Universidad de Oviedo
Universidá d'Uviéu
University of Oviedo

Programa de Doctorado en Administración de Empresas

Tesis Doctoral:

Diseño de redes logísticas sostenibles en entornos de riesgo

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2017

RESUMEN DEL CONTENIDO DE TESIS DOCTORAL

1.- Título de la Tesis	
Español/Otro Idioma: Diseño de redes logísticas sostenibles en entornos de riesgo	Inglés: Sustainable logistic network design under risk

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Programa de Doctorado: Programa de Doctorado en Administración de empresas.	
Órgano responsable: Centro Internacional de Postgrado. Comisión Académica Programa Administración Empresas	

RESUMEN (en español)

El diseño de redes logísticas sostenibles en entornos de riesgo ha sido ampliamente tratado en la literatura pero en la mayoría de los casos desde un punto de vista monoobjetivo (normalmente la minimización total de los costes del sistema). Dado el interés que suscita actualmente tanto el impacto sobre el medio ambiente de las actividades logísticas, el efecto que cierto tipo de riesgos puede llegar a tener sobre la cadena logística, así como la necesidad de reducir los desperdicios, especialmente de los productos alimenticios, que se generan en una red logística, parece adecuado incorporar todos estos objetivos al diseño de redes. Esta tesis aborda el problema del diseño de redes logísticas multiobjetivo con el fin de estudiar simultáneamente estos factores y sus conflictos. Para ello, se han diseñado diversos modelos usando como metodologías de resolución técnicas de optimización de tipo multicriterio.

En el primer trabajo realizado se ha diseñado una red de depósitos de contenedores en un hinterland. La ubicación de los depósitos de contenedores tiene un gran impacto ambiental, dada la gran carga de tráfico inherente a estas operaciones y a la creación y mantenimiento de los depósitos. Se ha diseñado un modelo de optimización biobjetivo y se ha aplicado al hinterland de Valencia. Los objetivos considerados son: el coste total de la red y el impacto medioambiental de los depósitos y las operaciones de transporte asociadas a ellos. Se ha utilizado el Analytic Hierarchy Process (AHP) para determinar el impacto ambiental de cada depósito y el método de las ε-constraints para obtener la frontera de Pareto del problema. Los resultados muestran claramente que el estudio realizado con el enfoque propuesto puede obtener soluciones que sean más rentables y tengan menores impactos ambientales que los actuales.

El segundo trabajo amplia los objetivos abordados en el anterior incluyendo varias modificaciones con el fin de buscar un modelo que se ajuste lo máximo posible a una situación real. Se utiliza un modelo de optimización de tres objetivos para minimizar el coste total de la red: el impacto ambiental generado por las operaciones de transporte por carretera asociadas a los depósitos y el impacto medioambiental generado por la creación y mantenimiento de los depósitos. Para determinar los impactos ambientales de cada depósito, se utiliza Fuzzy-AHP y como metodología de resolución una variación del Weighted Additive Model. Al comparar los resultados con el trabajo anterior, se consiguió reducir en gran medida el número de soluciones no dominadas.

Uno de los objetivos que más preocupan socialmente en las redes logísticas alimentarias es la reducción de los desperdicios. Para estudiar este hecho, se ha realizado un trabajo que trata el uso estrategias dinámicas de precios para reducir el desperdicio de alimentos y otros productos perecederos. Se ha propuesto un modelo matemático determinista para estudiar la influencia de una serie de factores, como la elasticidad-precio de la demanda, la sensibilidad a la edad de la demanda y el perfil de edad del inventario inicial, los desperdicios y los ingresos. Se considera un enfoque paramétrico, bi-objetivo, con el objetivo de estimar los trade-offs existentes entre los desperdicios y los ingresos. Se ha resuelto el problema en varios escenarios y se ha encontrado que aunque una estrategia dinámica de precios ayuda a reducir los desperdicios, en algunos casos específicos los ingresos totales pueden aumentar ligeramente o, al menos, mantener su nivel. En otros escenarios, la reducción de los desperdicios conlleva una pérdida en los ingresos totales. El enfoque propuesto permite la cuantificación de los trade-offs disponibles para cada escenario y permite el análisis de la distribución por edad de las unidades vendidas y su contribución respectiva a los ingresos.

