function for the random variable X. Because material is supplied in bins unit, there is extra number of parts with an average of $B/2$, and hence, the term $0.5B$ is used. Furthermore, because λ_s and I_s are for the protection period, $0.5B$ is multiplied by $C/(C+t_{ds})$ so that all the variables are in protection period units. In the case that J_s is not integer, interpolation can be used. Workstation starvation percentage is always lower than AC_s because the delayed parts due to that workstation starvation in the affected cycles are only some few ones. To estimate workstation starvation, the average percentage of these few ones is found, multiplied by

AC_s, and divided by λ_s. This is done later in equation (4.12). Generally the expected value for a section of Poisson distribution (from 0 to J) can be found using equation (4.8)

$$\bar{x} = \frac{e^{-\lambda}\sum_{k=0}^{J}\frac{k}{k!}\lambda^k}{F(J,\lambda)} \tag{4.8}$$

The total area of Poisson distribution is divided into two sections, namely, α and β, where section α is from 0 to J, and section β is from J+1 to infinity. To estimate workstation starvation, the average of section β is computed. The following steps find this average:

$$\lambda = \bar{x}_{\alpha}F(J,\lambda) + \bar{x}_{\beta}\big(1 - F(J,\lambda)\big) \tag{4.9}$$

$$\bar{x}_{\beta} = \frac{\lambda - \bar{x}_{\alpha}F(J,\lambda)}{1 - F(J,\lambda)} \tag{4.10}$$

Then $\bar{x}_{\alpha}$ is replaced by the right hand side in equation (4.8)

$$\bar{x}_{\beta} = \frac{\lambda - e^{-\lambda}\sum_{k=0}^{J}\frac{k}{k!}\lambda^k}{1 - F(J,\lambda)} \tag{4.11}$$

To represent the average starting from the end of section α, $\bar{x}_{\beta} - \mathrm{J}$ is used instead of $\bar{x}_{\beta}$. Neglecting the effect of starvation on $0.5B\ \frac{C}{(C+t_{ds})}$ value, an approximated value for starvation (δ_s) is:

$$\delta_s = \frac{\big(\bar{x}_{\beta s} - \mathrm{J_s}\big)(AC_s)}{\lambda_s} \tag{4.12}$$

$$\delta_s = \left(\frac{\lambda_s - e^{-\lambda_s}\sum_{k=0}^{\mathrm{J_s}}\frac{k}{k!}{\lambda_s}^k}{1 - F(\mathrm{J_s},\lambda_s)} - \mathrm{J_s}\right)\frac{1 - F(\mathrm{J_s},\lambda_s)}{\lambda_s} \tag{4.13}$$

$$\delta_s = \frac{\lambda_s - \mathrm{J_s} - e^{-\lambda_s}\sum_{k=0}^{\mathrm{J_s}}\frac{k}{k!}{\lambda_s}^k + \mathrm{J_s}F(\mathrm{J_s},\lambda_s)}{\lambda_s} \tag{4.14}$$

Utilization can be estimated by: U_s=1-δ_s

$$U_s = \frac{\mathrm{J_s} + e^{-\lambda_s}\sum_{k=0}^{\mathrm{J_s}}\frac{k}{k!}{\lambda_s}^k - \mathrm{J_s}F(\mathrm{J_s},\lambda_s)}{\lambda_s} \tag{4.15}$$

As the most important formulas in this chapter, Equations (4.14) and (4.15) find the workstation starvation and utilization respectively as functions of circulating inventory. The higher the circulating inventory is, the lower the workstation starvation is, and the better the utilization is.

4.2 Adjusted electronic kanban

Sometimes the needed demand in some periods is higher than the capacity of the train. This is not a problem if there are other non-bottleneck periods at which the capacity of the train is higher than the total demand of all workstations. If this behavior is just because of the randomness effect due to the high level of variability of workstation demand (such as the case in which demand follows Poisson distribution), and if generally the capacity of the train is at least equal to the average workstations demand, an approach defined by the author called AEK can be used. Figure 4.4 shows how the system's number of needed bins looks like, where the capacity of the train is only 8. Traditional kanban and normal e-kanban fail to deal with such a situation. In AEK, *two* pieces of information are sent to the supermarket, namely, the demand quantity and the time of demand signal. In this case the quantity is always one bin. So if the capacity of the train is K, then the first K signals are satisfied in the immediate cycle of the train. The other not satisfied signals are fulfilled at the next cycle where they have the highest priority. If enough capacity of trains is always available, AEK will be identical to normal e-kanban.

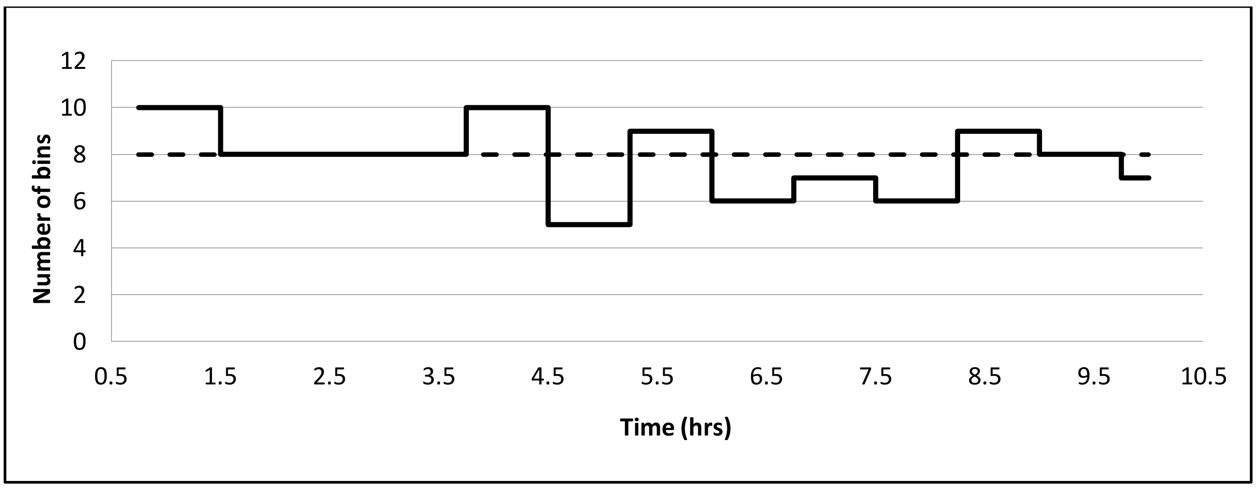


Figure 4.4 Total number of signals (bins demand) during cycles over time

As illustrated in equation (4.16), the available train capacity must be at least equal to the average cell demand during the train cycle, where the number of stations in the cell is N.

$$K \geq \left\lceil \frac{1}{B} \sum_{i=1}^{N} d_{ic} \right\rceil \tag{4.16}$$

Where $\lceil x \rceil$ is the rounded value of x to the upper integer, and $\lfloor x \rfloor$ is the lower rounded value of x to the lower integer. To find workstation starvation probability in the case of AEK, at first k_s is used instead of J_s, where k_s can be found using equation (4.17) (see figure 4.5).

$$k_s = \frac{Kd_{sC}}{\sum_{i=1}^{N} d_{iC}} \frac{(C + t_{ds})}{C} + 0.5B \frac{C}{(C + t_{ds})} \tag{4.17}$$

This formula computes the available capacity for one workstation in the units of protection period. This capacity has a positive relationship to the average workstation demand divided by the average demand of all workstations supplied by the same train. Then U_{ks} which is the associated utilization is found in the same way of equation (4.15).

$$U_{ks} = \frac{k_s + e^{-\lambda_s} \sum_{k=0}^{k_s} \frac{k}{k!} {\lambda_s}^k - k_s F(k_s, \lambda_s)}{\lambda_s} \tag{4.18}$$

This value means that on average after fulfilling U_{ks} percent of the parts demand in the current route, the rest of demand is fulfilled in the next route. So the system behaves as if t_{ds} of the next cycle is increased by $1\text{-}U_{ks}/U_s$ percent. So t_{ds} must be multiplied by $2\text{-} Uk_s/\mathrm{U_s}$ to get t_{AEKs} and then computations are repeated again for the new t_{AEKs} where:

$$t_{AEKs} = \left(2 - \frac{U_{ks}}{U_s}\right) t_{ds} \tag{4.19}$$

$$J_{AEKs} = I_s + 0.5B \; \frac{C}{(C + t_{AEKs})} \tag{4.20}$$

$$\lambda_{\mathrm{AEKs}} = \frac{\mathrm{C} + t_{AEKs}}{\mathrm{TBAD_s}} \tag{4.21}$$

The new utilization is based on the new J_{AEKs} and λ_{AEKs}.

$$U_{AEKs} = \frac{J_{AEKs} + e^{-\lambda_{\mathrm{AEKs}}} \sum_{k=0}^{J_{AEKs}} \frac{k}{k!} {\lambda_{\mathrm{AEKs}}}^k - J_{AEKs} F(J_{AEKs}, \lambda_{\mathrm{AEKs}})}{\lambda_{\mathrm{AEKs}}} \tag{4.22}$$

It was found using simulation that $ALSI_s$ values for both normal e-kanban and AEK are identical for the same level of starvation. So to evaluate $ALSI_s$ for certain I_s, the associated workstation starvation level for AEK is found, and then I_s is found for that starvation level if normal e-kanban is used. This new I_s can be represented as I_{as}. In other words, I_{as}, that makes J_s equals J_{AEKs}, is found.

$$I_{as} + 0.5B \; \frac{C}{(C + t_{ds})} = J_{AEKs} \tag{4.23}$$

$$I_{as} = J_{AEKs} - 0.5B\ \frac{C}{(C + t_{ds})} = I_s + 0.5B\ \frac{C}{(C + t_{AEKs})} - 0.5B\frac{C}{(C + t_{ds})} \tag{4.24}$$

$$I_{as} = I_s + 0.5BC\ \left(\frac{1}{C + t_{AEKs}} - \frac{1}{C + t_{ds}}\right) \tag{4.25}$$

I_{as} must be used in equation (4.6) instead of I_s. The average number of delayed signals (DS_s) to be fulfilled in the next route can be estimated by equation (4.26)

$$DS_s = \lambda_{\mathrm{AEKs}} - \lambda_{\mathrm{s}} \tag{4.26}$$

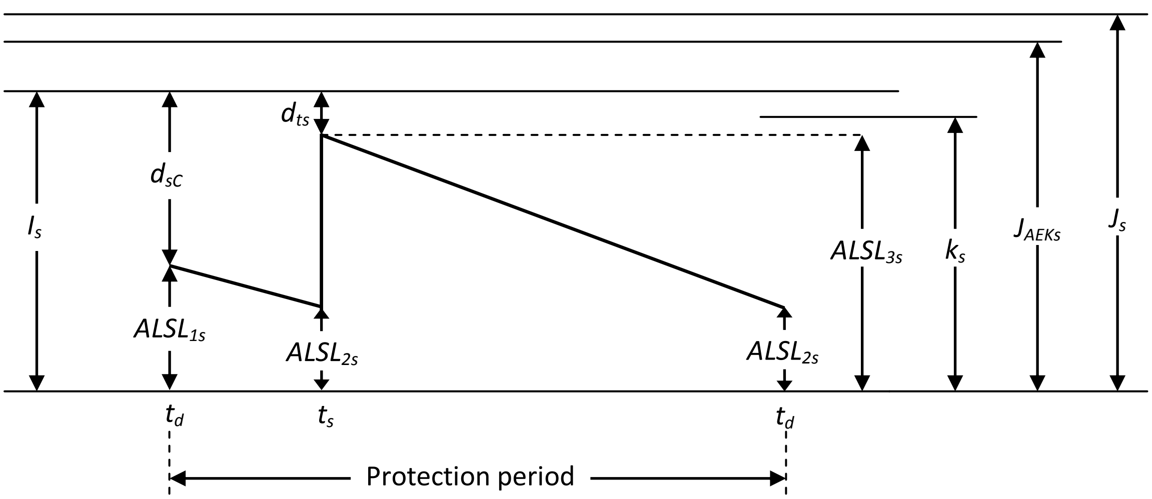


Figure 4.5 ALSI in AEK system

The advantage of using AEK will be more obvious when the capacity of the train is lower than the average parts demand. This can occur in the case of some disturbances such as material handler absence or tugger downtime. Assuming that the setting of AEK is set to have equal utilization probabilities among the stations, this utilization can be estimated using equation (4.27). U in the formula is the utilization level for each station in the cell.

$$U = \frac{KB}{NC\mu} \tag{4.27}$$

This can be done using time-based AEK with small deviation from the original one. Thus it is not necessary for the signal to be sent to the warehouse after the estimated time of parts consumption as explained before. Actually this time can be adjusted to get the equal utilization probabilities for all the stations. We call that *time-adjusted electronic kanban*. The circulating inventory levels can also be altered from those levels in the original AEK. In this study, times were adjusted using simulation. Future research can concentrate on how to exactly determine these times of the signals.

In traditional kanban and to estimate the workstation starvation and utilization in terms of number of kanbans, the same equations for normal e-kanban are used as before, but C is used instead of t_{ds}. So the value of J_s and λ_s are as in equations (4.28) and (4.29)

$$J_s = n_s + 0.25B \tag{4.28}$$

$$\lambda_s = \frac{2C}{TBAD_s} \tag{4.29}$$

It is obvious from the value of J_s in equation (4.28) that there is no effect of the distance between workstation and supermarket on the workstation starvation level. So, traditional kanban system is more stable in this case.

4.2.1 Routing in AEK system

A possible way for routing in the case of centralized warehouse system is to use the serpentine routes used in the study by Golz et al. (2012) (see figure 8.2a). As stated before, in centralized warehouse system one train can sometimes feeds several assembly lines in one trip. Because the assembly lines in one trip of the train are not necessary to be beside each other (according to serpentine routes method), it is possible to utilize the method introduced by Vaidyanathan et al. (1999) to solve the routing problem. However, Vaidyanathan et al. (1999) assumed constant demand rates. This is not a problem because AEK system guarantees good utilization levels even if the average cell cycle demand is up to the capacity of the train. So the calculations can be based on the average demand. However, the following changes are needed:

1. Each assembly line is treated as only one station where the total time consumed in loading and unloading of all the stations in the same assembly line besides the time needed to move from one station to another is assumed to be the loading and unloading time for this virtual station. This will make the problem small and can be easily solved even by the integer programming introduced by Vaidyanathan et al. (1999).
2. The average demand is expressed in parts unit.
3. All the different types of parts in the same assembly line are treated as one type.

4. On average, the results are optimal, but they are not optimal for every cycle because the demand changes from cycle to another.

4.3 Effect of adding a market attendant

The market attendant works in the supermarket area and is responsible for preparing the bins for the material handler. Using market attendant has some advantages but adds some extra workforce cost. The effect of market attendant is investigated for the two systems of kanban.

Effect in traditional kanban

If a market attendant is used, any collected kanbans by the train driver in a train cycle will be given to the market attendant when the driver comes to the warehouse. The driver then takes other bins in a new cycle. In the same time the market attendant will start preparing the associated bins for the received kanbans. These bins will wait until the next cycle when the train driver comes with new kanbans. In this case the protection period will be 3C instead of 2C. However C value can be decreased by t_{ul}, which is the normal loading and unloading time in the warehouse, because the train driver will find everything prepared for him, and can immediately starts his route. The only lost time for the driver in the supermarket area will be changing the trailers. If that time is negligible and the effect of increasing the workforce is ignored, using market attendant will be justified if $3(C- t_{ul}) < 2C$, where C is the train cycle time if there is no market attendants. So the condition $t_{ul}>C/3$ must be true. So the loading and unloading time in the supermarket area/warehouse must be more than one third of the cycle time to justify using the market attendant.

Effect in electronic kanban

In the case of using a market attendant, he can immediately start preparing the bins associated with the sent signals even before the train driver comes to the warehouse area. Therefore, unlike the previous case in which the protection period has been increased, the protection period here will be decreased to be $C-t_{ul} +t_{ds}$. Decreasing the protection period will decrease ALSI. So using the market attendant will be justified if the decrease in the costs of ALSI is higher than the cost of using the market attendant. So ALSI must be calculated for the two cases. This depends on how many stations are in the same cell and how far they are from the supermarket.

4.4 Factor affecting workstation starvation level

Using the previous formulas, figure 4.6 shows the effects of I_s, B, and t_{ds} on the resulting workstation starvation percentage in the case of normal e-kanban. As obvious, the higher the I_s or B values are, the lower the workstation starvation is. On the other hand, the higher the t_{ds} value, the higher the starvations value is, if I_s is kept in the same level. On the other hand, equation (4.6) indicates the opposite effect on $ALSI_s$. There is a positive linear relationship between I_s or B and the level of $ALSI_s$. Moreover, there is a negative relationship between t_{ds} and $ALSI$ because increasing t_{ds} increases d_{sC}. Furthermore, figure 4.6(d) shows the case when I_s value is changed to keep the same value for workstation starvation. In this case, I_s must be increased, and this will increase $ALSI_s$. This fact reveals the importance of not making the route too long to keep inventory holding cost under control.

4.4.1 Effect of train cycle time

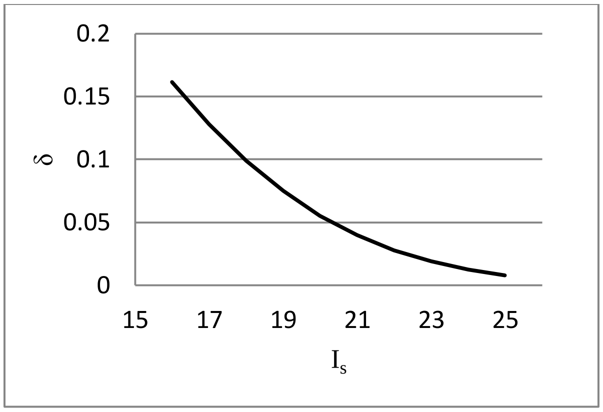
Assume that the loading and unloading time in the supermarket plus the time needed for coming back toward it from the last workstation is t_{lu}, and assume that t_{lus} represents the workstation loading and unloading time plus transportation time from workstation s-1 to workstation s. The total needed time for the cycle is:

$$C \geq t_{lu} + Nt_{lus} \tag{4.30}$$

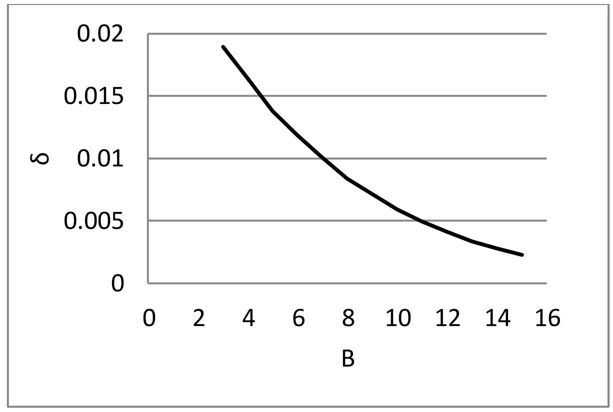
So the number of workstations in the same cell affects the cycle time of the train. Increasing the size of the cell increases the cycle time, and hence increases $ALSI_s$. Also, decreasing the size of the cell decreases the needed $ALSI_s$ but increases the needed number of trains. Assuming that the needed number of trains is the most important factor, the maximum number of workstations N^* in the cell can be estimated depending on the train capacity. The average cell cycle demand must not be higher than the capacity of the train. N can be determined as follows:

$$\frac{t_{lu} + Nt_{lus}}{\frac{\sum_{i=1}^{N} TBAD_i}{N}} \leq K \tag{4.31}$$

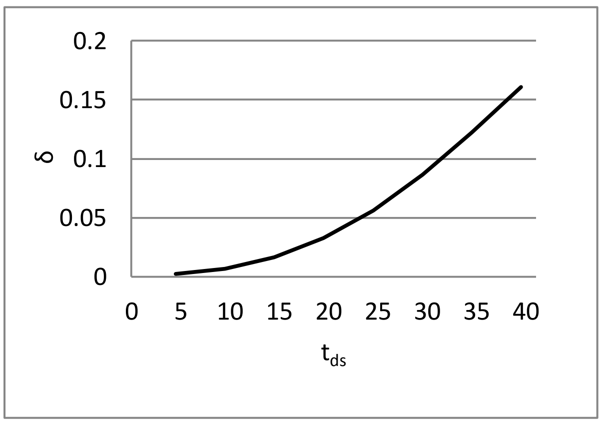
$$\frac{Nt_{lu} + N^2 t_{lus}}{\sum_{i=1}^{N} TBAD_i} \leq K \tag{4.32}$$



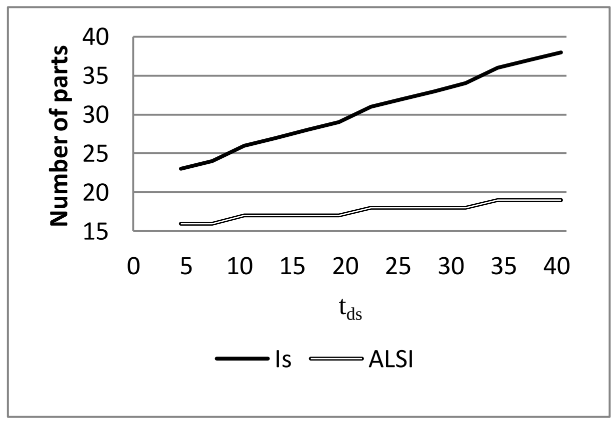
(a) Effect of I_s (t=13.5, B=3)



(b) Effect of B (t=13.5, I_s=23)



(c) Effect of t_{ds} (I_s=23, B=5)



(d) Changing of I_s and ALSI to get the same δ (I_s=23, B=5)

Figure 4.6 Factor affecting starvation percentage (C=45 min, TBAD=3 min)

$$t_{lus}N^2 + Nt_{lu} - K\sum_{i=1}^{N} TBAD_i \leq 0 \tag{4.33}$$

Assuming that TBAD is constant for all workstations, *N* can be found by the following formula

$$N \leq \left\lfloor \frac{K \cdot TBDA - t_{lu}}{t_{lus}} \right\rfloor \tag{4.34}$$

Minimum number of trains (*MNT*) can be determined using equation (4.35)

$$MNT = \left\lceil \frac{S^T}{N} \right\rceil \tag{4.35}$$

Where S^T is the total number of workstations in the facility and fed by tugger trains

4.5 Cost model

The total cost can be determined based on capacity needed, starvation costs, and inventory holding costs (Faccio et al. 2013a). Decreasing starvation level can increase ALSI. Starvation cost is related to lost sales and underutilization of resources. To estimate the total lost sales costs per day (*LSC*) for an assembly line, equation (4.36) is used.

$$LSC = \left(\prod_{i=1}^{S} \delta_i\right) \sum_{i=1}^{S} PP_i d_{iC}\, d^T \tag{4.36}$$

Where S is the total number of workstations in the same assembly line, d^T is the working time per day and PP_i is the price of the product i. Assuming that the demand rate is fixed during the day, the total costs (*TC*) can be estimated using the following equation.

$$TC = H \sum_{i=1}^{S} I_{ai} - d_{ti} + \frac{B - d_{iC} - 1}{2} + \left(\prod_{i=1}^{S} \delta_i\right) \sum_{i=1}^{S} PP_i d_{ic} d^T \; + C_k NT \tag{4.37}$$

Where C_k is the capacity cost for the train per day, NT is the number of trains, and H is inventory holding cost per day. This inventory holding cost is multiplied by ALSI. The average value of d_{ti} depends on the number of workstations in the cell. The larger the cell (the lower the number of trains) is, the higher the average value of d_{ti} is. So as found in figure 4.6(d), the average value of $ALSI_s$ depends on the number of trains, where the higher the number of trains is, the lower the value of $ALSI_s$ is. So the tradeoff here is to choose either to decrease the number of trains or to decrease $ALSI_s$. A possible way to find the optimal total costs in this complicated problem is by choosing the objective of reducing the number of trains to the minimum possible number, and by setting the workstation starvation to a certain level. Based on that, $ALSI_s$ size is determined. So in this case the final total cost can be easily found.