RESUMEN (en Inglés)

The design of sustainable logistic networks under risk has been extensively addressed in the literature but in most cases from a single objective point of view (usually the total minimization of system costs). Given the current interest in the environmental impact of logistic activities, the effect that a certain type of risk may have on the logistic chain, and the need to reduce waste, especially of foodstuffs, which are generated in a logistics network, it seems appropriate to incorporate all these objectives in network design problems. This thesis addresses the problem of multiobjective logistic network design in order to simultaneously study these factors and their conflicts. To this end, various models have been designed using multicriteria optimization techniques as resolution methodologies.

The first article of this thesis designs a container depot logistic network in a hinterland. The location of container depots has a major environmental impact, given the heavy traffic load inherent in these operations and the setting up and maintenance of the depots. A biobjective optimization model has been designed and applied to the hinterland of Valencia. The objectives considered are: the total cost of the network and the environmental impact associated to the depots and to the transport operations. Analytic Hierarchy Process (AHP) has been used to determine the environmental impact of each depot and the ε-constraints method has been implemented to obtain the Pareto Frontier of the problem. The results clearly show that the study carried out with the proposed approach can provide solutions that are more cost-effective and have lower environmental impacts than those currently existing

The second article expands the objectives addressed in the previous one including several modifications in order to look for a model that fits as much as possible to a real situation. A three-objective optimization model is used to minimize the total cost of the network, the environmental impact generated by the road transport operations associated with the depots and the environmental impact generated by the setting up and maintenance of the depots. To determine the environmental impacts of each depot, Fuzzy-AHP is used and as a solution methodology a variation of the Weighted Additive Model has been implemented. Comparing the results with the previous work, the number of non-dominated solutions has been significantly reduced.

One of the goals that most socially concern nowadays in food logistic neworks is the reduction of waste. In order to study this objective, an article has been done that deals with the use of dynamic price strategies to reduce the waste of food and other perishable products A deterministic mathematical model is proposed to study the influence of a number of factors, such as price elasticity of demand, age-sensitivity of demand and age profile of initial inventory, on revenue and spoilage. A parametric, bi-objective approach is considered with the aim of estimating the existing trade-offs between revenues and spoilage. The problem has been solved in several scenarios and it has been found that while a dynamic pricing strategy helps reduce waste, in some specific cases total revenues may increase slightly or at least maintain their level. In other scenarios, the spoilage reduction comes as a loss in total revenue that can go from small to significant, depending on the scenario and the speed of the price discounting strategy. The proposed approach allows the quantification of the trade-offs available for each

scenario and allows the analysis of the age distribution of units sold and their respective contribution to income.

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Prólogo

El presente documento ha sido preparado siguiendo las indicaciones de la Universidad de Oviedo para la realización de la tesis como compendio de publicaciones. Se presentan los siguientes capítulos:

1. Una introducción al diseño de redes logísticas.

2. Una sección en la que se exponen los objetivos principales de la tesis.

3. Una sección con la discusión de los resultados obtenidos en los diferentes trabajos realizados.

4. Una sección con las conclusiones obtenidas en dichos trabajos.

5. Una lista de las referencias utilizadas en las secciones previas.

6. Un apéndice en el que se incluye una copia completa de los trabajos en la que consta el nombre y adscripción del autor y de todos los coautores, así como la referencia completa de la revista en la que los trabajos se han publicados.

7. Un apéndice en el que se presenta un informe con el factor de impacto de las publicaciones presentadas.

8. Un apéndice con un último trabajo que está en revisión

Capítulo 1

Introducción

El diseño de redes logísticas es un campo que ha sufrido un enorme crecimiento en los últimos años. La competencia entre las empresas ha incrementado la importancia de una gestión eficaz de las redes logísticas como herramienta para mejorar sus operaciones y, por tanto, su rentabilidad. Dentro del estudio de las redes logísticas, uno de los principales problemas abordados es el de la gestión de la cadena de suministro. Beamon [1] define una cadena de suministro como un proceso integrado en el que varias entidades comerciales (es decir, proveedores, fabricantes, distribuidores y minoristas) trabajan juntas en un esfuerzo por adquirir materias primas, convertirlas en productos finales específicos, y entregar dichos productos finales a los minoristas. Por lo tanto, uno de los primeros temas a tratar al definir la estrategia logística global de una empresa es identificar cuáles son las entidades involucradas y cuáles son las relaciones entre ellas, para entregar los productos finales de la manera más eficiente.