4.6 Simulation and results

Using AEK makes the starvation probability a little bit higher than the normal situation if there is unlimited train capacity. The main question is: how much is this starvation probability? The answer is obtained using simulation which was performed using Promodel Software. Besides that, the effect of the factors such as B and t_{ds} were investigated by the simulation model. At first we check using simulation the performance of time-based AEK system in the case that the K value is equal to or higher than the average demand but lower than the maximum demand, and compare it to the normal electronic kanban in its ideal situation (unlimited train capacity and using part-based electronic kanban). Then we compare these two systems to traditional kanban assuming unlimited train capacities. The two cases are investigated for a starvation level of 3 ± 0.5 %. To get this level of utilization, several trials with different circulating inventory levels were tried until the appropriate one was found. As stated before, this circulating inventory can be controlled by the starting inventory. Simulation was done for the following scenarios:

- $TBAD_S$: Exp(1) min, Exp (3) min, Exp (7.5) min
- B: 0.25, 0.5, 0.75 of cycle average demand
- C: 30 min, 45 min, 60 min

So, there are 27 different scenarios.

Table 4.1 Simulation scenarios

#	*C*	$TBAD_s$	*B*	t_{ds}	*K*
1	30	1	8	3, 9, 15, 21, 27	19
2	30	1	15	3, 9, 15, 21, 27	10
3	30	1	23	3, 9, 15, 21, 27	7
4	45	1	11	4.5, 13.5, 22.5, 31.5, 40.5	21
5	45	1	23	4.5, 13.5, 22.5, 31.5, 40.5	10
6	45	1	34	4.5, 13.5, 22.5, 31.5, 40.5	7
7	60	1	15	6, 18, 30, 42, 54	20
8	60	1	30	6, 18, 30, 42, 54	10
9	60	1	45	6, 18, 30, 42, 54	7
10	30	3	3	3, 9, 15, 21, 27	17
11	30	3	5	3, 9, 15, 21, 27	10
12	30	3	8	3, 9, 15, 21, 27	7
13	45	3	4	4.5, 13.5, 22.5, 31.5, 40.5	19
14	45	3	8	4.5, 13.5, 22.5, 31.5, 40.5	10
15	45	3	11	4.5, 13.5, 22.5, 31.5, 40.5	7
16	60	3	5	6, 18, 30, 42, 54	20
17	60	3	10	6, 18, 30, 42, 54	10
18	60	3	15	6, 18, 30, 42, 54	7
19	30	7.5	1	3, 9, 15, 21, 27	20
20	30	7.5	2	3, 9, 15, 21, 27	10
21	30	7.5	3	3, 9, 15, 21, 27	7
22	45	7.5	2	4.5, 13.5, 22.5, 31.5, 40.5	15
23	45	7.5	3	4.5, 13.5, 22.5, 31.5, 40.5	10
24	45	7.5	5	4.5, 13.5, 22.5, 31.5, 40.5	6
25	60	7.5	2	6, 18, 30, 42, 54	20
26	60	7.5	4	3, 9, 15, 21, 27	10
27	60	7.5	6	3, 9, 15, 21, 27	7

The number of trials for each scenario was 20 and the simulation time was 40 hours. The average values were obtained. The cycle time was divided by 5 and the stations were assumed to be in the middle of these five periods. For example, if the cycle time is 60 min, the five stations will have t_{d1}=6, t_{d2}=18, t_{d3}=30, t_{d4}=42, t_{d5}=54 minutes. K value for each one of the 27 scenarios was chosen to be equal to the average demand of the train rounded to the upper integer number. Table 4.1 shows these scenarios. Besides these 27 scenarios, other scenarios were performed assuming that the initial inventory can only be full bins. Results showed that, in full bin scenarios, MLSI is about 20.4% higher than that for normal scenarios in the case of using electronic kanban. Figure 4.7 shows the MLSI divided by the average station cycle demand for the first 15 scenarios for the three systems, namely, traditional kanban, e-kanban, AEK. Similar behavior was found for the rest of the scenarios. The results in the figure are for the first station in the route. The average station cycle demand is calculated by dividing C by $TBAD_s$. Figure 4.7 shows that there is a large difference between the y-axis value for traditional kanban and the *y*-axis values for the other two kanban types. The difference between e-kanban and AEK is very small. This small difference shows that even if in AEK the train capacity is taken into consideration while it is not considered in e-kanban, the difference in the y-axis values is very small. This is important to show the performance of AEK and its ability to accommodate the condition of dynamic demand and limited resources.

The big difference between traditional kanban and the other two kanban types is because the t_{ds} value for the first station is low which means that the distance between the supermarket area and the first station is short. To show the effect of this distance on the difference between traditional kanban and AEK kanban, figure 4.8 shows the ratio of MLSI for AEK divided by MLSI for traditional kanban. The figure shows the result for the first and fifth stations. The fifth station is far away from the supermarket area while the first station is very close to it. Figure 4.8 shows that the ratio is very close to 1 for the fifth station which means that traditional kanban and AEK are almost identical for stations that are in the last part of the train route. The same behavior occurs for the rest of scenarios and also if the ratio is found by dividing the MLSI for e-kanban and MLSI for traditional kanban. The other general results of simulation are explained in the following paragraphs.

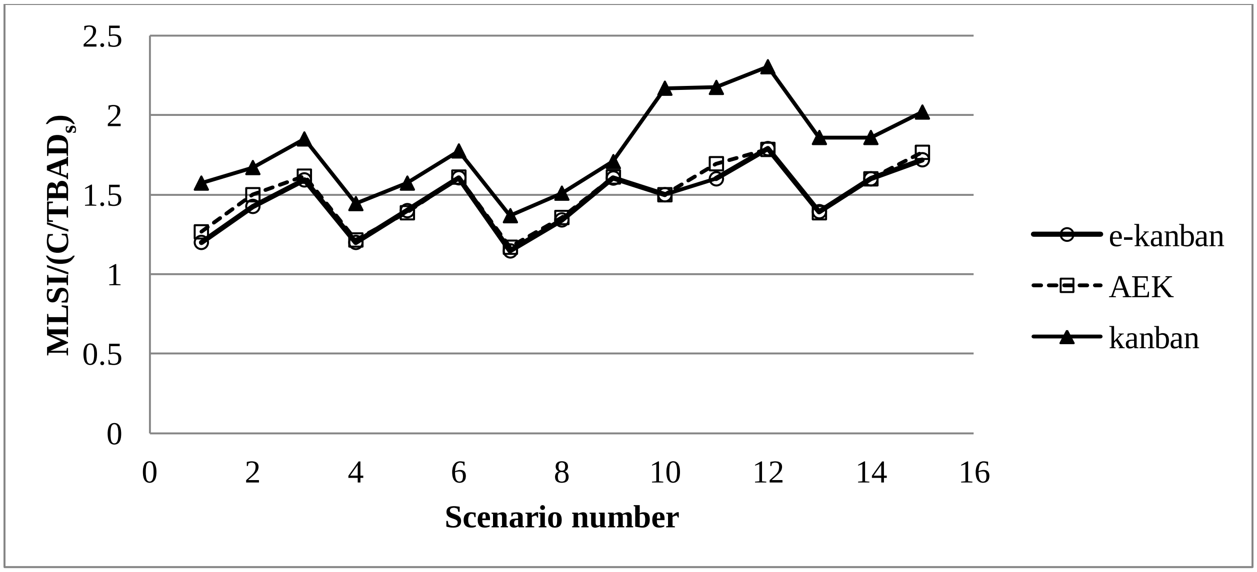


Figure 4.7 Performances of the three kanban systems for the first station in the route

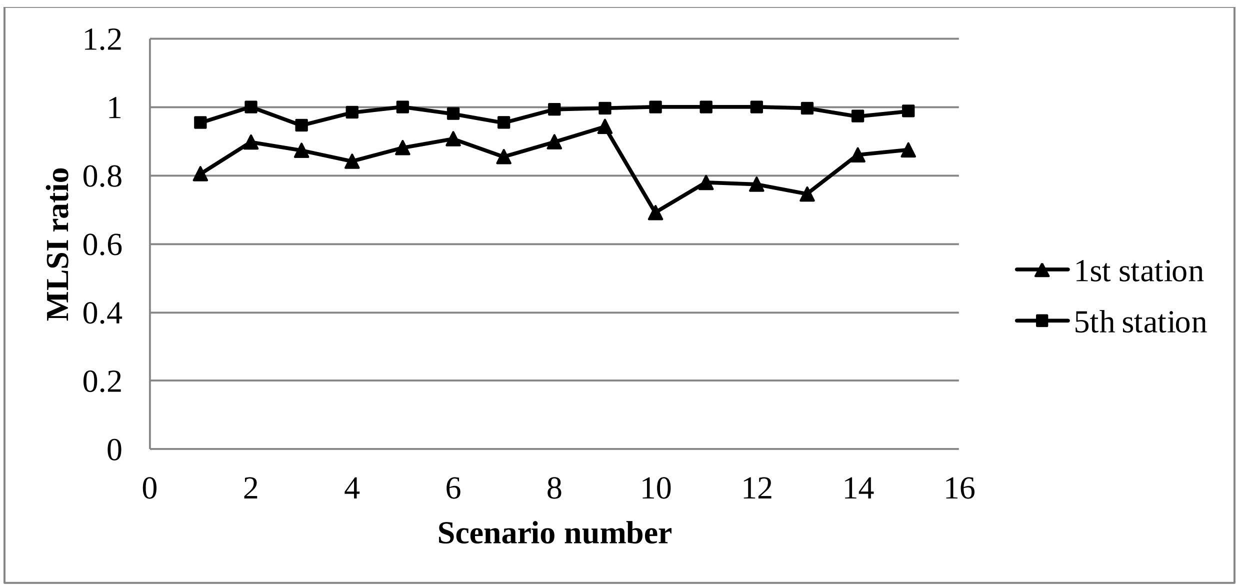


Figure 4.8 ALSI ratios for AEK and traditional kanban for the first and the fifth stations.

Results showed that the increases in MLSI (in parts unit) because of considering the limited capacity of the train using AEK were from 0 to 2.86%. This shows that if K is greater than or equal to average demand but lower than maximum demand, it cannot make any severe problem in the increase of MLSI if AEK is used. Results for normal electronic kanban also showed that the average increases in MLSI from station 1 to 2, to 3, to 4, and to 5 were 6.2%, 4.7%, 2.6%, and 3.1% respectively because of the increases in t_{ds} values. For AEK, these percentages were

5.5%, 4.1%, 2.9%, and 2.6%. This shows that the longer the distance from the warehouse is, the higher the MLSI is. This means that in the case of using electronic kanban, the stations with small space for line-side inventory should be at the beginning of the route. On the other hand, traditional kanban has stable performance, and the differences among stations are just because of the randomness effect. Generally, the performance of AEK was found to be better than traditional kanban even if we assume unlimited train capacity in traditional kanban and limited capacity in AEK and even if we assume using parts plus full bins in initial inventory for the two systems. Results showed that, on average, the increases in MLSI from using AEK to traditional kanban for the same station are 22.2%, 13.3%, 7%, 2.8%, and 0 for stations 1, 2, 3, 4, and 5 respectively. In the case of unlimited capacity in electronic kanban these percentages are 29.8%, 19.3%, 11.2%, 7%, and 2.5%.

The effect of increasing the bin capacity was obvious in the results. On average, increasing bin capacity from 0.25 to 0.5 of the average cycle demand increased MLSI by 11.1% for normal electronic kanban and by 9.2% for AEK. Increasing the bin capacity from 0.5 to 0.75 of the demand increased MLSI by 9.2% for electronic kanban and 8.5 % for AEK. This shows that decreasing bin capacity is advantageous regarding inventory level. Another way to check the effect of using AEK under condition in which K is less than the maximum demand and greater than or equal to average demand during the cycle is by trying to keep the initial inventory levels as in normal electronic kanban, and then measure the increase in workstation starvation. The average values for each scenario were computed. The minimum one was 0.36% and the maximum one was 1.4 %. For individual stations, the increases were from 0 to 3.15%. So the effect is very small. This is because any shortage in a station inventory will most probably be compensated in the next route where the stations with the unsatisfied demand have the priority to be satisfied in that next route.

In the case that K is less than the average demand of the stations, traditional kanban performance is deteriorated. The utilization levels of the stations were found in the case in which C=60, $TBAD_s$=3, B=15, and K=6 (less than the average cell cycle demand which is 6.67 bins) 96.00%, 95.62%, 94.47%, 83.63%, and 77.68% for the stations from 1 to 5 respectively. It will be better if these stations have the same average utilization. In the previous example, utilization levels for the five stations in time-adjusted electronic kanban were around 90% for all the stations which is the same result found from equation (4.27). Theoretically, traditional kanban may achieve the same results if we use parts plus full bins in initial inventory and if we set initial inventory levels to the right values, but this is not easy in the practice because in this case kanban must be put in kanban post when a certain part in the bin is consumed.

4.7 Summary

This chapter analyzes the system of in-plant milk run in which traditional kanban or e-kanban is used. $ALSI_s$ for each of the two systems is found. The starvation percentages are found based on the number of kanbans in the traditional kanban system and the circulating inventory in e-kanban system. Also a new system, namely, AEK is introduced. It is analyzed to find the workstation starvation and $ALSI_s$. The effects of the factors I_s, B, and t_{ds} are explained based on the resulting formulas. It is found that increasing I_s and B increases $ALSI_s$ and decreases the workstations starvation. The opposite effect is for increasing t_{ds}. The impact of t_{ds} is also analyzed by finding the associated $ALSI_s$ in the case of keeping the workstation starvation constant. It is found that to keep the starvation level constant, $ALSI_s$ must be increased in the case of increasing t_{ds}. This means that increasing the size of the cell increases $ALSI_s$ but decreases the number of trains. The tradeoff is studied in the cost model which contains starvation cost, inventory holding costs, and the capacity cost. It was found using simulation that the effect of limited train capacity on increasing workstation starvation is heavily moderated if AEK is used. Future research can investigate the effect of variable cycle time in traditional kanban system.

Chapter 5: Supermarket location problem

This chapter investigates the location problem of supermarkets feeding by material the mixed model assembly lines using tow trains. It determines the number and the locations of these supermarkets to minimize transportation and inventory fixed costs of the system. This is done using integer programming model and real genetic algorithm (RGA) in which custom chromosomes representation, two custom mating, and two custom mutation operators were proposed. The performance of RGA is very good since it gives results that are very close or identical to the optimal ones in reasonable CPU time. For the first time in supermarket location problem, limitation on availability of some areas for possible supermarkets locations and capacity of the supermarkets were taken into consideration. The contents of this chapter have been partially published in Alnahhal and Noche (2015b).

5.1 Integer programming model

IP model is introduced to compare its optimal results to RGA results later. The total costs of the system containing the costs of the weighted distances traveled by the trains plus the installation costs of the supermarkets should be minimized (Emde and Boysen 2012c). The weighted distances costs were obtained by multiplying the total distance traveled for cell supplied by the same supermarket, by the total demand of this cell. The distance is measured based on the center of the supermarket or the stations. The cell in this chapter means the group of stations that are supplied by one supermarket. This cell can contain a number of other smaller cells where each one of them is supplied by the train in one train route. These smaller cells are referred to in the other chapters.

Some notations were used before but they will be repeated here again. The following notations are used:

N	Total number of stations in the assembly line
n	The optimal number of supermarkets
θ	Fixed cost per supermarket
d_s	Demand (expected number of bins) at station s per shift
a_s	x-Coordinate of station s

b_s	*y*-Coordinate of station s
M	Total number of possible supermarkets locations
a_k	*x*-Coordinate of possible supermarket k
b_k	*y*-Coordinate of possible supermarket k
x_{ijk}	$= \begin{cases} 1, \text{if all stations from station } i \text{ to station } j \text{ are fed by the supermarket } k \\ 0, \ otherwise \end{cases}$
$Tdem_{ij}$	Total demand of all the stations from station i to station j
$dist_{kij}$	The total distance traveled by the train from supermarket k to supply all the stations from station i to station j
$wdis_{kij}$	total weighted distance, $wdis_{kij} = Tdem_{ij} \times dist_{kij}$
ϖ	Unit cost of moving one bin one unit distance
Dst_{ij}	the total standard deviation of the demand of materials and parts for all the stations from i to station j
$CAPACITY_K$	Capacity of supermarket k (number of bins)
Z	Service level for probability of not exceeding the capacity of the supermarket

The problem can be defined as follows

Objective Function:

$$min \sum_{k=1}^{M} \sum_{i=1}^{N} \sum_{j=i}^{N} \varpi wdis_{kij}\, x_{kij} + n\theta \tag{5.1}$$

Constrains:

$$\sum_{k=1}^{M} \sum_{i=1}^{N} \sum_{j=i}^{N} x_{kij} = n \tag{5.2}$$

$$\sum_{k=1}^{M} \sum_{i=1}^{b} x_{kib} = \sum_{k=1}^{M} \sum_{j=b+1}^{N} x_{k(b+1)j} \qquad \forall b = 1, \dots, N-1 \tag{5.3}$$

$$\sum_{i=1}^{N} \sum_{j=i}^{N} x_{kij} \leq 1 \qquad k = 1, \dots, M \tag{5.4}$$

$$n \geq 1 \ and \ integer \tag{5.5}$$

$$(dem_{ij} + ZDst_{ij}) \times x_{kij} \leq CAPACITY_k \qquad \forall \text{ k} = 1, \dots, M, \ \ i = 1, \dots, N, j = i, \dots, N \tag{5.6}$$

$$x_{kij} = 0 \ or \ 1, \qquad \forall i = 1, \dots N, j = i, \dots, N \ , k = 1, \dots, M \tag{5.7}$$

Where

$$dist_{kij} = \left(\left|b_j - b_i\right| + \left|a_j - a_i\right|\right) + \left(\left|b_k - b_i\right| + \left|a_k - a_i\right|\right) + \left(\left|b_k - b_j\right| + \left|a_k - a_j\right|\right) \qquad (5.8)$$

The parameter 'θ' is the cost of introducing a new supermarket such as area costs, maintenance costs, etc. These costs can be estimated by the decision maker based on his experience. The distance in equation (5.8) considers the first and the last stations without considering the others between them, because when the train moves from the first one to the last one it passes beside the other stations since all the stations belong to the same assembly line.

The objective function (5.1) minimizes the costs of the total weighted distance plus the fixed costs of the supermarkets. Constraint (5.2) guarantees that the number of cells is equal to the number of supermarkets. Constraint (5.3) guarantees that all the cells are supplied by supermarkets. To illustrate the idea of constraint (5.3), table 5.1 is used.

Table 5.1 Example containing five stations

From station	To station				
	1	2	3	4	5
1	$\sum_{k=1}^{M} x_{k11}$	$\sum_{k=1}^{M} x_{k12}$	$\sum_{k=1}^{M} x_{k13}$	$\sum_{k=1}^{M} x_{k14}$	$\sum_{k=1}^{M} x_{k15}$
2		$\sum_{k=1}^{M} x_{k22}$	$\sum_{k=1}^{M} x_{k23}$	$\sum_{k=1}^{M} x_{k24}$	$\sum_{k=1}^{M} x_{k25}$
3			$\sum_{k=1}^{M} x_{k33}$	$\sum_{k=1}^{M} x_{k34}$	$\sum_{k=1}^{M} x_{k35}$
4				$\sum_{k=1}^{M} x_{k44}$	$\sum_{k=1}^{M} x_{k45}$
5					$\sum_{k=1}^{M} x_{k55}$

Suppose that the solution contains $\sum_{k=1}^{M} x_{k13} = 1$, which means that there is a supermarket 'k' that supplies the first three stations together. We need now a constraint that insures that station 4 is supplied by another different supermarket which can supply only station 4 or the two stations 4 and 5 together. So, if $\sum_{k=1}^{M} x_{k13} = 1$, then $\sum_{k=1}^{M} x_{k44} + \sum_{k=1}^{M} x_{k45}$ must equal 1. This is the case also if $\sum_{k=1}^{M} x_{k23}$ or $\sum_{k=1}^{M} x_{k33}$ equals 1. Note that $\sum_{k=1}^{M} x_{k13}$, $\sum_{k=1}^{M} x_{k23}$, and $\sum_{k=1}^{M} x_{k33}$ are in the same column in the table which is the third one. Moreover, note that $\sum_{k=1}^{M} x_{k44}$ and $\sum_{k=1}^{M} x_{k45}$ are in the same row in the table which is the forth one. In other words, the total summation of the $\sum_{k=1}^{M} x_{ki3}$ terms in the third column must equal the total summation of the $\sum_{k=1}^{M} x_{k4j}$ terms in the fourth row. This must be done for all the columns and the rows.

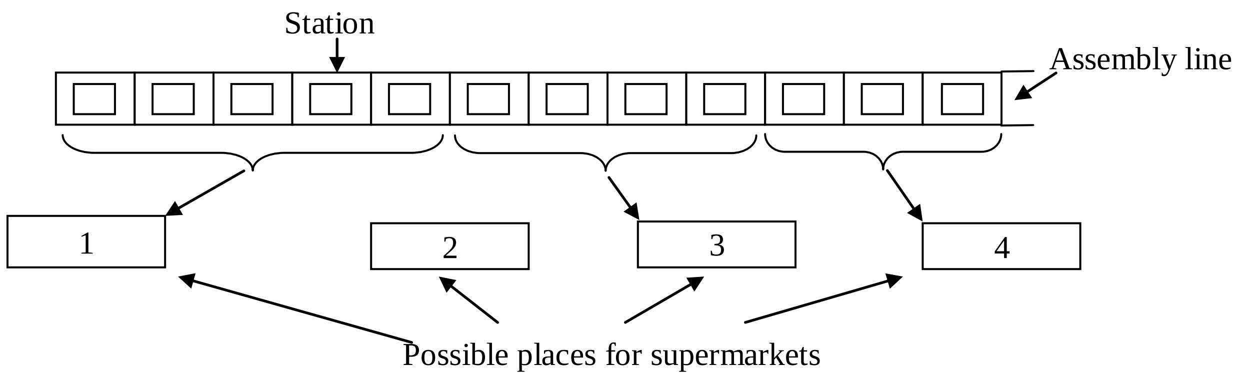
Constraint (5.4) guarantees that each station is fed by only one supermarket. Without constrain (5.5) all the variables will equal zero because of the minimization in the objective function. Constraint (5.6) guarantees that the capacity of the supermarket is sufficient not just for the average demand but also for the upper limit of it, because demand is changing from time to time. Constraint (5.7) defines the non-negativity constraints and the binary variables. It's known that IP is NP-hard (**N**on-deterministic **P**olynomial-time hard). That means that it needs a lot of CPU time to be solved on computers. So the previous model is effective to be solved only for small instances. For large instances, we need intelligent methods such as RGA to solve such a problem.

5.2 Using RGA.

Generally, genetic algorithm is used as a search technique for complicated or large problems. There are some initial randomly generated solutions for a population to start with. Each solution can be considered as a member in the population. The characteristics of this member are defined using genes where each gene represents a decision variable used in the objective function. Each member can be represented as a chromosome containing all these genes. From the initial population some members are chosen based on their object function (cost value) to survive. Other members are considered weak and are omitted. The surviving members are considered parents. The marriage (mating) between these members is done to create new members to be offspring to compensate the non-surviving ones. The children can carry some of good genes that help to enhance the cost function of them. This generation can be subject to some minor changes by mutation that might enhance the cost function for the altered members. The surviving parents together with their children form a new generation for which new selection process is done to determine the surviving members. After that, mating and mutation are done. Several generations are created until one or some of certain criteria occur. These criteria may contain the quality of solution, number of generation, or CPU time. The quality of solution is the difference between the cost function and a certain predetermined value. Genetic algorithm is flexible and easy to conduct but it is a little bit slow. Several new methods were derived from the original one. There are a lot of chromosomes representation selection, mating, and mutation methods that can be used. For more details about these methods, the reader may refer to Haupt and Haupt (2004).

The traditional way of chromosomes representation in genetic algorithm is using 0 and 1 in binary genetic algorithm. Due to the specific nature of the supermarket location problem, continuous (real) genetic algorithm is used. The name “continuous” or “real” is usually used in the literature to indicate these types of problems. Instead of 0 and 1, integer numbers are used to represent the chromosomes. The reason for selecting this method will be explained later. Figure 5.1 shows two ways of chromosomes representations. The first one shown at the lower part of the figure is the traditional way which is called Prüfer number representation (Reijmers et al. 1999). It is used in the literature to represent the allocation of different warehouses to different facilities. Note that the second supermarket isn’t considered in the assumed solution. There is a rectangle associated to each station. Each supermarket has a number, and the stations fed by a certain supermarket are identified by this supermarket’s number which is put in the associated rectangles. In its general form, there is no restriction about the sorting of the numbers. However, in the particular problem in this chapter, if Prüfer number is to be used, numbers must be sorted in the same direction (ascending or descending order). This is because it is assumed that if a train feeds stations i and i+2, it must also feeds station i+1. This assumption is important to guarantee that there is no overlap between different train routes. Any overlap may result in traffic jam.

The way of chromosomes representation in this study depends on the boundary of the cells (the most right station). So the first cell is from station 1 to 5; the second cell is from station 6 to 9, and the third one is from station 10 to 12. Each number here represents a gene. In RGA, the words ‘gene’, ‘supermarket’, and ‘cell boundary’ will be used interchangeably in this study. This way doesn’t give any information about the supermarkets index numbers feeding the cells. In figure 1, the total number of available supermarket locations is 4. However, only 3 of them are used. The best allocation (with the least cost function value) of the supermarkets to different cells is computed for each chromosome as will be explained later. So RGA here searches only for the cell boundaries, and this decreases the search region. Another advantage is that the array size of this representation is smaller than Prüfer number representation. As obvious, the number of genes is a decision variable. This is why RGA is used instead of binary genetic algorithm to give the needed flexibility to make number of genes a decision variable. Another reason is that the genes values are sorted in ascending order.



5	9	12	

Chromosomes representation in the study

1	1	1	1	1	3	3	3	3	4	4	4

Chromosomes representation using Prüfer number

Figure 5.1 Chromosomes representation

The initial population was randomly generated considering all the possible numbers of genes in different members. As stated before, the number of genes, in the problem in this study, is variable. In RGA, there are several generations until finding the best solution. In every generation, some of the members are replaced by new offspring obtained by mating the surviving chromosomes. It’s important that the number of surviving chromosomes isn’t too low to keep the possibility to maintain a diversity of number of genes. The selection method was *roulette wheel weighting* in which the chromosome with the lowest cost has the greatest probability of mating. In this selection method, there are *rank weighting* and *cost weighting* methods. In cost weighting, the probability of chromosome selection is calculated based on the cost of chromosome rather than its rank in the population. Rank weighting which is used in this study finds the probability of selection of a chromosome based on the rank of the chromosome in the chromosomes matrix (Haupt and Haupt 2004). The chromosomes with the lowest cost are ranked first in the matrix. So rank weighting is easier than cost weighting and needs fewer calculations. It is obvious that the two methods take into consideration the value of cost function.

5.2.1 Mating

Usually mating is between two parents that have the same number of genes. However, in this study, mating happens between members with different number of genes. Two types of mating, namely, *α-mating and β-mating* were invented. Usually there is a crossover point after which the genes of the two chromosomes are exchanged. In this research, this isn't the case. In the first mating type (*α-mating*), the crossover point is not the same for the two parents. So there is a different crossover point for each one of them. For mating to be successful, two conditions must hold. To explain that, figure 5.2 shows two parents where one of them has 10 supermarkets and the other one has nine supermarkets. The figure also shows three crossover points combinations. Mating A doesn't work because the cell ending by station 27 cannot be after the cell ending by the station 30. Mating B and C work but each one gives different number of genes. Mating B gives offspring with 10 and 9 supermarkets, while Mating C gives offspring with 8 and 11 supermarkets. Therefore the mating of two parents with certain number of supermarkets results in different combinations of number of supermarkets for their offspring. This is important to make sure that all the possibilities of number of supermarkets are considered. Another condition for successful mating is prohibiting the possibility to have offspring with number of supermarkets that is more than the maximum available one. At first, a random column for one of the parents is chosen, and then to enhance the probability to have a successful mating all the possible crossover points for the second parent is tried starting from the last cell until the two conditions previously mentioned are met.

For the previous successful mating, if the two new children are with the same number of supermarkets, then there is *β-mating* in which one of the children is randomly selected and altered where every gene in it can be found using equation (5.9)

$$\text{New gene}_{\text{newoffspring}} = \rho\ \text{gene}_{\text{offspring 1}} + (1-\rho)\ \text{gene}_{\text{offspring 2}} \tag{5.9}$$

Where ρ is a random number between 0 and 1. There were several tries to make successful mating reach 100%. Care was taken not to make new calculations for already altered chromosomes. This is done by memorizing the already altered chromosomes in a matrix. Figure 5.3 shows a pseudo code for the logic of mating process. The two parents, M (mother) and F (father), are selected using the selection method 'roulette wheel weighting' previously mentioned. Then different two crossover points are checked. If the two conditions of successful mating exist, then mating is done. If not, different crossover points are tried until successful mating is achieved. A and B represent the right boundary of a cell in F and M respectively. To check the second condition of α-mating, the term (number of genes of M -*B*) is used to estimate the number of genes that are to be taken from M and attached to the selected segment of F. These genes are on the right hand side of B. The selected segment of F is the genes containing A and genes to the left hand side of it. The same logic holds for the term (number of genes of F -*A*).

After *α*- mating is performed successfully, if the sizes of the two offspring are the same, then *β*-mating is performed.

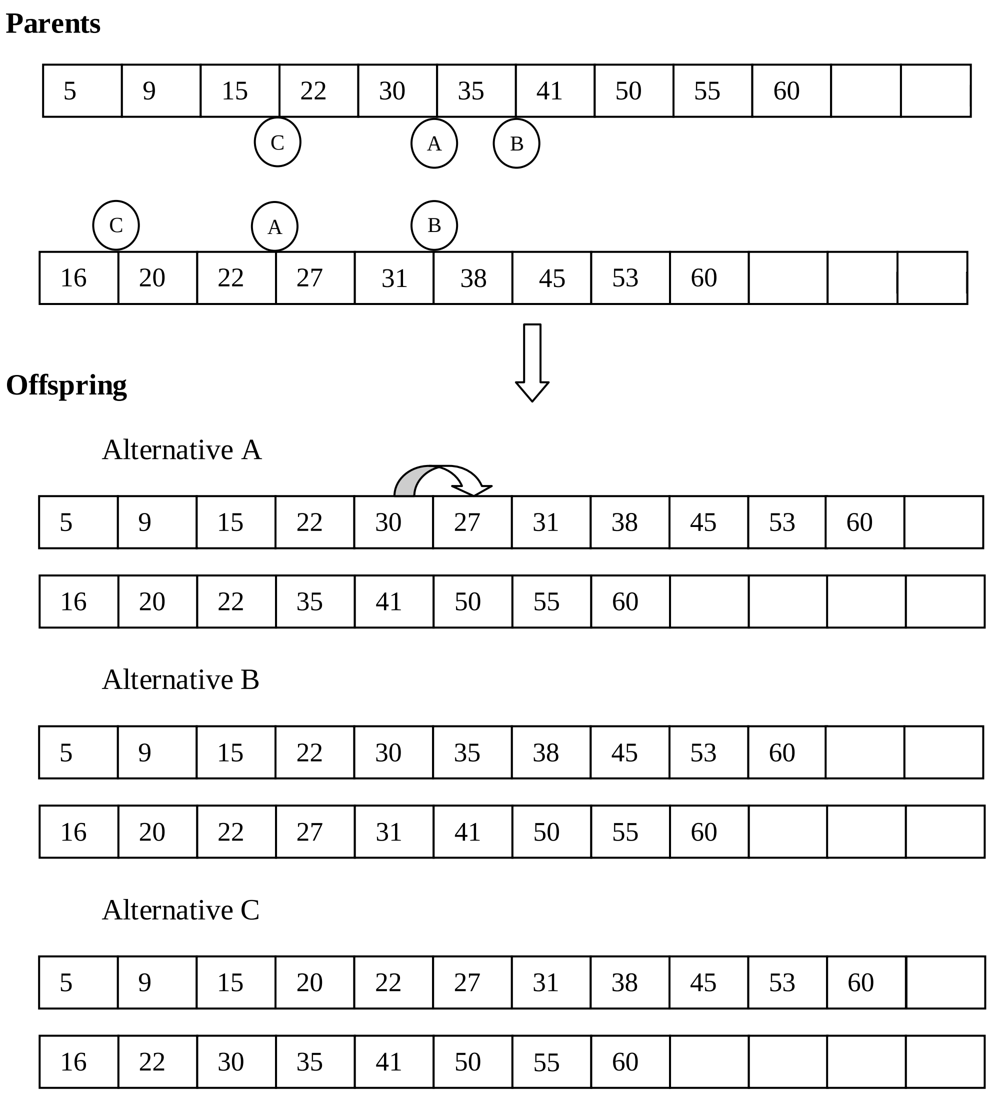


Figure 5.2 α-mating alternatives

α- mating:

Select two candidate chromosomes F and M to be the parents for each two new ones in offspring.

Randomly choose two gene numbers *A* and *B* (*A* for F, and *B* for M) representing crossover points

If *A*+1> B **& if** *B*+1>*A* **& if** *A*+ (number of genes of M -*B*) <= maximum number of supermarkets (*MNS*) & **if** *B* + (number of genes of F -*A*) <= *MNS*

Then

Make α- mating

Else

Choose another *B* and repeat until finding a successful mating

β- mating:

If number of genes for the two new chromosomes are the same **then**

Make β-mating

Figure 5.3 Pseudo code for mating

5.2.2 Mutation

It's very important that the mutation rate not to be too low to keep the chance to get chromosomes with different number of genes. The first (best) chromosome was set to be *elite* (it has no mutation). There is no need to change the best chromosome. Two custom types of mutations were invented in this study. They are *bounded mutation*, and *sensitivity mutation*. In the first one, the randomly selected cell boundary is randomly changed without exceeding the near boundaries on the two sides. For example, in figure 5.4, the second gene can be altered to be any value from 6 to 14, where the two sides are 5 and 15. It was noted that usually the changes to the best solutions are done through not changing just one gene but changing several adjacent genes. So it is possible to change one, two, three, or four adjacent genes together. After every change in a gene, a 90% possibility, that an adjacent gene will be altered, has been chosen. So the probability to have two, three, and four adjacent altered genes are 0.9, 0.81, and 0.729 respectively. This is without breaking the constraint about the number of possible supermarkets.

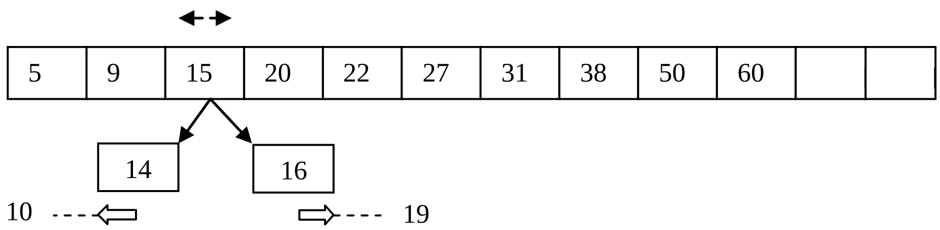


Figure 5.4 Sensitivity mutation

In the second type of mutation, the best (five) chromosomes are mutated. It's important that the number of mutated chromosomes isn't so high to save CPU time. To give more chance for chromosomes with different number of genes, only two chromosomes at most with the same number of genes can be mutated. But it was found that, at the first few generations, the number of genes in different chromosomes is diversified a lot. So, in this case, for any certain chromosome size (number of genes), at most one chromosome is mutated. It was found that most of the time, in any generation except the first few ones, the optimal number of genes is the number of genes for the best (first) chromosome plus or minus one. So, only the chromosomes with such numbers of genes are mutated using *sensitivity mutation*. This type of mutation is very important since it gives the different chromosomes with different number of genes the chance to be selected in the next generation. In this type of mutation, each gene is considered to be changed as follows:

1. At first, one step to the right (gene value is increased by one) and another one to the left (gene value is decreased by one) are made. The direction in which the cost function is improved is considered. If the improvement is in the two directions, both are considered. For example, in figure 5.4 for the third cell, the values 16 and 14 are investigated where the cost function is tested. If the improvement is for 16 for example, this direction will be considered.
2. After that, one more step (17 in the example) is considered.
3. If there is enhancement in the value of cost function, a new step (18 in the example) is considered.
4. However, if the cost function is worse, only one more step is considered, and if the new step isn't better, then stop.
5. If the new step is better, we give the direction a second chance and continue until two successive steps are worse than the one before or until we face the next boundary (20 in the example).

6. Steps, from 1-5, are repeated for all the boundaries (genes).
7. All the previous steps are repeated one more time. But to save time we check if the already obtained results occurred before. If yes, there is no need for repeating the previous steps.

This mutation type takes most of CPU time. So sensitivity mutation isn't done for chromosomes that are identical to already mutated chromosomes.

5.2.3 Cost function

In the calculation of the cost function value, the empty cell boundaries are ignored. These empty genes occur at the right hand side of the chromosomes that are with size less than *MNS*. In the case of breaking the capacity constraint (5.6) we set the cost function value to infinity. The chromosomes do not contain any information about which supermarkets will feed each cell. So for each chromosome for each generation, the best assignment of the supermarkets to the cells is computed as follows:

1. The weighted distances, $wdis_{kij}$, are computed for each combination of the supermarkets and the cell boundaries. This is done just once and memorized.
2. For each chromosome in each generation, a smaller weighted distances matrix (WDM) is formed containing only the cells in the chromosome. This matrix contains the transportation costs if each supermarket is allocated to each cell found in the chromosome.
3. Then the smallest value in WDM is found.
4. Then the column and the row containing this minimum value are set to be very large numbers to prohibit that a cell is fed by more than one supermarket, and to prohibit that one supermarket feeds more than one cell.
5. Go to step 3, and repeat the cycle until the best values are found for all cells.
6. Add the summation for the best values to ɵ value multiplied by the number of cells to get the fixed costs.

Four strategies are performed to keep the chance for moving from the nonoptimal-number of genes chromosomes to the optimal ones:

1. The initial populations must contain chromosomes with almost all the possible sizes (number of genes).

2. Different crossover points locations in *α-mating*.
3. The selection rate for mating (50%) and the mutation rate (20%) aren't too low
4. *Sensitivity mutation* considers chromosomes with different number of genes

The selection rate is the percentage of surviving members in each generation. The mutation rate is the number of altered genes divided by the total number of genes in the population.

5.3 Results and analysis

Table 5.2 shows the results of using RGA to solve the problem. The results analyze the performance of the proposed method using randomly generated instances. To generate data randomly, the demand values were obtained using uniform distribution U (1, 10), where 1 is the minimum value and 10 is the maximum one. The difference between a_s value for a station and the next one is obtained using U (3, 6) distribution. For simplicity, b_s and b_k values were set to be 1 and 5 respectively for all the stations and supermarkets. The available locations of supermarkets were randomly set in the range of the locations of stations, where the locations numbering was set in ascending order from the beginning to the end of the assembly line.

It's important to set an appropriate value for M because if it's too large, then the result of the model in the study and the model defined by Emde and Boysen (2012c) will be the same where almost all the locations are available. To do so, at first the data related to supermarkets availability is ignored and the problem is solved by the dynamic programming defined by Emde and Boysen (2012c). Then the optimal number of supermarkets is increased by 3 to get M, except for the case of N =20 where 2 or 1.5 is increased. The results in the table represent the optimal solution when the number of stations is 20, 40, and 60 where a comparison is made between the results of RGA and the results of IP. For the large data sets (N= 100, 150 and 200), the best known solution is used. This solution is obtained by running the RGA 10 times with 1000 generations for each one. The best result in all these runs is the best solution. For every row in the table, four different data sets were randomly generated. For each one of them RGA was run 5 times. So there are 20 trials for each row. So there are 480 trials. The column 'MS' contains non-integer values because it is the average of the optimal number of supermarkets since there are 4 different samples for each row. The sixth and seventh columns represent the average number of generations (ANG) and average CPU time, needed to reach the optimal/best known solution, respectively. $P_{o/b}$ represents the percentage of reaching the optimal/best solution before reaching the roof of 1000 generations. In the case of not getting the best known solution, new trials were made where the number of generations was set to be exactly as ANG instead of 1000. Then the difference between the obtained results and the best known ones were computed and averaged and presented by $D_{o/b}$ in the last column.

Table 5.2 RGA results

#	N	θ	*M*	*MS*	*ANG*	CPU time	$P_{o/b}$	$D_{o/b}$
1	20	500	7	6	1.55	0.11	100%	
2		1000	6	4	1.2	0.09	100%	
3		1500	5	3.5	1	0.07	100%	
4		3000	4	2.5	1	0.08	100%	
5	40	500	14	11.25	6.65	0.56	100%	
6		1000	12	9.25	5.68	0.41	100%	
7		1500	10	7.25	3.75	0.25	100%	
8		3000	8	5.25	1.85	0.15	100%	
9	60	500	21	17.5	17.1	2.32	100%	
10		1000	17	13.5	16.65	1.92	100%	
11		1500	14	11	9.5	0.87	100%	
12		3000	11	7.75	5.1	0.50	100%	
13	100	500	33	30	393.92	140.14	60%	0. 14%
14		1000	25	21.5	122.95	26.61	100%	
15		5000	13	10	11.35	1.21	100%	
16		10000	10	7	6.85	0.64	100%	
17	150	1000	37	31.5	356	124.17	50%	
18		3000	22	18.5	138.35	22.67	100%	
19		5000	18	14.75	88.3	11.32	100%	
20		10000	14	10.5	21.2	2.86	100%	
21	200	3000	29	25.5	374.6	127.69	50%	0.06%
22		5000	23	20	299	65.8	60%	0.03%
23		10000	17	14	164.35	23.66	100%	
24		20000	13	9.5	27.15	3.18	100%	

* *N*: number of stations; θ: fixed cost; *M*: total number of possible supermarkets locations; *MS*: number of supermarkets locations in the solution; *ANG*: average number of generations needed to reach the optimal/best known solution; $P_{o/b}$: the percentage of reaching the optimal/best solution before reaching the roof of 1000 generations; $D_{o/b}$: the average of the difference between the obtained results and the best known ones.

To check the effects of all mating and mutation factors on the results, similar 4 tables were obtained and in each table, one factor was omitted. Then the results were compared between the new tables and the original one using paired t-test. It was found that all the four factors have significant effects in enhancing the results all the time. The proposed RGA finds in most of the time the optimal/best solution in reasonable time periods. Its performance, in terms of time and quality, is better when ɵ value is higher. CPU time decreases because in this case the number of needed supermarkets decreases. Therefore the size of WDM decreases, and also the number of steps in sensitivity mutation decreases. Furthermore, the solution space the RGA searches in decreases, and this enhances the quality of the results.