Las interrelaciones entre las entidades empresariales que colaboran en el proceso de negocio se describen generalmente en forma de una red que captura todos los flujos de materiales, sus capacidades y los costos de mover todos los productos y subproductos a través de la estructura. Múltiples decisiones están involucradas en el problema general del diseño de una red de suministro, incluyendo la capacidad y ubicación de las plantas y almacenes, la planificación de la cantidad de productos a fabricar, la cantidad de materia prima utilizada, los niveles de inventario, el movimiento de materiales, etc.

Altiparmak et al. [2] consideran que el diseño de una cadena de suministro es determinar el número, la ubicación, la capacidad y el tipo de plantas, almacenes y centros de distribución que se utilizarán, establecer los canales de distribución y determinar la cantidad de materiales y productos a consumir, a producir y a enviar de los proveedores a los clientes. Ma y Suo [3] consideran como parte del diseño, la configuración, la política de planificación del inventario en cada nodo y las rutas de entrega del producto entre los diferentes nodos de la red.

Considerando una dimensión jerárquica, Akkerman et al. [4] hacen una distinción entre el diseño de una red de distribución (que se ocupa de decisiones a largo plazo, como la ubicación, el número y el tamaño de los almacenes, la asignación de los clientes y los enlaces de transporte), la planificación de una red de distribución (en lo que respecta a las decisiones a medio plazo como la satisfacción de la demanda) y la planificación del transporte (que se ocupan de las decisiones a corto plazo como la carga y la ruta a seguir).

1.1. Problema general de diseño de redes

Una red logística suele considerarse como un grafo en el que el conjunto de nodos representa a los proveedores, las plantas, los centros de distribución y los clientes mientras que los arcos son los flujos entre dichas instalaciones. Los escalones más comunes en el diseño de una red logística son los proveedores, los centros de producción, los centros de distribución o almacenes, y los clientes. Sin embargo, al modelar éstas redes se podrían considerar muchas otras alternativas incluyendo otro tipo de instalaciones que se encuentran en problemas reales y que en ocasiones son especialmente importantes desde el punto de vista logístico, tales como los centros de reciclaje, las plantas de recuperación u otras instalaciones intermediarias (Figura 1.1).

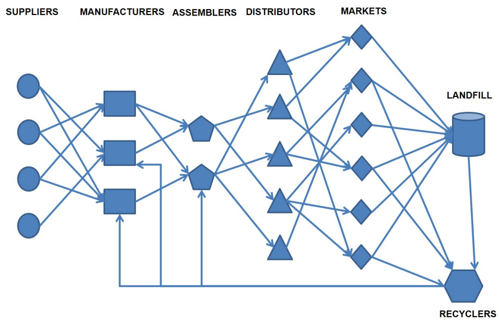

Figura 1.1: Ejemplo de red logística con retorno

En el ámbito del problema general de diseño de redes logísticas, podemos encontrar problemas clásicos que han atraído la atención de muchos investigadores durante años. Dentro de estos problemas clásicos podemos incluir el problema la selección de "p" instalaciones para minimizar el coste total del sistema, asumiendo el mismo coste de instalación para todas las nuevas instalaciones (p-median problem, [5]). También podemos encontrar el "uncapacitated facility location problem (UFLP)", que considera diferentes costes fijos para cada instalación pero no tiene en cuenta las capacidades de las mismas o de los arcos. Si a este problema le incluimos las restricciones de capacidad mencionadas, tenemos el "capacitated facility location problem (CFLP)". Otros problemas clásicos del diseño de redes logísticas son los problemas de flujo tales como el "multicommodity network flow problem (MCFP)" y el "capacitated multicommodity network flow problem (CMCFP)".