As stated before, four different samples were randomly generated for each row in table 5.2. To check the effect of using different samples on the performance of the proposed method, table 5.3 shows the coefficient of variance (*CV*) of the average number of generations and of CPU time needed to reach the optimal/best known solution. *CV* is computed by dividing standard deviation by the mean for the four averages obtained for the four samples. *CV* is used as a measure of variability of the numbers. So, low values indicate that there are no large differences among the results of different samples.

Table 5.3 Effect of different samples on the performance of the proposed method

#	CV_{ANG}	$CV_{CPU\ time}$
1	0.32	0.11
2	0.23	0.01
3	0.00	0.01
4	0.00	0.07
5	0.53	0.45
6	0.43	0.34
7	0.45	0.35
8	0.31	0.14
9	0.33	0.30
10	0.35	0.36
11	0.29	0.25
12	0.47	0.32
13	0.50	0.50
14	0.43	0.39
15	0.75	0.67
16	0.23	0.13
17	0.50	0.62
18	0.79	0.80
19	0.34	0.24
20	0.30	0.30
21	0.71	0.48
22	0.37	0.31
23	0.45	0.40
24	0.27	0.19

5.4 Summary

In this chapter, IP and RGA were used to formulate the supermarkets location problem in in-plant milk run system where the tugger train is used to feed stations in the same assembly line from different decentralized inventories (supermarkets). For large instances, methods such as RGA are a must to solve the problem. The chromosomes representations, mating factors, and mutation factors were defined in a custom way to fit the nature of the problem. Results showed that the proposed RGA gives very good results in reasonable CPU time periods. Future research can investigate the effect of number of supermarkets on the total safety stock needed.

Chapter 6: Demand-oriented decentralized supermarket system

After investigating the kanban system in chapter 4 and the supermarket location problem in chapter 5, this chapter continues working on the milk run concept considering the demand-oriented system. The results obtained in chapter 5 about the number and locations of decentralized supermarkets are the input for the problems investigated in this chapter. In the practice, the two systems, namely, demand-oriented and kanban, are used. So the study investigates both of them. In chapter 8, both of them are integrated to accommodate the assembly line disturbances.

In this chapter, material flow from decentralized supermarkets to stations in MMAL using tow (tugger) trains is investigated. Train routing, scheduling, and loading problems are investigated in parallel to minimize the number of trains, variability in loading and in routes lengths, and line-side inventory holding costs. The general framework for solving these problems in parallel contains analytical equations, Dynamic Programming (DP), and Integer Programming (IP). Matlab in conjunction with LP-solve software was used to formulate the problem. An example was presented to explain the idea. Results which were obtained in very short CPU time showed the effect of using time buffer among train cycles on the feasible space and on the optimal solution. Results also showed the effect of the objective, concerning reducing the variability in loading, on the results of routing, scheduling, and loading. Moreover, results showed the importance of considering the maximum line-side inventory besides the capacity of the train in the same time in finding the optimal solution.

In routing problem, the assignment of each tugger train to different stations is investigated where the stations in the same cell must be beside each other. This is important to avoid unnecessary movements of the train. So routing in this case is about determining the line segment of assembly line supplied by the same tugger train. The three problems are investigated to reduce several types of costs. In scheduling problem, TCT and time of the beginning of the movement of the train coming out from the supermarket are determined. The arrival time at the stations is dependent on the departure time of the train from the supermarket. In loading problem, the exact type and number of bins loaded on the train in each train cycle are determined. In ideal situation, these bins are exactly the demanded ones during the time interval between the arrival time of the train at a station and the next arrival time of the train at this station. However, sometimes the demand for bins needed by the cell is more than the maximum tugger train capacity. In this case, some bins are delivered before they are needed. This early loading task should be carefully designed so that the total inventory holding cost of line-side inventory is minimized. In traditional approaches, these problems are investigated step by step. However, investigating the three of them together in parallel further reduces the total costs of the system. The contents of this chapter have been partially published in Alnahhal and Noche (2013).

6.1 Material flow environment

The following assumptions are made in this chapter:

- Routing is the same for all train cycles during the shift
- TCT is constant over the shift
- The time interval between delivering bins for two adjacent stations in the same cell is exactly SCT. As will be explained later, some buffers are used to accommodate the restriction in this assumption.
- Workpieces (product models) sequencing is input.

To explain the methodology, an example is shown where there are 20 stations supplied by parts using tugger trains. The 20 stations are assumed to assemble only 4 types of product models (1, 2, 3, and 4). Table 6.1 shows the parts needed by each model in each station. It is assumed here that each station needs the same types of parts for all the four models. However, the parts are different from a station to another. This assumption is only for the example shown.

For simplicity, the sequence of assembling the four product models was chosen to be 1 → 2 → 3 → 4. However it can be any other sequence. The sequence is assumed to be an input for the problems investigated in this chapter and finding another sequence will not be investigated. In this chapter, SCT is used as the time unit. In the first station cycle of work, the first product model is assembled on the first station consuming two parts as it is obvious in table 6.2 which shows the first 10 station cycles in the shift and for the first 9 stations. To track any product model, the associated diagonal direction is considered. The shaded numbers in table 6.2 represent the demand for parts for the first product model. In the second cycle, the first product model does not require any part on the second station. Also in the same station cycle the second product model does not require any part in the first station. In the third station cycle, the third product model is assembled on the first station consuming only one part. In the same third station cycle, the first product model is assembled on the third station consuming one part. This mechanism is followed for all the work cycles during the shift.

Table 6.1 The needed number of parts required to assemble each model at each station

Stations	**Model**				**Stations**	**Model**			
	1	**2**	**3**	**4**		**1**	**2**	**3**	**4**
1	2		1		11	1		3	1
2			2	1	12	1		1	
3	1	2			13		1		1
4	1	3	1		14	1	2		2
5	1			3	15		1		1
6	1		1		16		2		
7		1		1	17	1			1
8	1	2			18	1	3		
9	3		1	1	19		1		2
10		1		1	20	1	2		1

Table 6.2 The needed quantity of materials required at each station cycle at each station

Demand in parts unit											Demand in bins unit*										
Station	Station cycle										Station	Station cycle									
	1	2	3	4	5	6	7	8	9	10		1	2	3	4	5	6	7	8	9	10
1	2		1		2		1		2		1	1						1			
2				2	1			2	1		2				1					1	
3			1	2			1	2			3			1					1		
4				1	3	1		1	3	1	4				1				1		
5					1			3	1		5					1					
6						1		1		1	6						1				
7								1		1	7								1		
8								1	2		8								1		
9									3		9									1	

* Bin capacity = 5 parts

After that and assuming that the capacity of the bins transported by the train is always 5 parts for all types of parts, the demand in bins unit is calculated as in the right side of table 6.2. For example at the first station, there is a demand at the first station cycle for two parts, so there is a demand for a bin at this station cycle. The bin must come one SCT earlier, which is the station cycle 0. The three remaining parts in the bin can fulfill the demand in the third station cycle and also in the fifth station cycle. However in the seventh station cycle, there is a demand for a new bin. This way is followed for all the station cycles and stations.

It is assumed that the tugger is capable of delivering the needed bins to a station after feeding the previous one in duration of one station cycle. After delivering all the needed bins to a station, the tugger can deliver the other needed bins to the next station in duration of one station cycle. However, on the ground this duration is variable and depends on the number of delivered bins. Because of that, the decision maker may consider using three different types of buffers, namely, safety stock, time buffer among train cycles, and line-side empty inventory buffer. So if the needed bins arrive too late, the safety stock is useful to replenish the stations until the next arrival of the train. Moreover, for this delay not to affect the next cycles of the train, the time buffer among train cycles is useful in this case. However, time buffer should not be too long because this will decrease the feasible solution space as will be explained later. On the other hand, if the arrival of bins is too early, empty line-side space can be useful.

6.2 Procedures and objectives

In this chapter, the routing, scheduling, and loading problems will be investigated together in parallel to minimize the number of trains, inventory costs, and system variability as shown in the right side of figure 6.1. The three problems and their interrelationships which will be explained later are shown in figure 6.2. During working on these problems, four limitations, which are tugger train capacity, line-side inventory limit, time buffers, and routing time, as shown in the corners of figure 6.2 are considered.

To achieve the objectives, the general procedures of the study are shown in the left hand side of figure 6.1 where there are 5 major steps. The first step which is computing the demand in bins unit was explained above in the example. The rest of the steps are explained in the next sections. Analytical equations are used in the second step, and the DP is used in the third and fourth steps. Step 5 is the longest one and it contains a lot of calculations. It needs, besides others, DP and IP, and it will be explained later in figure 6.4.

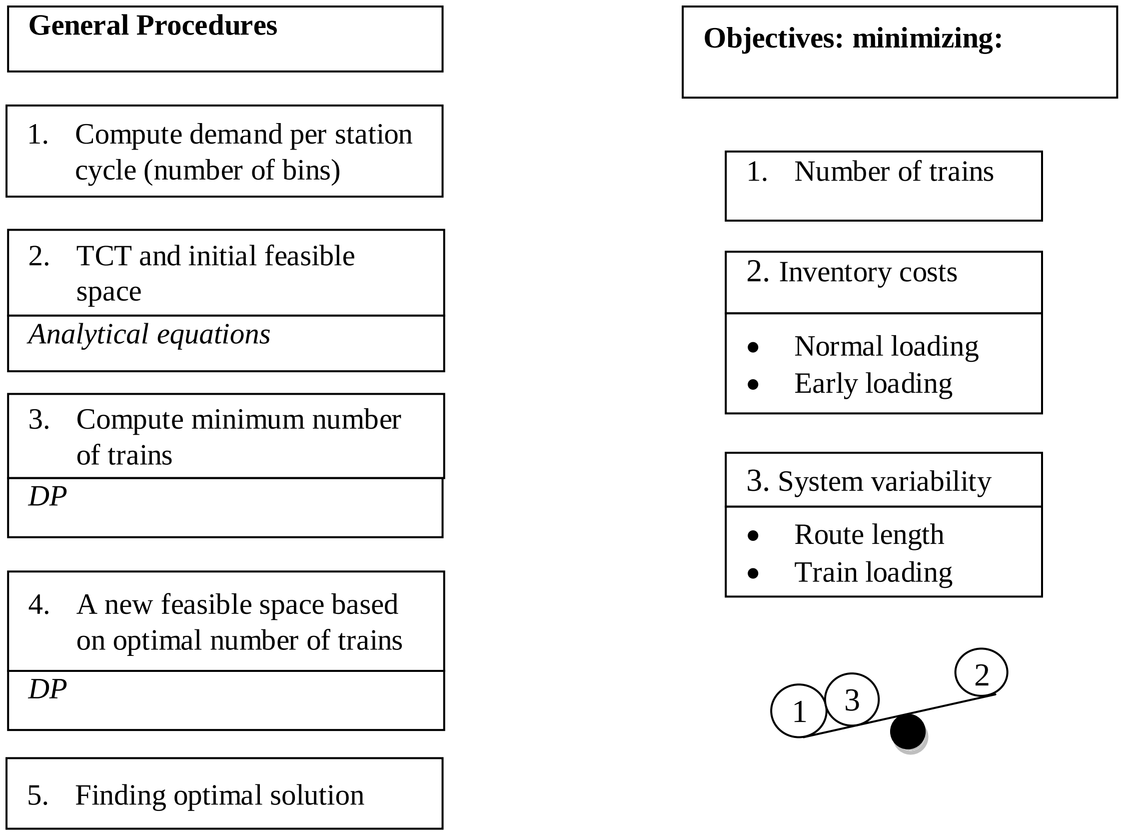


Figure 6.1 Major steps and objectives

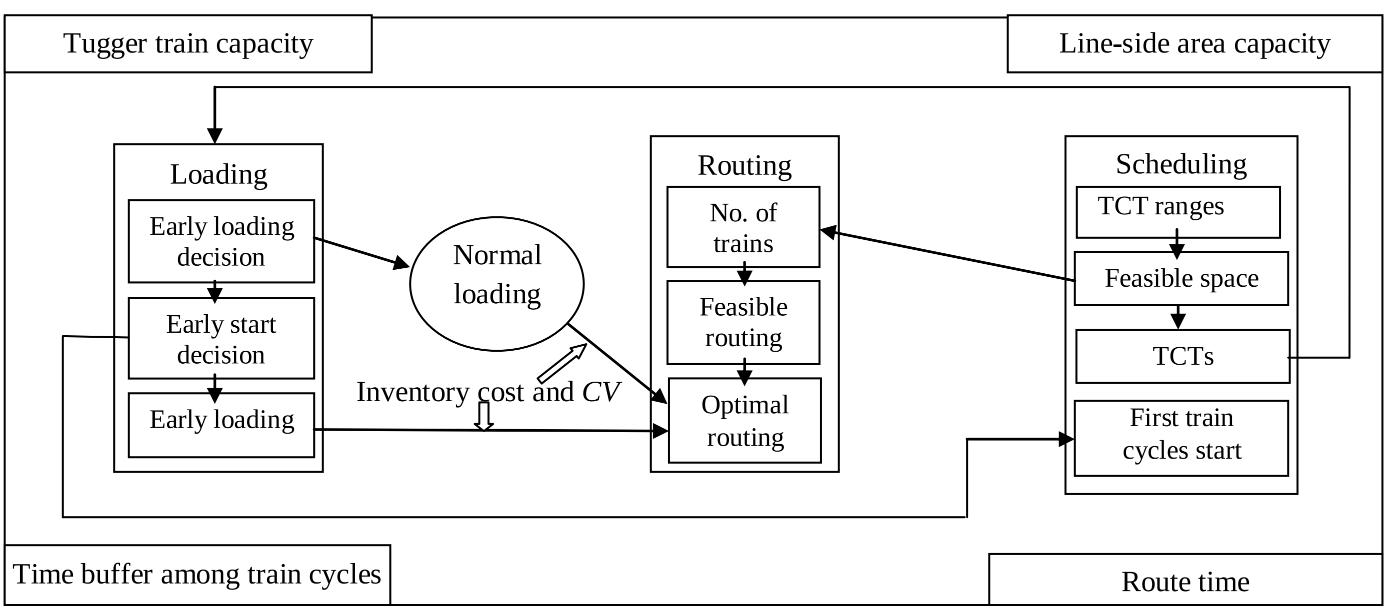


Figure 6.2 General problems, their interrelationships, and constrictions

6.3 TCT determination

It is assumed that if a tugger train feeds some stations in the first train cycle, the same train will also feed the same stations in every next train cycle. It is assumed in this chapter that the TCTs are the same during the shift, that is, the train feeds some certain stations every 30 minutes for example. Therefore, if the train makes its first cycle in just 20 minutes, it must wait another 10 minutes until it starts the next cycle.

Train capacity and line-side area capacity are two restrictions that push TCT not to be too long. On the other hand, the TCT must consider the time needed for the train to move from the decentralized supermarket to the stations, from a station to the next one, and from the stations back to the supermarket including all the times of loading and unloading of full and empty bins. To find the TCT for each cell, at first the maximum possible TCT for the train with a cell from station s_i to station s_j including the station 's' is computed. To do that, at first, the minimum number of train cycles is computed based on line-side area capacity and the train capacity. Minimum number of train cycles in the shift for the cell from s_i to s_j, MNC_{ij}, can be estimated based on equation (6.1)

$$MNC_{ij} = \max\left(\max\ Q_s, \left\lceil \frac{TDS_{ij}}{K} \right\rceil\right) \tag{6.1}$$

Where TDS_{ij} is the total cell demand during the shift, and Q_s which computes the number of train cycles based on MLSI can be estimated using equation (6.2)

$$Q_s = \left\lceil \frac{dS_s}{\mathrm{K^{LS}}} \right\rceil, \qquad \forall\, station\ s\ \in cell\ from\ station\ \ s_i\ to\ station\ s_j \tag{6.2}$$

Where $\lfloor X \rfloor$ is the lower rounded integer value for the variable X, and $\lceil X \rceil$ is the upper rounded integer value for the variable X. Moreover, dS_s is the total station demand during the shift for station 's'. K^{LS} is the line-side area capacity which is the maximum capacity of the area beside a station for the inventory for immediate use. In this study, K^{LS} is assumed to be the same for all stations in the cell. It is assumed that any bin from which some parts were consumed by the station is not considered in the calculation of the line-side inventory. The maximum TCT, $MAXC_{ij}$, can be estimated using equation (6.3)

$$MAXC_{ij} = \left\lfloor \frac{\Gamma}{MNC_{ij}} \right\rfloor \tag{6.3}$$

Where r is the number of the station cycles in the shift. The time unit for $MAXC_{ij}$ is number of station cycles. The minimum TCT which is $MINC_{ij}$ is computed based on the time buffer, the Routing Time Inside the cell (RTI_{ij}) and Routing Time Outside the Cell ($RTOC$)

$$MINC_{ij} = RTI_{ij} + \mathrm{RTOC} + time\ buffer \tag{6.4}$$

In the example above, RTI_{ij} is estimated to be s_j-s_i +1 since the loading and unloading of bins are assumed to take 1 station cycle for each station inside the cell. $RTOC$ was assumed to be the same for all cells and equal to 2.

The feasible TCT Range (CR_{ij}) can be computed using equation (6.5)

$$\mathrm{CR_{ij}} = \max(MAXC_{ij} - MINC_{ij}, 0) \tag{6.5}$$

In the case that $MAXC_{ij}$-$MINC_{ij}$ is less than zero, the solution is not feasible. So in this case and based on the previous constrictions, there can be no cell starting from station s_i to station s_j. After finding the feasible space, the optimal TCT for the cell containing the stations from s_i to s_j is set to be the minimum since it gives minimum inventory costs, and this coincides with the principle of JIT in which frequent small replenishments of materials are done. So the maximum TCT shown above was only computed to find the feasible solution space. As stated before, the scheduling problem consists of two parts: finding the value of TCT, and finding the point of time at which the first movement of the train is started. So far, the first part was done, but the second part is interrelated to the loading problem, as will be shown later.

6.4 Number of trains and new feasible solution space

In this study, it is assume that the most important objective is minimizing the number of trains. So the first step is to find the minimum possible number of trains (MNT) regardless of the other two objectives. DP is used to find this number. As shown in the study by (Emde and Boysen 2012b), DP in routing problem can be formulated as in figure 6.3. It was programmed by Matlab software which does not accept zero indexing in which the index is zero. Therefore, 1 is added to zero. The idea of DP model is not to try all the possible combinations in the feasible solution space, and this is to save time. So, in an intermediate step, if the optimal routing for a group of stations (from 1 to j-1) is known, then in a next step if the optimal routing for the same group of stations is to be found, there is no need to repeat the solution since the model “memorizes” the best solution found before. In this case, the time needed to find the final solution is reduced.

```
G(0+1)=0;
S=No_Stations;

for j= 2:S+1
G(j)=9999999;
MNT(j)=0;
end
for j=2:S+1
fori= 1:j-1
if feasible(i,j-1)==1
if function_to_be_minimized+G(i)<G(j)
p(j)=i;
G(j)= function_to_be_minimized+G(i);
N(j)=MNT (i)+1;
end
end
end
end

tuggers=   MNT(S+1);
```

Figure 6.3 DP in routing problem

Theoretically, the minimum possible number of trains is one. In this case the cell size is exactly the total number of stations supplied by the supermarket (N^S).The function to be minimized here is set to represent the difference between N^S and the cell size. This function can be written as in equation (6.6)

$$function\ to\ be\ minimized = N^S - (j - i) \tag{6.6}$$

Where, the value (j-i) represents the real cell size containing the stations from i to j-1. Minimizing this function will increase the cell size and decrease the number of needed trains. The output of this step is MNT represented by the variable "tuggers" in the last equation. Based on the found MNT, a new and smaller feasible solution space is found. To do that, DP will be used again for every possible cell based on the previous feasible space in which the cell from s_i to s_{j-1} was determined to be feasible or not based on the range of TCT. For each feasible cell, DP is tried, where the function to be minimized now is (N^S-(j-i) + $cost_{i,j-1}$). *cost* matrix contains high values, for example 1000, except for $cost_{i,j-1}$ which contains very low value, for example 1. By this way, the cell from station s_i to s_j is very "attractive" to be chosen by the model in the optimal routing. However, there is another factor (N^S- $(j$-$i))$ which prohibits any cell that causes the number of trains to be more than the optimal one found before. However, for a lot of cells if they are considered in the solution, the number of trains will be more than the optimal one. These cells will be omitted from the second feasible solution which is based on the found MNT. This step is done to minimize the computation time in the next step in which the final optimal solution is found.

Figure 6.4 represents the general framework of the last step found in figure 6.1. In this step the other types of objectives are considered. At first, the Average Route Length (*ARL*) is computed by dividing the number of stations by the number of tuggers. The cell sizes in the final solution should not be very far away from ARL. So the deviation from ARL represents the first type of variability in the system. The second type is the variability in loading. The loaded quantity by each train should be almost the same during the whole shift. To measure that, *CV* for the quantity loaded by the train during the shift is computed. This value is computed for all the feasible cells. However, if this variability in demand is so high to the level that in some train cycles the needed quantity is more than the capacity of the train, the loaded quantity does not need to be equal to the demand all the time. In this case, *early loading* is used, where some of the bins are loaded in previous non-bottleneck train cycles. However, early loading will increase the inventory holding costs. In this chapter, a simple rule is followed: if increasing one type of the costs will decrease two types of costs, it should be done, and this rule is shown in the lower right part of figure 6.1. Early loading of bins will increase the inventory holding costs, but it will give the chance to decrease the number of trains and also to decrease the variability in the system.

However sometimes even early loading is not enough to minimize the needed capacity of trains. This can happen if the first train cycle demand is more than the capacity of the train. Therefore, the train can adopt *early start* which is needed to define the time of the beginning of the first train cycle. In ideal situation that time is one cycle before the demand of stations. For example, if the first station needs parts at cycle number one, the needed parts must be delivered one cycle before (cycle number zero). ‘Early start’ decreases the demand of the first train cycle where the train starts its movement several station cycles before the first time the parts are needed. The demand of the stations in each train cycle including the first one will be changed. The first train cycle will cover a period that is equal to usual TCT minus the early start period.

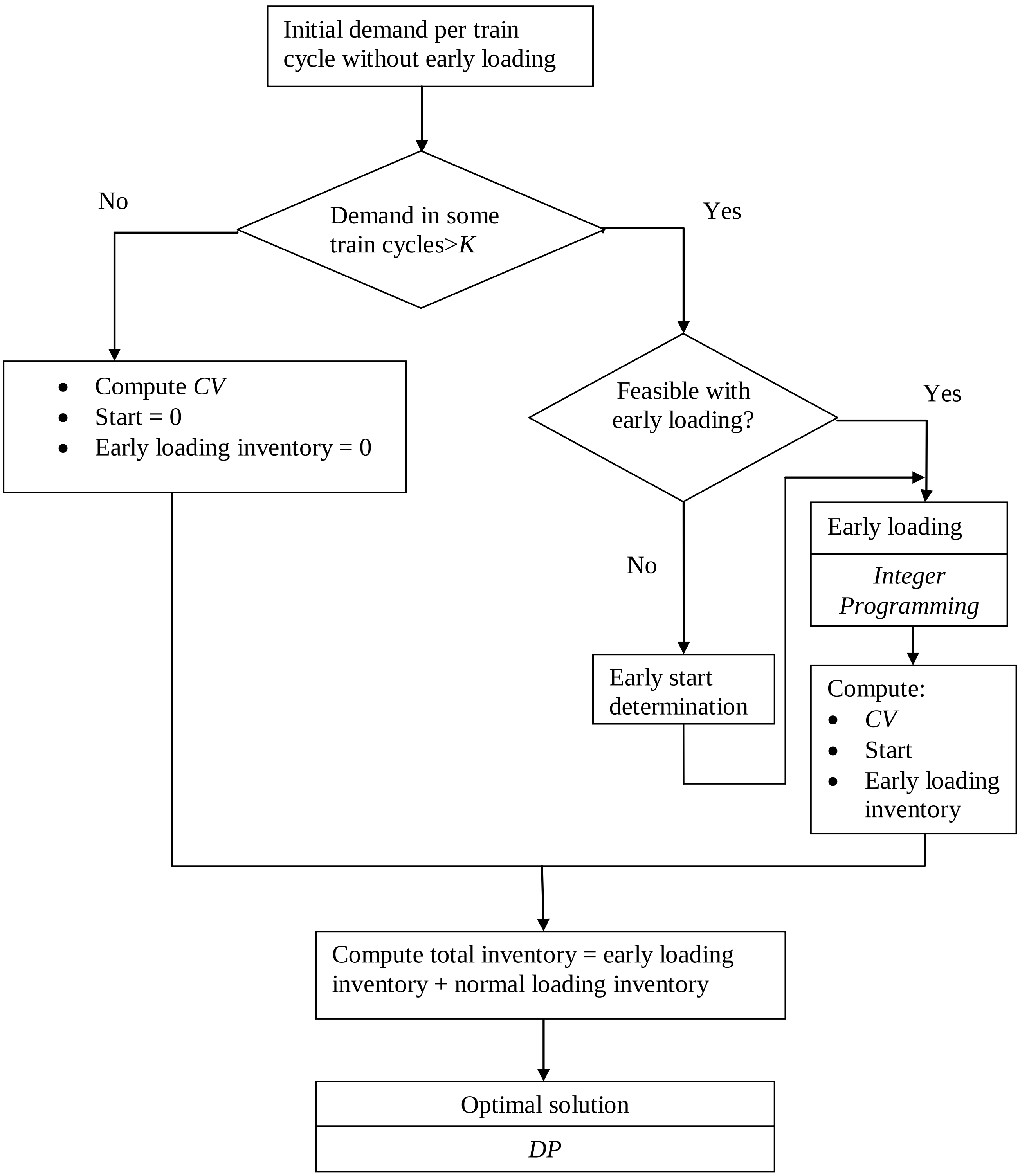


Figure 6.4: General Framework for the last step.

The decision maker may want the number of train cycles not to be increased. In this case, the last train cycle will cover a period that is longer than the usual TCT before. The methodology to find the early start is to try different early start periods from zero to the first feasible one. The feasibility is checked by constraint (6.7). If it is true for all train cycles, then feasibility is achieved. After finding the starting point, the loading problem is investigated.

$$\sum_{t'=1}^{t}\sum_{s=1}^{N} \mathrm{d}_{st'} \leq \mathrm{tK} \qquad \forall\ \mathrm{t} = 1 \ldots \mathrm{T} \tag{6.7}$$

Where,

T Total number of train cycles

K Capacity of the train

d_{st} Demand bins of the station s for the train cycle t

6.5 Loading problem

Loading problem was formulated by (Emde et al. 2012). The constraints were as follows

$$\sum_{s=1}^{N} x_{st} \leq K \qquad \forall t = 1, \ldots, T \tag{6.8}$$

$$\sum_{t'=1}^{t} x_{st'} \geq \sum_{t'=1}^{t} d_{st'} \qquad \forall t = 1, \ldots, T, s = 1, \ldots . N \tag{6.9}$$

$$x_{st} \in IN_0 \qquad \forall t = 1, \ldots, T, s = 1, \ldots . N \tag{6.10}$$

And there were two objectives as follows:

$$\text{Minimize } f_{sum} = \sum_{t=1}^{T}\sum_{s=1}^{N}\sum_{t'=1}^{t} (x_{st'} - d_{st'}) \tag{6.11}$$

$$\text{Minimize } f_{max} = max\left\{\sum_{t'=1}^{t} (x_{st'} - d_{st'}) \,\middle|\, t = 1, \ldots, T; s = 1, \ldots, N\right\} \tag{6.12}$$

Where, x_{st} is the delivered number of bins at station s in the train cycle t. Constraint (6.8) guarantees that the capacity of the tow train will not be exceeded. Constraint (6.9) guarantees that for each train cycle, the accumulated number of delivered bins to a station is at least equal to the accumulated number of demanded bins by this station until the current train cycle. Constraint

(6.10) defines the positive integer number of containers that can be delivered to different stations. The objective function (6.11) aims at minimizing the difference between the needed demand and the delivered number of bins. Furthermore, the maximum number of containers stashed at any one station should be minimal, therefore, there is another objective (6.12) which minimizes the maximum difference between the numbers of delivered bins and the number of demanded bins. Emde et al. (2012) used a new heuristic to solve the problem to find the value of f_{max}. However, there is another simpler but slower way to solve it by adding a new constraint (6.13) instead of the second objective, and also by adding the variable f_{max} to the first objective.

$$\sum_{t'=1}^{t}(x_{st'} - d_{st'}) \leq f_{max} \qquad \forall t = 1, \dots, T; s = 1, \dots, N \qquad (6.13)$$

To formulate all the problems together in the same program, Matlab software in conjunction with LP-solve software was used.

Further investigation in this loading model can be considered. For example constraint (6.14) can be added

$$K - \sum_{s=1}^{N} x_{st} \leq v \qquad \forall t = 1, \dots, T \qquad (6.14)$$

The variable v is added to the objective function. This constraint is to minimize the maximum difference between the train capacity and the loaded quantity. This will decrease the variability in the loading since it pushes the lowest loaded quantity to be higher. However, this can increase inventory costs since it increases the early loaded quantity.

In its original formulation, the loading problem can have a lot of alternative optima. An additional factor that can be considered is that MLSI must not be greater than the capacity of the line-side area. To take that into consideration, constraint (6.15) is used. The left side of it equals MLSI.

$$\sum_{t'=1}^{t} x_{st'} - \sum_{t'=1}^{t} d_{st'} + d_{st} \leq \mathrm{K}^{\mathrm{LS}} \qquad \forall t = 1, \dots, T, \quad s = 1, \dots . N \qquad (6.15)$$

Another dimension that can be added to the model is minimizing the frequency of f_{max}. Of course, the less times f_{max} appears, the better the results are. This can be done by adding two constraints (6.16) and (6.17)

$$Y1_{st} \leq f_{max} - \sum_{t'=1}^{t}(x_{st'} - d_{st'}) \qquad \forall t = 1, \dots, T; \quad s = 1, \dots, N \tag{6.16}$$

$$Y1_{st} + Y2_{st} = 1 \qquad \forall t = 1, \dots, T; \quad s = 1, \dots, N \tag{6.17}$$

Where $Y1_{st}$ and $Y2_{st}$ = 0 or 1. The variable $Y1_{st}$ equals zero if the number of accumulated delivered bins minus the number of accumulated demanded bins equals f_{max}. Therefore, the value $Y2_{st}$ equals 1 if f_{max} appears at station s and in the train cycle t. So the value $\sum_{t=1}^{T}\sum_{s=1}^{N} Y2_{st}$ must then be added to the objective function. For this objective not to affect the original objectives, this value must have a very small weight compared to the two original objectives.

The decision maker may want to further investigate the f_{max} value by reducing the maximum number the f_{max} values appear for the same station at successive train cycles by adding the objective (6.18)

$$min\ Pmax = max\left\{(t' - t'' + 1)\prod_{t''=t}^{t'} Y2_{st'} \,\middle|\, t = 1, \dots, T; t' = t \dots T; s = 1, \dots, N\right\} \tag{6.18}$$

This can be accomplished by adding a new constraint (6.19) and by adding the variable '*length*' in the objective function.

$$(t' - t'' + 1)\prod_{t''=t}^{t'} Y2_{st'} \leq length \qquad \forall t = 1, \dots, T; t' = t \dots T; s = 1, \dots, N \tag{6.19}$$

However, this may complicate the problem and make it difficult to solve. Another factor that the decision maker may consider is the number of stops of the tugger train. This may be useful to reduce the "traffic jam" of tugger trains especially in the case of using narrow aisles in the facility. This can be done by adding a new constraint (6.20) and adding the term $\sum_{t=1}^{T}\sum_{s=1}^{N} Y_{st}$in the objective function.

$$x_{st} \leq LY_{st} \qquad \forall t = 1, \dots, T; \quad s = 1, \dots, N \tag{6.20}$$

Where Y_{st} is a 0 or 1 binary variable and L is a very large number. The idea is to increase the number of times in which x_{st} is zero. When x_{st} is zero, Y_{st} is also zero. However, this objective contradicts the objective of minimizing MLSI. The decision maker can decide if he wants to add such an objective or not according to the situation on the ground.

6.6 Optimal solution

DP is used one more time to find the final solution. The function to be minimized contains all the types of costs except the number of trains since it was already considered before in finding the second feasible space. So the function to be minimized for the cell from station i to station j-1 is as in equation (6.21)

$$function\ to\ be\ minimized = w_1|ARL - j + i| + w_2 CV + w_3 Total\_INV\_costs \tag{6.21}$$

Where w_i is the weight of objective i, and *total_INV_costs* represents the normal loading inventory holding costs plus early loading inventory holding costs. The values of the weights can be estimated according to the judgment of the decision maker. Because the early loading inventory is in the system for TCTs but the normal loading inventory is for SCTs, the last inventory type is divided by TCT. Normal loading inventory is computed by multiplying the amount of needed inventory in each station cycle by the time interval from the time of delivering that inventory to the station cycle in which the demand occurs. In table 6.2, assume that the first 5 stations form a cell with TCT of 7. For the first train cycle for the third station in the table, the train comes and unloads two bins in the second station cycle which is one station cycle before the third one. In the third station cycle, station 3 will start consuming the first bin immediately. So the inventory cost for that bin is zero. The inventory cost for the second bin is 5 since it will wait 5 station cycles until it is started to be consumed. Inventory holding cost is divided by TCT to be equal to 5 divided by 7. The early loading inventory is computed based on the objective function value introduced in equations (6.11) and (6.12). The method above about computing the normal loading inventory cost is also applied for bins that are consumed in the current train cycle but delivered in a previous train cycle.This is because these bins will also wait for few station cycles in the current train cycle besides the waiting from a train cycle to another.

6.7 Interrelations among problems

As it is obvious in Figure 6.2, to do routing problem, feasible range of TCT must be defined first, and this feasible range is part of scheduling problem. Moreover, to define early start which is part of scheduling problem, loading problem must be considered. However, loading problem cannot be done without knowing the TCTs found in scheduling problem. Furthermore, the optimal routing needs information about the values of the objective function from loading problem (inventory costs and *CV*), and also the minimum possible number of trains which must be found based on the feasible range found in scheduling problem. All these relations reveal the importance of investigating the three problems together in parallel.

6.8 Results and analysis

In the example presented, at first, the weight of the objective function in equation (6.21) was set to be 100 for the *CV* value since it is usually very small and this value should affect the results. Each one in the other two terms in the objective function was given a weight of 1. The time buffer among train cycles was set to be 1 station cycle. All the problems were run together and needed just few seconds on a normal personal computer. The results of the example are in table 6.3 where the feasible space is in the left-hand side of the table. The value of 1 is for the active cells in the feasible space. For example it is shown in table 6.3 that the final solution must have a cell containing the first 5, 6 or 7 stations. In the optimal solution on the right side of the table, there are three trains, and one of them supplies the stations from 1 to 7, the second one supplies the stations from 8 to 14, and the last one supplies the rest of the stations. The scheduling results are shown in the right side of table 6.3 where the results are expressed in the form (x, y) where x is the TCT and y is the early start. There was no early start or early loading at all in the optimal solution. However, early loading occurs in the third cell if the weight of *CV* value is increased to be 102, and the results will contain three cells, where the first one contains the stations from 1 to 6, the second cell contains the stations from 7 to 13, and the third cell contains the remaining stations. These changes in results show the effect of the objective of decreasing the variability in loading on the results of the three problems of routing, scheduling, and loading. The effect on routing is not in the number of trains but in the cells formation (the assignment of stations to cells).

Table 6.4 shows the results when the time buffer is set to be zero where the value of the objective function is decreased from 487.3 to 452.1 and the feasible space is increased to contain more cells. Furthermore, the last cell from station 13 to station 20 has early loading and also early start of 1 station cycle. The first route is too short compared to the other two ones. To fix this problem, the weight w_1 in equation (6.21) must be increased. If it is set to be 21 for example, the new solution will contain a cell from station 1 to 6, another cell contains stations from 7 to 12, and the last one contains the other stations. However, if this weight is increased to be 67, the first cell will be from station 1 to 7, the second cell will be from station 8 to 13, and the last cell will contain the remaining stations.

Table 6.3 Feasible space and optimal solution when time buffer is 1 station cycle

Feasible space							Optimal solution			
	Station cycle							Station cycle		
Stations	5	6	7	13	14	20	Stations	7	14	20
1	1	1	1				1	(10, 0)*		
6				1			6			
7				1			7			
8				1	1		8		(10, 0)	
14						1	14			
15						1	15			(9, 0)

*(*x*, *y*): *x* is the TCT and *y* is the early start

Table 6.4 Feasible space and optimal solution when time buffer is 0

Feasible space												Optimal solution			
	Station cycle												Station cycle		
Stations	4	5	6	7	8	12	13	14	15	16	20	Stations	4	12	20
1	1	1	1	1	1							1	(6, 0)		
5						1						5		(10, 0)	
6						1	1					6			
7						1	1					7			
8						1	1	1				8			
9						1	1	1	1	1		9			
13											1	13			(10, -1)
14											1	14			
15											1	15			
16											1	16			
17											1	17			

Table 6.5 shows several trials in which the K and K^{LS} values were changed to get the optimal objective function value and the number of needed trains. The 4th trial represents the current status. If the K value is decreased to be 10, four trains are needed. It is noted that no matter how much the K value is increased more than 16, it cannot affect the results. This is because of the

fixed value of K^{LS}. So to get lower number of trains, the K^{LS} value must be increased as in the 10th trial. This result is important since it shows that it is not very helpful to get tugger trains with high capacities if the K^{LS} cannot be increased.

Table 6.5 Effect of K and K^{LS} values on the results

Trial	K	K^{LS}	Number of trains	O.F. value
1	17	3	3	474.96
2	16	3	3	474.96
3	15	3	3	452.12
4	14	3	3	452.12
5	13	3	3	526.17
6	12	3	3	592.30
7	11	3	3	600.93
8	10	3	4	548.33
9	14	4	3	452.12
10	21	4	2	630.67

6.9 Summary

In this chapter, the routing, scheduling, and loading problems of the tow train were investigated together in parallel in decentralized supermarket system. The objective function decreases the number of trains, variability in loading and in route lengths, and inventory holding costs in normal and in early loading. This was done using analytical equations, DP, and IP techniques. Constraints related to tugger capacity, capacity of line-side area, routes times, and time buffer among train cycles were taken into consideration. Besides the time buffer, safety stock and empty space capacity for line-side inventory can be used. Further investigation about loading problem was presented using IP.

This chapter shows the importance of studying the three problems together since they are interrelated, and this parallel investigation should be done to minimize the total inventory holding costs to the minimum possible value and to take into account decreasing the variability in the loaded quantities. It also shows the effect of time buffer on the feasible solution space. Moreover, it shows the importance of considering the capacity of line-side area and the capacity of the train in the same time, where getting tugger trains with so high capacities does not enhance the system because the line-side area is usually limited to small amounts. It also shows the importance of the objective regarding decreasing the variability in loaded quantities since it affects all the results of routing, scheduling, and loading.

This chapter is a part of investigating the demand-oriented system in which the demand of stations for bins is known at least for the next shift. In the next chapter, further investigation is done for this demand-oriented system in terms of scheduling, and loading problems to accommodate the capacity problems of trains and line-side area. In chapter 8, routing, scheduling, and loading will be investigated one more time to accommodate assembly line disturbances. In chapter 7 and 8, the environment investigated contains both the centralized and decentralized supermarket system.

Chapter 7: Capacity problems

In the previous chapter the routing was assumed to be variable from one shift to another. In the practice, however, sometimes the routing is fixed over a long period. This may cause problems regarding the capacity of the train and the area beside stations because of the ever changing demand from a shift to another. A feasible routing in a shift may not be feasible in another shift especially when TCT is fixed over the shift as in the previous chapter. To deal with this problem, this chapter continues the investigation of demand-orient system and deals with train capacity problems due to the dynamic nature of workstations demand where several unique product models needing unique demand requirements are assembled. Dynamic scheduling, early loading, and minimizing extra number of trailers are the main tools used to minimize the needed train capacity keeping the area beside stations not to be crowded with bins more than its capacity. This is done step by step using four integer programming models. Results showed that combining the three tools results in great decrease for the extra needed number of trailers, but small reduction in the maximum needed number of trailers. The fixed routing is investigated in chapter 8 as a part of a complete strategy to accommodate the effect of disturbances. The contents of this chapter have been partially published in Alnahhal and Noche (2014).

7.1 Strategies to accommodate capacity problems

Four strategies to face the effect of dynamic demand on exceeding the line-side space and train capacities can be used:

- Variable TCT
- Early loading
- Minimizing the number of extra trailers.
- Using market attendant or technical solutions.

In the practice and in a lot of cases it was found that routing is assumed to be fixed. Because of the dynamic nature of demand from hour to hour and from day to day, sometimes the available capacity of the trains is not enough for some routes and more than enough in others. Because of that, flexibility in other decisions such as scheduling of trains is necessary. In this chapter the focus is on one cell containing several workstations supplied by one train from one supermarket/central warehouse.

Table 7.1 shows 5 stations that are supplied by the same tugger train. The first three stations belong to the same assembly line. The fourth and fifth stations belong to a second assembly line. The table shows the demand for each station cycle for each station. Suppose that the loading/unloading time at each station plus movement from the station to another in the same assembly line is one SCT. Also suppose that station loading/unloading time plus movement from assembly line to another is two SCTs. Because the second station cannot start its work until it gets the product model from the first assembly station, the demand for the first bin in the second station appears after one cycle of the demand for the first bin by the first station. The same relation is for stations 2 and 3. However, for stations 3 and 4 and because station 4 belongs to a different assembly line, the demand for the first bin in station 4 is assumed to appear in the first cycle. Assuming that the time needed by the train from the last station in the cell to the supermarket and then to the first station in the cell is 3 SCTs, the minimum possible TCT is 9 SCTs.

Table 7.1 Representation of stations demand

Station	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1	2	0	0	1	0	0	2	0	0	1	1	0	0	1	0	0	2	0	0
2	0	1	0	0	0	0	0	1	0	2	0	0	0	0	0	0	0	1	0
3	0	0	1	0	1	0	1	0	1	1	0	2	1	0	1	0	1	0	1
4	1	0	0	1	0	0	0	2	0	0	1	0	0	1	0	0	0	0	0
5	0	1	0	1	2	0	0	1	0	0	0	1	0	1	2	0	0	1	0

A) Stations demand per station cycle

Station	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1	2	0	0	1	0	0	2	0	0	1	1	0	0	1	0	0	2
2	1	0	0	0	0	0	1	0	2	0	0	0	0	0	0	0	1
3	1	0	1	0	1	0	1	1	0	2	1	0	1	0	1	0	1
4	1	0	0	1	0	0	0	2	0	0	1	0	0	1	0	0	0
5	1	0	1	2	0	0	1	0	0	0	1	0	1	2	0	0	1
Sum	6	0	2	4	1	0	5	3	2	3	4	0	2	4	1	0	5

B) An alternative way to represent stations demand per station cycle

For the train to arrive on time one cycle before the demand is needed, the train has to start its movement and be beside station 1 in the cycle -4. This is because if the movement is later than that the train will not arrive on time at stations 4 and 5. So the train in this case must be loaded to cover at least the demand of cycles from -3 to 0, plus cycles 1 to 5. In Table 7.1b, stations demands were reorganized to start with the first time the demand appears. In other words, the row of station 2 was moved one step backward, the row of station 3 was moved two steps, and the row of station 5 was moved one step. This way is useful to simplify model 1 and 3 in which the variables x_{ij} and d_{ku} are related to such table organization.

The following four models should be investigated step by step. Table 7.2 shows the models problems, objectives, and inputs. Routing and stations demands are added to the inputs shown in the table. *y2* is the train capacity needed, and *y1* is the needed area beside stations in terms of number of bins, where *y1* represents the maximum line-side inventory (MLSI). In this chapter *y1* and MLSI are used interchangeably. *y1* as input can be obtained from the results of model 1 or the real value on the ground. If the capacity problems are solved by a certain model, there is no need to use the later models. For example, if variable scheduling in model 1 is enough in a certain case to solve the capacity problems, then there is no need to make early loading or other strategies.