Sin embargo, a medida que la complejidad de los problemas de diseño de redes logísticas ha aumentado a lo largo de los años, se han ido estudiando más decisiones simultáneamente, dado que las decisiones aisladas no son realistas ya que están interrelacionadas con otras decisiones afectándose mutuamente.

Además, la clásica minimización de costes (o maximización de beneficios) ya no es el único objetivo que los departamentos de logística están considerando al diseñar sus redes. La presión social debida a la preocupación por el medio ambiente (y por supuesto el endurecimiento de las sanciones por parte de los gobiernos a las empresas que no respetan las directrices establecidas), implica que se tengan en cuenta cuestiones como el impacto ambiental a la hora de gestionar las decisiones a considerar. Por otro lado, los recientes conflictos políticos (ataques terroristas o guerras en algunos países estratégicos) también han planteado la cuestión del "riesgo" al diseñar estructuras para la elaboración o el transporte de productos. Del mismo modo, se deben tener en cuenta otras métricas clásicas en los negocios como son la maximización de los niveles de servicio al cliente, el cumplimiento de los plazos de entrega, la calidad de las entregas, etc. Además, como se están considerando simultáneamente diferentes decisiones, también hay que tener en cuenta simultáneamente diferentes objetivos cuando se buscan redes realistas. Es por ello, que en este momento las redes logísticas multiobjetivo han cobrado un enorme interés entre los investigadores de nuestro campo.

1.2. Toma de decisiones multiobjetivo

La realidad tiene muchas facetas y el estudio de un solo objetivo es generalmente insuficiente. Esta no es la forma en la que las empresas toman sus decisiones, ya que normalmente es necesario considerar varios objetivos simultáneamente, lo que convierte los problemas de decisión en problemas de optimización multiobjetivo. De todos modos, no todos los autores han estudiado estas decisiones de la misma manera. Por ejemplo, Eskigun et al. [6] consideraron que la satisfacción del cliente medida como cumplimiento de las limitaciones de tiempo de entrega debe tenerse en cuenta en el diseño de su red logística, pero para resolver el problema para una empresa automotriz dan un valor monetario a dicho tiempo de entrega. Por otra parte, Chen et al. [7] y Guillén et al. [8] comentan que las empresas están tratando de mejorar su nivel de servicio al cliente, pero que es difícil cuantificar esto como una cantidad monetaria, por lo que han tenido que introducir el nivel de servicio como un objetivo independiente en su trabajo.

La optimización multiobjetivo es el proceso de optimización sistemática y simultánea de una colección de funciones objetivo [9]. En general, los objetivos estudiados simultáneamente están en conflicto entre sí. En este sentido, los problemas de optimización multiobjetivo no tienen una única solución que sea mejor para todos los objetivos. El objetivo de estos problemas es encontrar un conjunto de soluciones óptimas de Pareto para las que no existe otra solución que sea mejor para todos los objetivos (soluciones no dominadas [10]).

Hay muchos métodos para resolver un problema de optimización multiobjetivo. Marler y Arora [9] dividen estos métodos en cuatro categorías: la primera incluye los métodos con una articulación a priori de preferencias (el "weighted sum method", el "lexicographic method", el "weight min-max method" o el ε-constraints method). La segunda categoría incluye los métodos con una articulación a posteriori de las preferencias (el "normal boundary intersection method". el "normal constraint method" o "physical programming"). La tercera categoría incluye métodos sin articulación de preferencia (como los "global criterion methods", el "Nash arbitration", el "objective product method" y el "Rao's method"). Por último, la cuarta y última categoría se refiere a los "genetic algorithms".

La optimización multiobjetivo ha sido utilizado para muchas aplicaciones en diferentes áreas de negocios como finanzas, ciencias de gestión, teoría de juegos e ingeniería [11]. En este sentido, se han considerado hasta ahora muchos criterios diferentes en el estudio de las redes logísticas. El criterio más comúnmente estudiado es la minimización del coste total, incluyendo muchos tipos diferentes de costes (como pueden ser los de instalación, operación, transporte, producción, etc.). Otro de los criterios más utilizados es la consideración del impacto ambiental el cuál es especialmente importante en las redes logísticas inversas y, en general, cuando se trata de producción ecológica y el reciclaje de los productos. Además, otros criterios que han estudiado hasta el momento son la minimización de los tiempos de transporte, la maximización de los niveles de servicio al cliente, la maximización del beneficio total o la minimización del riesgo financiero.