Table 7.2 The four models

Model number	**Problem type**	**Objectives**	**Inputs**
Model 1	Scheduling	find TCTs, *y1*, and *y2*	
Model 2	Early loading	train loading and new *y2*	*y1* and results of Model 1
Model 3	New scheduling	minimize average number of extra trailers, and find new *y2*	
Model 4	New early loading	train loading and new *y2*	*y1* and results of Model 3

7.1.1 Model 1

It is assumed that the loading/unloading time plus the movement from a station to another; and also the loading/unloading time in the supermarket area and movement time from the last station to supermarket and then to the first station in the route can be represented by integer number of SCT. The objective of this model is to find the variable TCTs over the shift.

The following parameters and variable are defined:

MC: the minimum possible TCT minus one represented in SCT unit.

TSC: total number of station cycles in the shift

d_{ku}: the demand (in bins unit) of station k during the station cycle u

$$x_{ij} = \begin{cases} 1, \text{if there is a train cycle that covers the cell demand during the station cycles from } i \text{ to j} \\ 0, \text{otherwise} \end{cases}$$

Objective

$$\min y1 + y2 + \sum_{i=1}^{TSC-MC} \sum_{j=i+MC}^{TSC} x_{ij} \sum_{k=1}^{N} \sum_{u=i}^{j} d_{ku} \tag{7.1}$$

Subject to

$$\left(\sum_{u=i}^{j} d_{ku} \right) x_{ij} \leq y1 \qquad \forall k = 1..N, \forall i = 1 \dots TSC - MC, \forall j = i + MC \dots TSC \tag{7.2}$$

$$x_{ij} \sum_{k=1}^{N} \sum_{u=i}^{j} d_{ku} \leq y2 \qquad \forall i = 1 \dots TSC - MC, \qquad \forall j = i + MC \dots TSC \tag{7.3}$$

$$\sum_{i=1}^{j-MC} x_{ij} = \sum_{v=j+1+MC}^{TSC} x_{j+1,v} \qquad \forall j = MC + 1 \dots TSC - MC \tag{7.4}$$

$$\sum_{j=1+MC}^{TSC} x_{1j} = 1 \tag{7.5}$$

$$\sum_{i=1}^{TSC-MC} x_{iTSC} = 1 \tag{7.6}$$

$$x_{ij} = 0 \; or \; 1 \qquad \forall i = 1 \dots TSC - MC, \qquad \forall j = i + MC \dots TSC \tag{7.7}$$

The objective is to decrease MLSI and the maximum needed train capacity. The third term in the objective function is used to guarantee that there is no overlap in the cycles. The decision maker can choose the weights of the terms in the objective function. y1 is used as a variable. This is useful even if the resulted value is lower than the available line space because it will reduce inventory costs. Also it is useful to represent y2 as a variable in the objective function even if the resulted one is less than the capacity of the train, because this will result in smaller number of trailers in the current route used by the train. So other trains can use the saved number of trailers. However if one of the two variables is more than the capacity on the ground, then at first the other one can be omitted from the objective function and used in the constraints with its maximum capacity. The constraints (7.2) and (7.3) are to define the values of y1 and y2. Constraint (7.4) is to guarantee that all the station cycles demands are satisfied. The constraints (7.5) and (7.6) are to guarantee that the first and final station cycles demands are satisfied.

```
for k=2:TSC+1
p(1,k)=1;
[y1 y2]=floc(cycles_demand,MC,N,1,k);
G(1,k,1:2)=[y1 y2];
End

for n=2:TSC

for k=1:TSC+1
G(n,k,1:2)=999999999;
End

for k=n+1:TSC+1

for j=n:k-1
[y1 y2]=floc(cycles_demand,MC,N,j,k);

if max(G(n-1,j,1),a)+max(G(n-1,j,2),b)<sum(G(n,k,1:2))
p(n,k)=j;
G(n,k,1)=max(G(n-1,j,1),y1);
G(n,k,2)=max(G(n-1,j,2),y2);
End

end

end
end

for n=1:TSC
locf1(n)=sum(G(n,TSC+1,1:2));
end

min_cost =min(locf1)
```

Figure 7.1 DP for model 1

To solve model 1, integer programming is very slow. So it must be solved by a faster way. In this chapter the same logic of DP used by Emde and Boysen (2012a) is used. They used DP in the supermarket location problem in which several decentralized supermarkets can be used instead of one central warehouse. The problem was to determine the number and locations of the supermarkets that reduce the objective function. To use this DP, some changes are done. At first the stations cycles are used instead of stations. Then the costs computed by G-function are separated in two terms, namely, *y1* and *y2*, where they cannot be summed together for the same train cycle. The computations for model 3 are much similar to the way in Emde and Boysen (2012a). Figure 7.1 shows the logic of altered DP done by Matlab software. *Floc* function is used to compute *y1* and *y2* values for a given train cycle. Sometimes the maximum loaded quantity is still higher than the capacity of the train. In this case, the other three alternatives can be investigated. The output from the last model is considered as input for the next step, where the demand for each train cycle is computed by aggregating the demand for stations cycles.

7.1.2 Model 2

New variables and parameters are needed in model 2:

x_{st}: the number of bins loaded in the train cycle t at the station s.

lw: a very low number

T: total number of train cycles

Loading problem was formulated by Emde et al. (2012). The constraints were as follows

$$\sum_{s=1}^{N} x_{st} \leq K \qquad \forall t = 1, \dots, T \tag{7.8}$$

$$\sum_{t'=1}^{t} x_{st'} \geq \sum_{t'=1}^{t} d_{st'} \qquad \forall t = 1, \dots, T, s = 1, \dots . N \tag{7.9}$$

$$x_{st} \in IN_0 \qquad \forall t = 1, \dots, T, s = 1, \dots . N \tag{7.10}$$

Constraint (7.11) is added:

$$\sum_{t'=1}^{t} x_{st'} - \sum_{t'=1}^{t} d_{st'} + d_{st} \leq MLSI \qquad \forall t = 1, \dots, T, s = 1, \dots . N \tag{7.11}$$

A different objective to decrease the maximum capacity needed is used. *K* is considered as a variable. The objective is:

$$min\ K + lw \sum_{t=1}^{T} \sum_{s=1}^{N} \sum_{t'=1}^{t} (x_{st'} - d_{st'}) \tag{7.12}$$

The second term which was also used by (Emde et al., 2012) is added to guarantee that early loading is done only if it is needed where the very low number lw is used so that it does not affect the K value. Constraint (7.8) is to define K. Constraint (7.9) is to guarantee that the delivered bins are greater than or equal to the needed demand. Constraint (7.10) means that variables are integer and nonnegative. Constraint (7.11) is to guarantee that MLSI which was found in model 1 or set based on the conditions on the ground is not exceeded. The model is expected to reduce the needed train capacity in terms of number of bins. If the MLSI entered is not the real one but the one found in the first model and if the train needed capacity is still higher than the real capacity, then a try can be made by using the real MLSI. If, however, the capacity problem is not completely solved, then the next step which is decreasing the number of trailers is needed.

7.1.3 Model 3

Usually there are two reasons for the maximum train capacity determination: safety and turning radius. Usually safety limits the number of trailers not to be more than 4. However, the turning radius based on the facility layout and the aisles width can let for example for 6 trailers. So in this study, two maximum limits are defined. A penalty is used for any increase over the first limit, but exceeding the second one should not be allowed. Model 3 may not decrease the maximum number of needed trailers by a train in the shift but at least it will decrease the number of times it appears. This is useful for safety and also for the case when a limited number of trailers exists in the facility and is shared by all the trains. So in the time that one train needs extra trailers another one does not. The following model is based on the assumption that the first maximum train capacity is 4 trailers and the second maximum train capacity is 6 trailers. However, it can be easily altered to be with any two train capacities.

Other parameters are needed:

L: very large number.

P1: penalty value for exceeding the first maximum train capacity (4)

P2: penalty value for exceeding the first maximum train capacity plus 1 trailer

KL1=trailer capacity multiplied by 4.

KL2=trailer capacity multiplied by 5.

Objective

$$min \sum_{i=1}^{TSC-MC} \sum_{j=i+MC}^{TSC} x_{ij} \sum_{k=1}^{N} \sum_{u=i}^{j} d_{ku} + \sum_{i=1}^{TSC-MC} \sum_{j=i+MC}^{TSC} P1z1_{ij} + P2z2_{ij} \qquad (7.13)$$

Constraints

Constraints from (7.2) to (7.7)

$$x_{ij} \sum_{k=1}^{N} \sum_{u=i}^{j} d_{ku} - KL1 \leq Lz1_{ij} \qquad \forall i = 1 \dots TSC - MC, \qquad \forall j = i + MC \dots TSC \qquad (7.14)$$

$$x_{ij} \sum_{k=1}^{N} \sum_{u=i}^{j} d_{ku} - KL2 \leq Lz2_{ij} \qquad \forall i = 1 \dots TSC - MC, \qquad \forall j = i + MC \dots TSC \qquad (7.15)$$

$$z1_{ij} \,\&\, z2_{ij} = 0 \; or \; 1 \qquad \forall i = 1 \dots TSC - MC, \qquad \forall j = i + MC \dots TSC \qquad (7.16)$$

The value of *y1* found in the first model is entered here in the constraints as input. y2 must represent the second maximum capacity. The penalty for using a trailer is the same regardless how many bins are loaded on it. This will enforce the model to keep the trailer full as much as possible. Constraints (7.14) and (7.15) define the values $z1_{ij}$ and $z2_{ij}$ which are used to set the total penalty value in the objective function. Further enhancements on the results can be obtained by integrating the first three strategies together as in model 4.

7.1.4 Model 4

In model 3, dynamic scheduling is done taking into consideration the number of extra trailers. For the schedule obtained, early loading is investigated in model 4. The previous penalty related to the usage of extra trailers is also used here in the objective function. This is besides the last term in the objective function to guarantee that early loading is only done when it is needed.

Objective

$$min \sum_{t=1}^{T} P1z1_t + P2z2_t + \mathrm{lw} \sum_{t=1}^{T} \sum_{s=1}^{N} \sum_{t'=1}^{t} (x_{st'} - d_{st'}) \qquad (7.17)$$

Constraints

Constraints (8) to (11)

$$\sum_{s=1}^{N} x_{st} - KL1 \leq Lz1_t \qquad \forall t = 1, \dots, T \tag{7.18}$$

$$\sum_{s=1}^{N} x_{st} - KL2 \leq Lz2_t \qquad \forall t = 1, \dots, T \tag{7.19}$$

$$z1_t \,\&\, z2_t = 0 \text{ or } 1 \qquad \forall t = 1, \dots, T \tag{7.20}$$

Constraint (7.18) and (7.19) are to define the values $z1_t$ and $z2_t$ which are used to set the total penalty value in the objective function. For example if the number of delivered bins for the cell is more than four multiplied by the capacity of the trailer, then the left-hand side of the constraint (7.18) is positive. This means that the variable $z1_t$ is also positive. The only positive value for it is 1. The same condition is for constraint (7.19). The 1-values are multiplied by the associated penalty in the objective function. The penalty value is consistent over time but different based on the needed number of trailers. If this number is 5, then the penalty value is lower than that for 6 trailers. If the number of trailers is 6 for a given train cycle, then the two values $z1_t$ and $z2_t$ equal 1 for that cycle. This means that the two penalties are added. Therefore, the penalty for 6 trailers is more than the penalty for 5 trailers.

Besides the previous models used to deal with the capacity problems, two solutions can be considered. The existence of a market attendant or technical solutions can enhance the system by reducing TCT. Market attendant is a person who prepares the needed bins and loads them on other trailers before the tugger train drivers comes to the supermarket area (Haris and Haris 2004). He/she just attaches the trailers to the truck which does not need a lot of time. Also, the loading process can automatically be done (Klenk et al. 2012). This reduces the total time for loading the needed bins and unloading the empty bins in the supermarket area. So the loading/unloading plus transportation to the first station can be reduced to be 2 or even 1 station cycles. Minimizing the TCT reduces the average needed demand but increases the number of routes per shift. Decreasing the demand will reduce the probability to have bottlenecks period in which demand is larger than the capacity of the train. However, market attendant and technical solutions add costs and a feasibility study to use them must be investigated at first.

7.2 Results and analysis

To test the effect of each previous model on reducing the needed train capacity, randomly generated data sets were generated where:

- Number of stations supplied by the same train (cell size): 5, and 20
- Number of station cycles in the shift: 200
- MLSI: the one found in the first model
- Train capacity: for the cell size of 5 stations (K1=8, K2=10, trailer capacity: 2 bins), and for the cell size of 20 stations (K1=24, K2=30, trailer capacity: 6 bins)
- Number of trials for each case: 20.
- Demand during the station cycles: the cell size of 5 station: |normal (0, 0.5)|, and the cell size of 20 stations: |normal (0, 0.3)| rounded to the closest integer

Where $|x|$ is the absolute value of x. The selected numbers of stations were set to include both a short and a long group of stations. The capacity of the train was set to be 4 trailers in the normal cases and 6 trailers in the overloaded periods. The demand for bins was set in a way that makes the maximum number of bins demanded by a station in one train cycle to be 4. This was done by try and error. For simplicity, all the stations were assumed to be in the same assembly line. Table 7.3 shows the changes in the average number of extra trailers per cycle and maximum number of trailers after using models 2, 3, and 4. The values are percentages which were obtained by dividing the values of the model by the values for model 1. So 100% means that there is no any change at all compared to model 1. Values lower than 100% means improvements in the results. Based on average number of extra trailers per cycle, on average, the performance of models can be arranged from the worst to the best as: model 1, model 2, model 3, and model 4. For trial number 8 and 15, model 1 is better than model 2. Table 7.4 shows the reason. The table shows the delivered bins for each station for each train cycle, where there are 19 train cycles in the shift. The number of extra trailers needed if Model 1 is used is 12. This number increases to be 15 if the problem is solved based Model 2. So there is an increase of 125% in the number of extra trailers. In model 1 the sum of needed bins for some cycles is 10. This value is greater than the maximum value in model 2. Therefore in model 2, some bins are loaded before they are needed and the number of cycles containing 9 (more than 8) bins increased. So, more extra trailers are needed. In other words, the number of 9s increased and there is no any 10s in table 7.4b. This means that the maximum number of loaded bins decreased and the number of extra trailers increased since an extra trailer is needed even if one extra bin is needed.

Table 7.3 Results for N=5 stations and P1=10, P2=15.

Trial #	Change in average number of extra trailers per cycle (%)			Change in maximum number of trailers (%)		
	Model 2	Model 3	Model 4	Model 2	Model 3	Model 4
1	90.91	45.45	9.09	83.33	100	83.33
2	80	24	8	83.33	100	83.33
3	100	45	30	83.33	100	83.33
4	84.21	47.37	33.16	83.33	100	83.33
5	80	25.60	12.80	100	100	83.33
6	100	31.75	23.81	100	100	83.33
7	100	37.50	28.13	100	120	120
8	125	52.78	15.08	100	120	100
9	92.31	42.86	23.08	100	100	100
10	100	32.08	24.06	100	100	100
11	100	31.88	0	83.33	100	66.67
12	90.48	32.38	24.29	100	100	100
13	85	54	40.50	83.33	100	83.33
14	92.86	12.03	12.03	100	100	100
15	112	37.89	25.26	100	100	100
16	78.26	73.91	69.57	83.33	100	83.33
17	76.19	18.80	15.04	100	100	100
18	80.38	48.72	0	83.33	100	66.67
19	88	15	6	100	100	83.33
average	92.40	37.32	21.05	92.98	102.11	89.65

For the change in the maximum number of trailers, sometimes model 3 is worse than model 2. This depends on the penalty value *P2*. If it is low, then to decrease the average number of extra trailers sometimes in some train cycles, the maximum number of trailers is increased. However, if the penalty value *P2* is large enough then the change in maximum number of trailers cannot be more than 100%. If *P2* = 50 for example, it was found that the change in maximum number of trailers is altered to be 100 for all the trials. In this case, the average number of extra trailers per cycle remains the same. Generally, improving average number of extra trailers per cycle is guaranteed more than improving maximum number of trailers. Table 7.3 contains only 19 trials because in one of the trials the maximum numbers of bins were 14, 13, 12, and 10 for model 1, 2, 3, and 4 respectively. This means that the first two models are infeasible where the capacity of 12 bins is exceeded. This shows the importance of model 3 and 4 to solve capacity problems. The same general results found when N = 5 were also found for N = 20 stations. Table 7.5 and 7.6 show the results when $P2$ = 15, and $P2$ = 50 respectively.

Table 7.4 Results for trial 8 in table 7.3

Station	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**
1	2	1	1	2	0	0	2	2	0	3	0	1	1	1	3	0	0	1	2
2	1	1	1	3	2	1	3	3	1	0	2	2	3	1	3	1	3	0	2
3	1	1	2	2	0	2	1	0	2	4	3	4	1	2	2	2	1	3	0
4	2	1	1	1	2	4	0	2	3	1	3	2	3	2	0	3	2	2	1
5	3	2	3	2	2	2	3	3	1	2	2	1	2	4	2	3	2	2	2
sum	9	6	8	10	6	9	9	10	7	10	10	10	10	10	10	9	8	8	7
Extra trailers	1	0	0	1	0	1	1	1	0	1	1	1	1	1	1	1	0	0	0

a) Number of delivered bins for each station for each train cycle based on Model 1

Station	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**
1	2	1	1	2	0	0	2	2	0	3	1	0	2	0	3	0	0	1	2
2	1	1	1	3	4	2	1	2	1	0	2	2	4	1	2	1	3	0	2
3	1	3	0	2	1	1	1	1	3	2	3	4	1	2	2	2	1	3	0
4	2	1	4	0	0	4	3	1	2	3	1	2	2	2	0	3	2	2	1
5	3	2	3	2	4	2	2	3	3	1	2	1	0	4	2	3	2	2	2
Sum	9	8	9	9	9	9	9	9	9	9	9	9	9	9	9	9	8	8	7
Extra trailers	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0

a) Number of delivered bins for each station for each train cycle based on Model 2

The effect of changing $P2$ value is not high for average number of extra trailers per cycle. It appeared only in model 4 indirectly because of the effect on the maximum number of extra trailers in model 3. The two tables show that, on average, model 4 is the best.

7.3 Summary

In this chapter, some strategies are investigated to keep JIT material supply in in-plant milk run system without breaking the line-side space and tugger train capacities. Dynamic scheduling, early loading, and minimizing extra number of trailers were investigated step by step in four integer programming models where the last model integrates all of them. DP was used to facilitate the computations in model 1 and 3. Several randomly generated instances were used to show the effect of each model. Generally, going from model 1 to 4 decreases the average number of extra needed trailers. Model 4 sometimes decreases the maximum number of needed trailers.

Table 7.5 Results for *N*=20 stations and *P1*=10, *P2*=15.

Trial #	Change in average number of extra trailers per cycle (%)			Change in maximum number of trailers (%)		
	Model 2	Model 3	Model4	Model 2	Model 3	Model 4
1	133.33	66.67	66.67	100	100	100
2	83.33	66.67	16.67	100	100	100
3	150	75	25	100	100	100
4	100	100	100	100	100	100
5	100	35	26.25	100	100	100
6	200	66.67	33.33	83.33	100	83.33
7	75	43.75	10.94	83.33	100	83.33
8	66.67	66.67	33.33	100	120	100
9	100	58.33	29.17	100	120	100
10	100	14.29	14.29	100	100	100
11	100	100	80	83.33	100	83.33
12	0	100	0	80	100	80
13	100	50	37.5	100	100	100
14	100	66.67	66.67	100	100	100
15	75	175	50	100	100	100
16	120	100	80	100	120	100
17	100	75	25	83.33	100	83.33
18	70	80	60	83.33	100	83.33
19	100	75	50	100	120	120
20	0	114.29	114.29	80	120	100
Average	93.67	76.45	45.95	93.83	105	95.83

This chapter is the last chapter in the demand-oriented systems. In the next chapter, a hybrid system is presented to take the advantage of both the demand-oriented and e-kanban systems to accommodate assembly line disturbances. The current chapter does not investigate the fixed routing based on which scheduling and loading problems were investigated. The routing problem in the next chapter can be applied in the current chapter.

Table 7.6 Results for N = 20 stations and P1 = 10, P2 = 50.

Trial #	Change in average number of extra trailers per cycle (%)			Change in maximum number of trailers (%)		
	Model 2	Model 3	Model 4	Model 2	Model 3	Model 4
1	133.33	66.67	66.67	100	100	100
2	83.33	66.67	16.67	100	100	100
3	150	75	25	100	100	100
4	100	100	100	100	100	100
5	100	35	26.25	100	100	100
6	200	66.67	33.33	83.33	100	83.33
7	75	43.75	10.94	83.33	100	83.33
8	66.67	66.67	33.33	100	100	100
9	100	58.33	43.75	100	100	100
10	100	14.29	14.29	100	100	100
11	100	100	80	83.33	100	83.33
12	0	100	0	80	100	80
13	100	50	37.5	100	100	100
14	100	66.67	66.67	100	100	100
15	75	175	50	100	100	100
16	120	100	60	100	100	100
17	100	75	25	83.33	100	83.33
18	70	80	60	83.33	100	83.33
19	100	75	50	100	100	100
20	0	114.29	114.29	80	100	100
Average	93.67	76.45	45.68	93.83	100	94.83

Chapter 8: Dynamic material flow control

This chapter combines the techniques that were investigated in previous chapters combining the advantages of demand-oriented and e-kanban systems to investigate an environment with disturbances. This chapter investigates the dynamic control of material flow considering a strategy to deal with disturbances such as machine breakdown, line stoppage, defective parts, and resequencing of product models. These disturbances lead to unexpected fluctuations in stations demand for parts. The strategy is applied using a mix between the demand-oriented and e-kanban systems to facilitate the planning of three problems, namely, train routing, scheduling, and loading. The information obtained using e-kanban is combined with the information about the expected stations demand based on previously known sequence of product models and the materials needed for each model. So these problems in this chapter are specially designed to facilitate the strategy of accommodating line disturbances. Routing was investigated analytically while scheduling and loading problems were investigated using integer programming. Results showed that the method proposed outperforms the traditional methods of material flow planning. The contents of this chapter have been partially published in Alnahhal and Noche (2015a).

8.1 The need for dynamic system

Routing is investigated at first. The routing problem is assumed to be independent from disturbances and resequencing. This is because the routing problem depends on the total average demand which is usually stable even after resequencing. Stable routing will give some stability in the system. On the other hand, scheduling and loading problems should by dynamic to respond for the changes in the detailed demand of stations. However, in the routing problem in this chapter, the effect of early loading will be taken into consideration. The results of the scheduling problem are used as inputs for loading problem. However, scheduling was investigated in a way that guarantees the feasibility of loading problem regarding the capacity of the train. Scheduling and loading problems in this chapter take into consideration the existing material amounts in line-side inventory after each disturbance. The objective is to make these amounts of materials as close as possible to the normal safety stock level as early as possible. The objective is done considering minimizing the number of train cycles, the probability of early loading, and the deviation of actual line-side inventory from the ideal safety stock level.

The following basic assumptions are made in this chapter:

- There is no any disturbance in the movement of the tugger trains. The disturbances only occur in MMAL
- The demand of stations can be represented by Poisson distribution
- If there is no disturbances for a certain period of the shift, the stations exact demand for parts can be expected in this period.
- The time between two disturbances is long enough to fix the problems caused by the first disturbance. These problems are basically the deviation of the size of line-side inventory from the ideal safety stock size.

Basically the material control system can be categorized as demand-oriented or kanban. In demand-oriented system, the exact demand is assumed to be known in at least the next shift. This fact makes the demand oriented-system able to deal with peaks period of demand using early loading. However, there are some cases that make it difficult to anticipate the exact stations demand for parts. Some of these cases are:

1. Resequencing: as stated before, the sequence of the product models can be changed during the shift based on changes in demand or some disturbances. In this case the total demand during the shift remains the same but deviates from the original plan over time.
2. Disturbances: for example in the case of line stoppage, the demand can be shifted by stoppage time. Some minor changes in demand can occur in the case of utility work. In this case the demand can be delayed. Another problem arises when the next station in which utility work is done has the same type of material of the previous station. In this case the utility worker may use the material of this next station. So the exact quantity of material in the two stations line-side inventory is no longer known. The same problem can occur in the case of work deficiency.
3. Quality problems: if there are some defective parts, some extra parts must be provided to compensate for the defective ones.
4. Unpaced MMAL: in an *unpaced line*, the tasks of the workstations can be decoupled from each other.

This chapter does not cover the last case. In the other cases, the kanban system can be used since it depends on the continuous feedback sent to the supermarket area about the status of the parts consumptions. To enhance the performance of the system, e-kanban can be used to send the signals instantly. However, this chapter is about getting the advantages of both the e-kanban and the demand-oriented systems to design a dynamic planning system. In this system, the expected demand during the next few train cycles after disturbances is determined. This is done depending on the information gathered from the signals sent by e-kanban system to the supermarket area about the parts consumptions and resequencing details. This is important to know the demand in the next train cycles and to exactly know the amount of parts in line-side inventory. The exact parts consumption can be obtained using RFID system or bar code. Traditional kanban system is not very effective in the proposed approach in this chapter because there are some delays in sending the information about the exact size of consumption of each station.

The following parameters must be known:

dp_i is the number of defective parts of type i during the previous disturbance period

d_{ik} is the expected number of parts i demanded in station cycle k according to the new workpieces sequence.

CP_i is the number of consumed parts of type i during the previous disturbance period

PD_i is the planned number of delivered parts of type i during the previous disturbance period

β_i is ideal safety stock size for parts i

Then current line-side inventory for parts i (α_i) can be estimated as follows:

$$\alpha_i = \beta_i - (CP_i - PD_i + dp_i) \tag{8.1}$$

This value will be used later as input in scheduling and loading problems. The disturbance period is the time interval at which dpi>0 or $CP_i \neq PD_i$. The RFID or bar code is important to detect dp_i and CP_i values. The previous five parameters can be converted to bin size units if the detection of each part is not possible. In this case, the bar code or RFID tag can be attached to each bin. In this chapter, it is assume that there is no any disturbance for the delivery of the train. The disturbances can only occur in the assembly line. This means that PD_i is not affected by disturbances. In the case that early loading is not used, the planned number of delivered parts is equal to the expected demand in previous train cycles. Another possibility for that equivalence is that disturbances occur in bottleneck periods of demand.

In the case of disturbances, the term $\mathrm{CP_i} - \mathrm{PD_i} + \mathrm{dp_i}$ in the previous equation can be with a positive or a negative sign depending on the following factors:

- The possibility of using early loading: if early loading is used the term tends to be negative
- The time of disturbances: if they happen just after peak-demand period, the extra material resulted from early loading is consumed. Therefore, the sign in this case is based on the nature of disturbances.
- The nature of disturbances: defective parts make it positive while delays caused by line stoppage or machine breakdown make it negative.

In the case of machine breakdown in a station, it is expected that the stations before that station have consumed parts more than the stations after it. Therefore it is expected that the first group of stations have lower line-side inventory. So its probability for starvation increases. In the following three sections, routing, scheduling, and loading problems, specially designed to be suitable for dynamic planning, are presented.

8.2 Fixed routing and effect of early loading

In the case of dynamic material flow control, there are two main advantages for fixed routing:

1. Making planning easier: after resequencing, for example, some tugger trains are in the supermarket area while others are still in their routes. If variable routing is to be done, a plan must take into consideration these two groups of trains and assign each train to the right stations. This complicates the planning process.
2. Providing some extra train capacity that is useful to absorb the effect of sudden increases in demand in some cycles

Although the stations demand is very dynamic, in the practice sometimes the routes are fixed, where certain colors are used to determine certain routes. The main question is: what is the maximum possible average demand of stations in the cell that is permitted to maintain a certain probability of *capacity fill rate* (η). Capacity fill rate, or simply *fill rate*, in this study refers to the probability of providing the cell with all the needed bins. In this study, fill rate depends only on the capacity of the train. The fill rate for all the cycles in the shift can be obtained by multiplying the fill rate for each cycle. Low fill rate causes high level of workstation starvation.

So if early loading is not used, it is possible to write

$$\eta_i = \min\left(\frac{K}{D_i}, 1\right) \tag{8.2}$$

$$\eta = \prod_{i=1}^{T} \eta_i \tag{8.3}$$

Where D_i is the cell demand in the train cycle i. The cycle demand for each station in the cell is for the time interval from the arrival of the train at the station to the next train arrival at the same station in the next train cycle. Later the fill rate is investigated if early loading is used. The average demand can be controlled by determining the number of stations in the cell. But before that the fill rate is found if the average demand is exactly as the capacity of the train. The calculations assume that early loading will be done later.

Decreasing fill rate increases stations starvation. This starvation is different from another type of starvation which occurs when an operator needs to wait for a workpiece to enter the upstream boundary of his workstation area. Generally, the station starvation is caused by the following points:

1. The total accumulated demand of all stations in the cell must always be less than or equal to the capacity of the train multiplied by the number of train cycles.
2. In the case of early loading, for each station the maximum line-side inventory (MLSI) must not exceed the capacity of the area beside the station.
3. In the case of traditional kanban system, the number of kanbans affects the starvation probability

The previous first point is related to the fill rate. If any of the two constraints in the first two points were not realized, workstation starvation occurs. The effect of MLSI can be negligible if the number of stations is high. This is because there are a lot of chances to make early loading without exceeding MLSI.

Suppose that the average cell demand per cycle is equal to the capacity of the train ($D = K$), and assume that the demand of stations for bins can be represented by Poisson distribution. η_{EL2} (i) represents the fill rate for the current and previous routes (i and i-1) if early loading is used. It can be obtained using equation (8.4) and equation (8.5)

$$\eta_{EL2}(i) = \sum_{j=0}^{D(i-1)} \mathrm{pmf}\big(D(i-1)-j, D(i-1)\big)\, CDF(D+j, D), \qquad D = K \qquad \forall\, i = 2 \ldots T \quad (8.4)$$

$$\eta_{EL2}(1) = CDF(D, D)\,, \qquad D = K \qquad (8.5)$$

Where,

pmf (k, λ) = Pr (X= k) is probability mass function

CDF (k, λ) = Pr ($X \leq k$) is cumulative distribution function

It was found using simulation that η_{EL}(i) which is the fill rate for routes from 1 to i can be estimated as in equation (8.6)

$$\eta_{EL}(i) = \eta_{EL2}(1) i^{-\eta_{EL2}(i)} \qquad D = K \qquad (8.6)$$

So the fill rate for all the routes is

$$\eta_{EL}(T) = \eta_{EL2}(1) T^{-\eta_{EL2}(T)} \qquad D = K \qquad (8.7)$$

It was found using simulation that the effect of the number of train cycles is very small when fill rate is high. So fill rate is almost independent from the number of cycles. This fact makes calculations easier. Using simulation, it was found when fill rate is high that:

$$\eta_{EL} \cong CDF(K, D) \qquad K \gg D \qquad (8.8)$$

Figure 8.1 shows how the values obtained using simulation and the values obtained using equation (8.8) approaches each other when the fill rate is high. The two lines are almost the same in the right side of the figure. The data used to obtain this figure was the following: there are10 workstations each of which has an average demand of 2 bins per train cycle, and there are 10 train cycles in the shift. The demand is assumed to be Poisson distributed for all the stations. To obtain the simulation line, 20,000 randomly generated instances were used, where the average value for the fill rate is used in figure 8.1. Equation (6.7) in chapter 6 was used to check the feasibility of a given instance containing the detailed demand of a group of workstations. The probability of feasibility based on equation (6.7) is the fill rate in this chapter. Increasing the number of train cycles will decrease the fill rate. The ‘Estimated’ line is obtained using equation (8.8). The data previously mentioned was altered several times and in each time the same behavior shown in figure 8.1 occurs. Since equation (8.8) ignores the effect of the number of train cycles, using simulation table 8.1 shows the difference between the obtained fill rate assuming two cases. In the first one, the number of train cycles equals 1, and in the second one the number of train cycles equals 10. This difference is obtained by subtracting the two values in the two cases and dividing the result by the value in the second case. The effect of the number of the train cycles decreases when the fill rate increases. Figure 8.1 and table 8.1 shows the accuracy of equation (8.8).

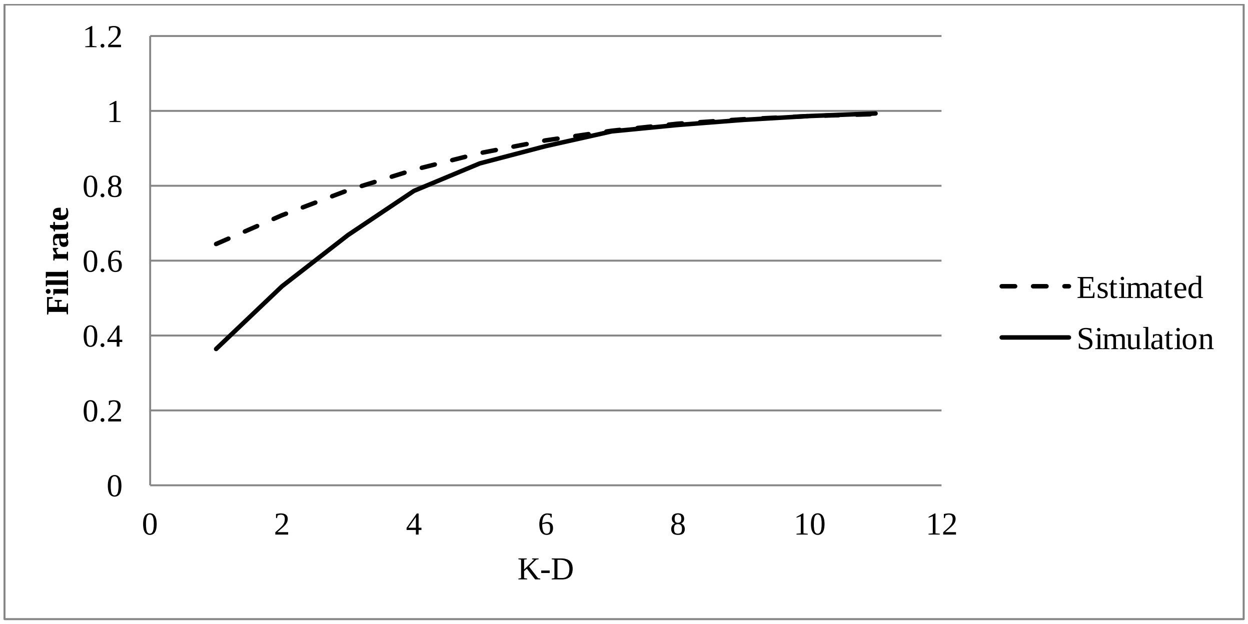


Figure 8.1 The difference between the results of equation (8.8) and the results of simulation

Table 8.1 Effect of number of train cycles per fill rate.

K-D	Fill rate when there are 10 train cycles	Difference between fill rates when there are 1 and 10 train cycles
1	36.38 %	75.42 %
2	53.17 %	35.02 %
3	66.76 %	16.83 %
4	78.60 %	7.53 %
5	86.04 %	3.32 %
6	90.64 %	1.66 %
7	94.47 %	0.71 %
8	96.20 %	0.31 %
9	97.63 %	0.11 %
10	98.71 %	0.03 %
11	99.25 %	0.02 %

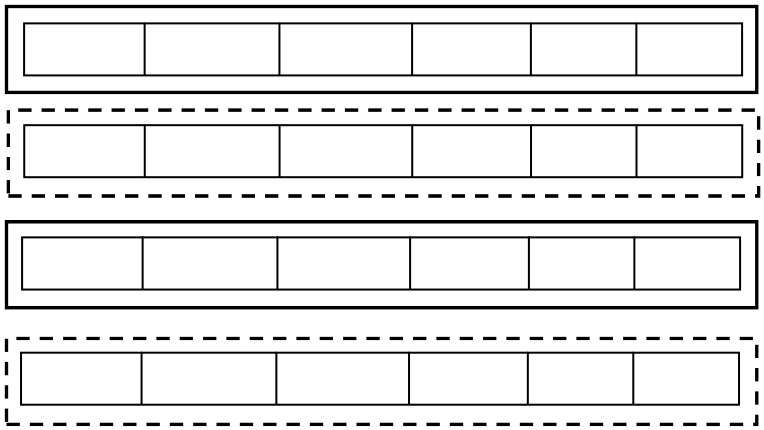
So based on equation (8.8) and to estimate the number of stations (N) that should be supplied by one train (cell size), it is possible to write

$$K \geq F^{-1}\left(\eta_{EL}, \sum_{i=1}^{N} d_i\right) \qquad\qquad K \gg D \qquad\qquad (8.9)$$

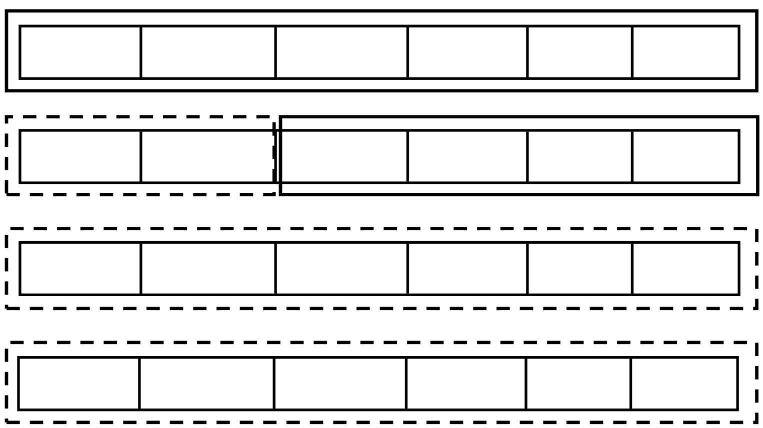
Where d_i is the average cycle demand for station i, and F^{-1} is the CDF inverse. N should be the maximum value that does not break constraint (8.9).

The transportation and loading/unloading times must be considered in the determination of TCT. The summation of these times for all the stations increases when the number of stations increases. This means that TCT must be increased and hence d_i increases. So the values of d_i are recalculated every time the number of stations is changed. The demand can be based on the minimum possible TCT for the given number of stations. This is because the priority is to decrease the number of tugger trains as much as possible. This means that in the peak periods of demand, TCT must be the minimum possible one to be able to provide the needed cell demand using the maximum possible capacity without waiting in the supermarket area.

The cell can be supplied by a central warehouse or by a decentralized supermarket. One decentralized supermarket may feed several assembly lines. However, sometimes one decentralized supermarket supplies just part of the assembly line (Emde and Boysen 2012a; Emde et al. 2012). In the case of using a central warehouse or a decentralized supermarket feeding more than one assembly line, a different approach from those found in the literature is used in this chapter. The serpentine routes method used in Golz et al. (2012) is not very effective in the case of using fixed routing since it results in high level of underutilization of tugger trains. The stations in figure 8.2 in the solid line belong to the same cell. The stations in the dotted line belong to another cell. So in this chapter the assembly line can be supplied by more than one tugger train. In the case of using a decentralized supermarket feeding just part of the assembly line, routing is simpler. In the two cases, the routing is as follows: just start from the first station and go until the final possible station while keeping the constraint in equations (8.9) in mind. When reaching the last station in the cell, begin a new cell starting from the station after it and continue in the same way.



a. Routes in literature



b. Routes in the proposed system

Figure 8.2 Two ways for routing

8.3 Scheduling

In the period just after disturbances, there are two main special factors for the scheduling process:

1. It must consider the size of the current line-side inventory. MLSI resulted from scheduling taking into consideration the line-side inventory remaining from previous period must not exceed the maximum capacity of the space near the stations.
2. More attention is paid for the capacity of tugger trains, where sometimes, the train capacity is still not enough even after using early loading. So scheduling process must take into consideration that the loading problem that will be conducted later is feasible regarding the accumulated stations demand. So high fill rate should be guaranteed. This factor and the previous one make the scheduling in this chapter unique.

The first factor is also in loading problem. The objective function of scheduling problem is minimizing the number of train cycles and the possibility of early loading. The maximum train capacity and the maximum capacity of the space near the stations must be taken into consideration. Minimizing the number of cycles reduces the efforts and the traffic jam in the facility, while minimizing the probability of early loading reduces the inventory holding costs.

Some of the following parameters and variable are used in chapter 7 but they are repeated again here:

MC is the minimum possible TCT minus 1 (represented in SCT unit).

TSC is the total number of station cycles in the shift

$$x_{ij} = \begin{cases} 1, & \text{if there is a train cycle that covers the cell demand during the station cycles from } i \text{ to } j \\ 0, & \text{otherwise} \end{cases}$$

d_{ku} is the demand (in bins unit) of station k during the station cycle u

K^{LS} is the maximum capacity of the area beside the station dedicated for the inventory for immediate use.

w_i is the weight of the term i in the objective function

Table 8.2 Stations demand representation method

k (station number)	Station cycles		
	u= τ	u=τ + 1	u=τ + 2
1	τ	τ + 1	τ + 2
2	τ + 1	τ + 2	τ + 3
3	τ + 2	τ + 3	τ + 4
4	τ + 3	τ + 4	τ + 5
d_{ku}	$d_{k\tau}$	$d_{k(\tau + 1)}$	$d_{k(\tau + 2)}$

The minimum possible TCT is based on the total needed time for train transportation and loading and unloading of bins beside the stations and in the supermarket area. For the estimation of d_{ku}, for a group of stations belonging to the same assembly line if the station cycle 'u' for a station 'k' is 'τ', then the associated 'u' for the station k+1 is τ+1. This is because it takes one SCT for a workpiece to move from the station 'k' to the station k+1. Table 8.2 shows the associated 'u' values for different stations and cycles. For example, in the third column (τ + 2) and for the second station, the demand in the fourth station cycle (τ + 3) is written instead of the demand of the third station cycle (τ + 2). That means that the second station demand values have been shifted backward by 1 because the distance between the first station and the second station is 1 station cycle. Any column in the table represents the cycles in which the demand of the same workpiece take places on different stations. As it is obvious, even when u=τ+3 for the fourth station, d_{ku} is written not as $d_{k(\tau+3)}$ but as $d_{k\tau}$. In other words, the station cycle number depends not only on the time of the cycle but also on the station number. In the case that the stations belong to more than one assembly line, table 7.1b in chapter 7 shows how to deal with this situation.

There are some similarities to scheduling and loading problems in chapter 7. However, the similar constraints are repeated again here. The model for scheduling is as follows:

Objective function

$$\min w_1 \sum_{i=1}^{TSC-MC} \sum_{j=i+MC}^{TSC} {y^+}_{ij} + w_2 \sum_{i=1}^{TSC-MC} \sum_{j=i+MC}^{TSC} x_{ij} + w_3 \sum_{i=1}^{TSC-MC} \sum_{j=i+MC}^{TSC} x_{ij} \sum_{k=1}^{N} \sum_{u=i}^{j} d_{ku} \qquad (8.10)$$

Subject to

$$x_{ij} \sum_{u=i}^{j} d_{ku} \leq K^{LS} \qquad \forall i = 1 \ldots TSC - MC, \qquad \forall j = i + MC \ldots TSC, \qquad \forall k = 1..N \qquad (8.11)$$

$$x_{ij} \sum_{k=1}^{N} \sum_{u=i}^{j} d_{ku} - {y^+}_{ij} + {y^-}_{ij} = K \qquad \forall i = 1 \ldots TSC - MC, \qquad \forall j = i + MC \ldots TSC \qquad (8.12)$$

$$\sum_{i=1}^{I-MC} \sum_{j=i+MC}^{I} x_{ij} \sum_{k=1}^{N} \sum_{u=i}^{j} d_{ku} - \sum_{k=1}^{N} \alpha_k \leq K \sum_{i=1}^{I-MC} \sum_{j=i+MC}^{I} x_{ij} \qquad \forall I = MC + 1 \ldots TSC \qquad (8.13)$$

$$\sum_{i=1}^{j-MC} x_{ij} = \sum_{v=j+1+MC}^{TSC} x_{j+1,v} \qquad \forall j = MC + 1 \ldots TSC - MC \qquad (8.14)$$

$$\sum_{j=1+MC}^{TSC} x_{1j} = 1 \qquad (8.15)$$

$$\sum_{i=1}^{TSC-MC} x_{iTSC} = 1 \qquad (8.16)$$

$$x_{ij} = 0 \text{ or } 1, \qquad {y^+}_{ij}, {y^-}_{ij} \geq 0 \qquad \forall i = 1 \ldots TSC - MC, \qquad \forall j = i + MC \ldots TSC \qquad (8.17)$$

Appropriate weights for the objective function terms can be determined by management staff according to the importance of minimizing inventory holding costs and the number of cycles. The first term in the objective function is to minimize the possibility of early loading in loading problem. This objective is important to minimize the inventory holding cost because early loading increases the average line-side inventory. The second term is to decrease the number of train cycles. The third term is to guarantee that there is no overlap in the cycles. Constraint (8.11) is to guarantee that demand does not exceed the capacity of area beside stations. Constraint (8.12) is to define the variable y^{+}_{ij} used to minimize the possibility of early loading. When y^{+}_{ij} is larger than zero, it means that the demand is more than the capacity for certain train cycle, and that means the necessity for early loading. In the objective function, y^{+}_{ij} is put because the objective is reduce it. On the other hand, if y^{-}_{ij} is larger than zero, it means that the capacity is more than the demand. Constraint (8.13) is to prepare for early loading in the next section where it guarantees that early loading will be feasible regarding the accumulated demand constraint. The current line-side inventory for parts k (α_k) computed in equation (8.1) has been taken into consideration. Constraint (8.14) is to guarantee that all the station cycles demand is fulfilled. If a certain train cycle for the station cycles ‘i’ to ‘j’ is chosen in the solution, there must be a new train cycle starting from the station cycle j+1. Together with constrains (8.15) and (8.16), the fulfilling of cycle demands are guaranteed by using constraint (8.14). Constraints (8.15) and (8.16) are to guarantee that there is an initial train cycle covering the first station cycle, and a final train cycle to cover the last station cycle demand. Without these two constraints, all variables x_{ij} will be zeroes. Even if y^{+}_{ij} and y^{-}_{ij} are greater than or equal to zero, the result will make them integers because the stations demand is usually written as integer number of bins. So this problem is still IP and not mixed integer programming (MIP)

To show the effect of the weight of each term in the objective function, a simple example is presented in table 8.3, where 1 represents the demand for one bin in the station cycle. For the first station, there was no any demand until the 17th station cycle because the station has some parts from the previous shift. Only the station cycles in which the demand occurs were shown. In the real life, the numbers of station cycles and stations are usually larger. In the example, it was assumed that MC=8, K^{LS}=4, and K=6. Moreover, α_k=2 for all the stations.

Table 8.3 Stations demand for bins during the station cycles

Station	Station cycles												
	1	11	12	14	17	18	21	25	33	34	35	38	40
1					1		1						
2	1	1				1						1	1
3	1			1					1				
4	1	1				1				1			
5	1		1					1	1		1		

The third term in the objective function can be multiplied by a very small number because it is only to guarantee that there is no extra number of train cycles. For the first and second terms, the results depend on the value that is multiplied by each term, where the results are as in table 8.4

Table 8.4 Results for different weights of the first term in the objective function

Weight	Train cycle number			
	1	2	3	4
0	7 (1-12)*	12 (13-40)		
1	7 (1- 12)	6 (13- 25)	6 (26- 40)	
10	6 (1- 11)	5 (12-20)	2 (21-30)	6 (31- 40)

*D (i- j) means that the train cycle covers the station cycles from 'i' until 'j' and the demand is 'D' bins in this cycle

As in the first scenario if the weight is zero, there is no penalty if the demand is more than the capacity of the train. In this case the penalty will only be for the number of the cycles of the train. Therefore, there are only two cycles, and the demand for the train is more than its capacity by 1 bin in the first cycle and 6 bins in the second cycle. Because α_k=2 for all the stations, the solution is still feasible, but the line side inventory size will be deviated from its initial one. In the second scenario the weight for the first term was set to be 1, and there are three cycles. There is still one cycle with demand more than K. In the third scenario, the importance of the first term was set to be very high on the expense of the number of train cycles, where there are 4 train cycles with no any cycle with demand more than the capacity of train. The weights of the first two terms of the objective function are left for the decision maker based on his/her judgment. Results were obtained using LPsolve software.

The scheduling and loading problems found in the literature assume that there is no any disturbance. Moreover, the scheduling problem in this study prepares for early loading considering the current size of line side inventory. It guarantees that the loading problem is feasible, where the scheduling problem is an input for the loading problem. Ignoring this fact can lead to infeasible loading problem which leads to workstation starvation. Without using the signals about the real consumption of materials, a lot of problems can happen depending on the type and level of disturbance. Rescheduling may not be problematic because it is a major change that can be easily known by the material handlers using simpler methods of information sharing. However, the effect of some problems in the quality of some parts can be gradually increased and not be known or estimated by the material handlers except if sever workstation starvation happens. The effect of machine breakdowns or line stoppage for short times can be detected only if the line side area is full with bins. It is important for the signals to be electronically sent for fast response by the material handling system. If the current size of line side inventory is not known because the electronic signals are not used and if it is higher than the ideal safety stock level, then the real needed capacity of the tugger train will be less than the assumed one. This may not make any problem in scheduling. However, the problem will occur if the size of the current line side inventory is lower than the ideal safety stock assuming that the scheduling problem takes into consideration the safety stock level. This is because the real needed capacity will be higher than the assumed one.

In the case that the electronic signals are not used, the planner has two strategies. The first one is to assume that the line side inventory is zero. Usually, the safety stock should not be used except if it is very necessary in some bottleneck periods where the shortage of material will occur. Usually to cover such a shortage, some emergency tugger trains routes are used. The problem for these tugger trains is that if the real line side inventory is not zero, they add cost which is not necessary and may result in excessive material accumulation beside the stations. The second strategy is to assume that the current line side inventory is equal to the ideal safety stock level. Suppose that in normal situations that the system suffers from 10% probability of workstations starvation if the safety stock is needed. If that system does not use the electronic signals to detect the depletion of all the safety stock, then the system will suffer from 10% probability of workstations starvation. The above discussion reveals the importance of integrating the electronic signals in the planning tasks to avoid a lot of problems.

There are some differences between the scheduling problem in chapter 7 and the scheduling problem in the current chapter in the objective function and also the constraints. Besides considering the current inventory size beside stations and the ideal safety stock levels, this scheduling problem is loading-oriented. It is not completely independent from loading problem and in the same time not parallel to it. This means that the scheduling problem facilitates the use of early loading. Therefore, in loading problem, the problem will most probably be feasible regarding the train capacity.

8.4 Loading problem

The objective function in loading problem is minimizing the difference between the line-side inventory and ideal safety stock levels. The model will minimize the total inventory holding costs. In the case that sudden large demand quantities higher than the capacity of the train are required in the first few cycles and they cannot be accommodated by early loading, emergency train routes can be used. This case is not considered in the loading problem below. So it is assumed that the system can accommodate the peak demand caused by disturbances without the need for the emergency routes.

The following variables and parameter are used

ε_{st} is the difference between the actual line-side inventory and β_s

d_{st} is the demand of station s for bins in the train cycle t.

x_{st} is the decision variable which represents the number of delivered bins for station s in the train cycle t.

The definition of d_{st} and x_{st} was also in chapter 7 but they are repeated here. If there is no early loading, x_{st} and d_{st} will be identical. The model for loading problem is as follows:

Objective function

$$min \sum_{s=1}^{N} \sum_{t=1}^{T} |\varepsilon_{st}| \qquad (8.18)$$

Constraints

$$\sum_{s=1}^{N} x_{st} \le K \qquad \forall t = 1, \dots, T \qquad (8.19)$$

$$\sum_{t'=1}^{t} x_{st'} \geq \sum_{t'=1}^{t} d_{st'} - \alpha_s \qquad \forall t = 1, \dots, T, \quad s = 1, \dots. N \qquad (8.20)$$

$$\sum_{t'=1}^{t} x_{st'} - \sum_{t'=1}^{t} d_{st'} + d_{st} + \alpha_s \leq \mathrm{K}^{\mathrm{LS}} \qquad \forall t = 1, \dots, T, \quad s = 1, \dots. N \qquad (8.21)$$

$$\sum_{t'=1}^{t} x_{st'} - \sum_{t'=1}^{t} d_{st'} + \alpha_s - \beta_s = \varepsilon_{st} \qquad \forall t = 1, \dots, T, \quad s = 1, \dots. N \qquad (8.22)$$

$$x_{st} is\ positive\ integer \qquad \forall t = 1, \dots, T, \quad s = 1, \dots. N \qquad (8.23)$$

Constraint (8.19) is to guarantee that the capacity of the train is not exceeded. Constraint (8.20) guarantees that the accumulated delivered number of bins is at least as the accumulated demand. In the same constraint, the size of line-side inventory at the moment of disturbance is taken into consideration. This inventory is also considered in constraint (8.21) which guarantees that the MLSI does not exceed the maximum capacity of the area beside stations. The value of deviation stated before is defined in constraint (8.22) to be used in the objective function. To represent the absolute value for the variable ε_{st}, some changes are added to the objective function and constraints, where

$$\varepsilon_{st} = \varepsilon_{st}^{+} - \varepsilon_{st}^{-}$$

$$|\varepsilon_{st}| = \varepsilon_{st}^{+} + \varepsilon_{st}^{-}$$

$$\varepsilon_{st}^{+}, \varepsilon_{st}^{-} \geq 0$$

So the objective function is rewritten as:

$$\min \sum_{s=1}^{N} \sum_{t=1}^{T} \varepsilon_{st}^{+} + \varepsilon_{st}^{-} \qquad (8.24)$$

Constraint (8.22) is rewritten as

$$\sum_{t'=1}^{t} x_{st'} - \sum_{t'=1}^{t} d_{st'} + \alpha_s - \beta_s = \varepsilon_{st}^{+} - \varepsilon_{st}^{-} \qquad \forall t = 1, \dots, T, \quad s = 1, \dots. N \qquad (8.25)$$

8.5 Results and analysis

This section concentrates mainly on the effect of using the dynamic control of material flow and compares it to the traditional demand-oriented and kanban systems. In demand-oriented system a complete failure is expected due to the fact that the accuracy of future expectations about demand is deteriorated after disturbances especially in the case of resequencing. So the concentration is more on comparing the system in this chapter to kanban system.

To compare the proposed system in this chapter to kanban system in the case of high level of fill rate, table 8.5 shows the fill rate for the two systems. The effect of the current line-side inventory was neglected. K values were chosen so that fill rate is greater than or equal to 99%. Actually the difference comes from the usage of early loading. Usually early loading is used in demand-oriented system but this system is not appropriate in the case of disturbances. So early loading is used in the approach in this chapter. Early loading makes the system almost independent from the number of cycles. It is obvious that the system proposed in this chapter outperforms the demand-oriented and kanban systems.

Table 8.5 Effect of early loading on fill rate

		The proposed system	Kanban system		
			η^*		
D^*	K^*	$\eta_{EL}{}^*$	T^*=10	T=15	T=20
5	11	0,995	0,947	0,921	0,896
6	12	0,991	0,915	0,875	0,838
7	14	0,994	0,944	0,918	0,892
8	15	0,992	0,921	0,883	0,848
9	17	0,995	0,948	0,923	0,899
10	18	0,993	0,930	0,897	0,866
11	19	0,991	0,911	0,869	0,830
12	21	0,994	0,941	0,913	0,885
13	22	0,992	0,926	0,892	0,858
14	23	0,991	0,911	0,869	0,829
15	25	0,994	0,940	0,911	0,883

*D is average cell demand during the train cycle time, K is train capacity, η is fill rate, η_{EL} is fill rate if early loading is used, and T is number of the train cycles in the shift

Equation (8.26) is to find η_{diff} which is the difference between the two systems in terms of fill rate.

$$\delta_{diff} = CDF(K, D) - CDF(K, D)^T \tag{8.26}$$

Another direction to investigate the effect of using the proposed approach is to examine the effect of using fixed routes on the underutilization of trains. The (K-D)/D value found by equation (8.27) is plotted against D based on certain fill rate. The nominator represents the extra needed capacity higher than the average cell demand. If this value is so large compared to the average cell demand, the underutilization of trains is high.

$$\frac{K-D}{D} \cong \frac{F^{-1}(\eta_{EL}, D) - \mathrm{D}}{D} \tag{8.27}$$

Figure (8.3) shows the results for η_{EL}=99%. It is clear from figure 8.3 that using fixed routes for low level of demand (number of bins) affects severely the underutilization of trains. However, when the average demand is high, the level of utilization is enhanced. In the case that there are only some few stations in the cell, there is a probability that MLSI affects the results when MLSI>K^{LS}, and hence the performance of early loading will not only depend on the accumulated demand of stations but also on the MLSI value. This is because there are only few possibilities for early loaded quantity which may be added to the already large demanded quantity in a certain cycle. However, from figure 8.3 it is not recommended to use fixed routes for the cell with small number of stations because in this case the demand will be low, and the low cell demand increases the underutilization of tugger trains.

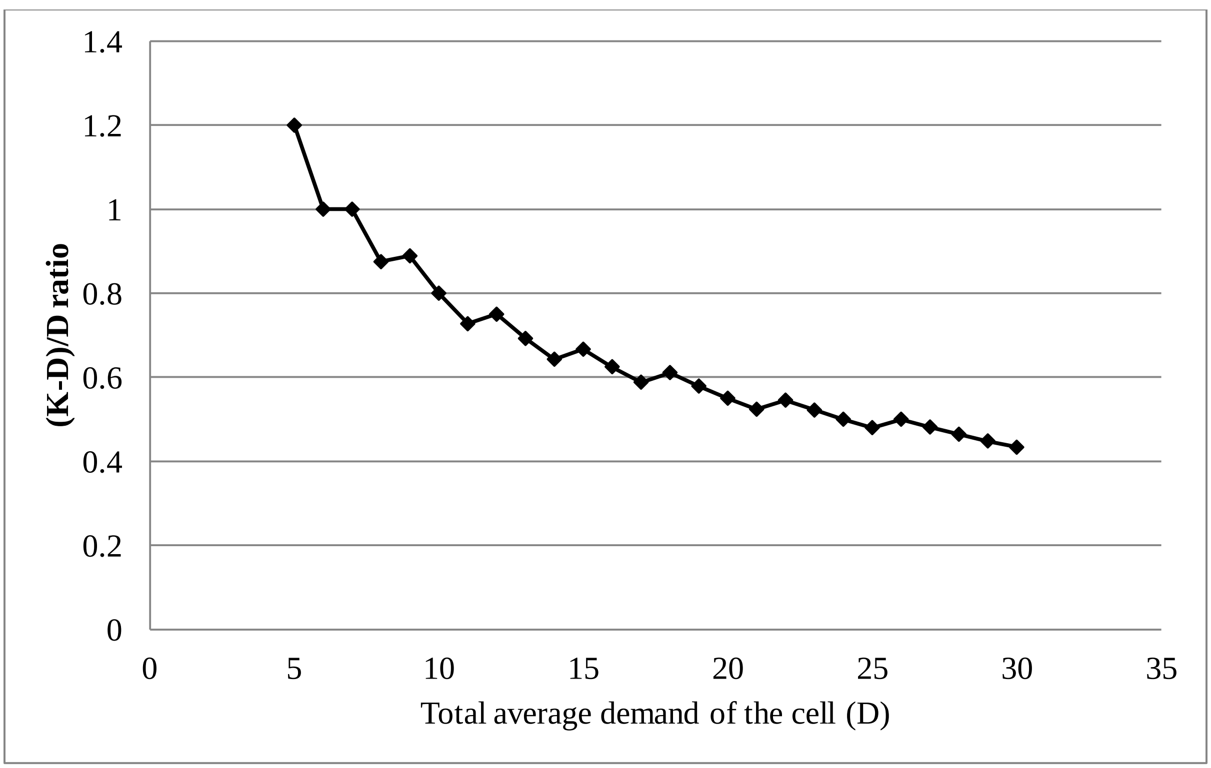


Figure 8.3 Effect of fixed routing on underutilization of trains (η_{EL}=99%)

The example in scheduling problem shows the possibility of getting different solutions based on the weights of the terms of the objective function. These weights can be set by the decision maker. The main trade-off is between reducing the number of train cycles to decrease the material handling costs, and reducing the probability of early loading and hence reducing the inventory costs. For the loading problem which is necessary if the demand in some train cycles is more than the capacity of the train, it is important to know that the penalty of deviation of the current line side inventory from its ideal level is measured in two dimensions: the quantity (number of bins) and time (number of train cycles). For example, if a deviation of one bin occurs in the first two cycles, the penalty will be 2 not 1.

8.6 Summary

In this chapter, an approach for dynamic material flow control is presented. This approach accommodates the effect of assembly line disturbances on the fluctuations of the stations demand for materials and parts. A mix between the demand-oriented and e-kanban systems is used. To fit into this situation, fixed routing is presented taking into account the effect of early loading. Moreover, scheduling and loading problems were investigated taking into consideration the current available amount of inventory beside stations. The objectives considered are minimizing the possibility of early loading, number of train cycles, and the deviations from the ideal safety stock size. These objectives guarantee minimizing inventory holding costs and traffic jam of tugger trains. The presented approach outperforms the traditional ones by enhancing the fill rate depending on better utilization of tugger trains capacity. However, the underutilization level increases when cell demand decreases. Future research can focus on finding a suitable approach for routing in the case that cells are with low demand for bins.

Chapter 9: Conclusion and recommendation for future research

This study focuses on the efficient material flow of in-plant milk run system needed to feed MMAL. In this system, tugger trains are used to repetitively transport materials and parts in small containers. Due to the limited literature size on the topic, the study gives a good contribution since it investigates the topic from different angles and in different situations. The study divides the investigation based on five different systems, namely, demand-oriented central warehouse, demand-oriented decentralized supermarket, traditional kanban, e-kanban, and dynamic hybrid system. The situation on the ground determines which system exists. These different systems were investigated in detail in 5 chapters which represent the methodology in the study. This methodology depends on integer programming, dynamic programming, genetic algorithm, analytical investigation, and simulation to minimize the system costs. Examples that are similar to the examples found in the literature were used to present the ideas. There are some similarities and differences between the five systems.

Generally, if the accuracy of expecting the detailed demand of each workstation is high and if the there is no assembly lines disturbances, demand-oriented system outperforms the other systems. If decentralized supermarkets are used, the investigation can be different from the main warehouse environment depending on two factors, namely, the need for supermarket location problem, and if each supermarket feeds only some workstations in the assembly line. In this case the approach used is different from the approach used for main warehouse environment. If the accuracy of expecting the detailed demand of stations is not so high, then there are two cases. If this low accuracy is caused by assembly line disturbances, then dynamic planning is used. If there is no a lot of disturbances and if there is a technical support in the form of RFID or bar code, then e-kanban is used. If the technical support is the existence of traditional kanban, then it can be used only if there is enough train capacity or if the demand is not very dynamic. Traditional kanban is most probably the worst system because of the need for emergency routes which occur in the peak demand periods.

In e-kanban, the relationship between the size of the circulating inventory in the system and both ALSI and workstation starvation is analytically investigated. The circulating inventory in the system can be controlled using the initial inventory delivered at the beginning of the shift or inventory remaining from previous shifts. Increasing circulating inventory decreases workstation starvation but increases ALSI. The effects of bin size and the distance between the supermarket and workstation are also investigated. A new system, AEK, was proposed to accommodate train capacity problems in the peak demand period by delivering the first K requested bins. Its effect on workstation starvation was tested using simulation which illustrated its high performance. Moreover, a cost model that concentrates on the line-side inventory is presented. The analytical investigation on the e-kanban was utilized to investigate the traditional kanban in which the circulating inventory in the system is the number of kanbans which is the number of bins in this case.

In the case that demand-oriented decentralized supermarket system is used, the first step is to determine how many supermarkets are needed and in which locations they should exist considering the limitation of the area around the assembly line. This is done in supermarket locations problem which was investigated using IP and genetic algorithm. IP is slow. The performance of genetic algorithm was tested based on CPU time, quality of solutions, and variability in the two of them. Reasonable CPU time and high quality of results were obtained. After the supermarket location problem, the routing, scheduling, and loading problems were investigated in parallel to minimize number of trains, inventory costs, and system variability using analytical investigation, IP, and DP. Minimizing the number of trains was considered the most important objective. Constraints such as train capacity, buffer time, line-side areas, and tours times were considered. An example was used to show the idea. Results showed the effect of using time buffer on the feasible space.

In the case that demand-oriented main warehouse system is used, the case of fixed routing was investigated. In fixed routing, the routes are assumed to be fixed over a long time in spite of the dynamic nature of demand from a day to another. To accommodate train and line-side area capacities problems that arise in fixed routing, four strategies were investigated. The same idea can also be applied in decentralized supermarket system. These four strategies are dynamic scheduling, early loading, minimizing the number of extra trailers, and using market attendant or technical solutions. The first three strategies were investigated using four IP models which apply the strategies step by step until the problem of exceeding the capacities of tugger trains and line-side area is solved. This investigation decreases the line-side inventory and the needed number of trailers even if there is enough capacity in the two of them. This is to minimize inventory holding costs and to make some trailers available just in case that any capacity problem occurs in the future.

In the case that there are a lot of assembly line disturbances, the advantages for both e-kanban and demand-oriented systems should be utilized in one approach. Some disturbances are assembly line stoppage because of delay on a workstation, resequencing based on changes in demand or machine breakdown, quality problems that increase the demand for some parts, and others. The advantage of e-kanban is the continuous feedback about the status of the work in different workstations. The advantage of demand-oriented system is the accurate expectation of demand for parts if there are no disturbances in the next few train cycles. This is important to do early loading to prepare for peak demand periods. The strategy is based on fixed routing problem, and special scheduling and routing problems to reduce the difference between the ideal safety stock and the current safety stock sizes. These tasks are investigated analytically and also using IP to reduce the number of cycles and the possibility of early loading to minimize trains traffic jam and inventory holding costs.

The following directions are for future research because there is no enough research found in the literature about them:

- 'Multiple routed vehicles' should be studied to reduce train capacity and inventory costs to the optimum levels
- More real case studies are needed.
- In the case of dynamic planning, the 'multiple routed vehicles' can be investigated instead of fixed routing
- Some deviations of the normal e-kanban can be checked analytically and using simulation. One of these directions is to prioritize the delivery for lower on-hand-inventory stations or higher-expected-demand stations.
- The supermarket location problem should theoretically be studied based on factors other than the transportation and fixed costs. This should be done based on the experience of decision makers.
- Enough research is needed in industries other than automotive industry.

- A general framework should be investigated in the case that emergency routes are needed because of severe assembly line disturbances or because of using traditional kanban in environments with high dynamic demand.
- The effect of directional stability techniques that are sometimes used for trailers to increase the number of trailers attached to the train can be investigated

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