1.3. Diseño de redes logísticas multiobjetivo

Como se mencionó anteriormente, los problemas de diseño de redes son muy diversos en términos de las decisiones y objetivos que estudian.

Considerando que el diseño de una red logística desde un único punto de vista parece ser insuficiente, en los últimos años han comenzado a aparecer numerosos estudios que abordan el diseño de redes analizando dos o más objetivos simultáneamente. A este proceso de optimización de forma sistemática y simultánea de una colección de funciones objetivo se le llama optimización multiobjetivo.

La formulación general de un problema de optimización multiobjetivo es:

$$\begin{aligned}
&\min_{x} F(x) = [F_1(x), F_2(x), \ldots, F_k(x)]^T \\
&\text{sujeto a:} \\
&\qquad\qquad \begin{cases} g_j(c) \leq 0, & j = 1, 2, \ldots, m \\ h_l(x) = 0, & l = 1, 2, \ldots, e \end{cases}
\end{aligned} \tag{1}$$

donde k es el número de funciones objetivo, m es el número de restricciones de desigualdad y e es el número de restricciones de igualdad. $x \in E^n$ es un vector de variables de decisión donde n es el número de variables independientes x_i. $F(x) \in E^k$ es un vector de funciones objetivo $F_i(x) : E^n \longrightarrow E^1$. El espacio de soluciones factibles es:
$X = \{x \mid g_j(x) \leq 0,\ j = 1, 2, \ldots, m \ \wedge\ h_i(x) = 0,\ i = 1, 2, \ldots, e\}$. Por su parte, el conjunto alcanzable es $\mathcal{Z} = \{F(x) \mid x \in X\}$.

Las tres áreas que originalmente dieron vida a la optimización multiobjetivo son la teoría de juegos, el equilibrio económico y las teorías de bienestar y las matemáticas. Es por ello, que no es raro encontrar términos que tengan varias definiciones derivadas de las diferencias existentes entre la jerga económica, la ingeniería y las matemáticas. Veamos cuáles son los principales términos básicos que tienen influencia en la optimización multiobjetivo.

- *Preferencias*: Las opiniones relativas a los puntos que encontramos en el conjunto alcanzable que da un decisor es lo que se conoce como preferencias. En los casos en los que nos encontramos ante un método que tiene una articulación a posteriori de las preferencias, éstas son impuestas por el decisor sobre un conjunto de potenciales puntos solución. De este modo, las preferencias del decisor quedan reflejadas con bastante precisión en la solución final. Cuando el método tiene una articulación a priori de las preferencias, las opiniones del decisor han de ser cuantificadas antes de obtener los puntos en el conjunto alcanzable. Por lo general, el término preferencia, está relacionado con la importancia relativa de las funciones objetivo del problema.

- *Función de preferencia*: Una función de preferencia es una función abstracta (de puntos en el conjunto alcanzable) en la mente del decisor, que contiene sus preferencias.

- *Función de utilidad*: En optimización multiobjetivo se define para cada objetivo una función de utilidad individual, que representa la importancia relativa que tiene dicho objetivo. La función de utilidad U es una expresión matemática que pretende modelar las preferencias del decisor por medio de la fusión de las funciones de utilidad individuales. Como la función de preferencia no suele poder expresarse matemáticamente, se utiliza la función de utilidad como una aproximación de ésta. Por su parte, en economía la función de utilidad representa el grado de satisfacción de un individuo o grupo [12].

- *Criterio Global*: Un criterio global es una función escalar que combina matemáticamente funciones objetivo múltiples.

1.3.1. Optimalidad de Pareto.

Al contrario de cuando tratamos un problema de optimización de un solo objetivo, del que sabemos que se obtiene una/s solución/es objetivo/s, a la hora de resolver un problema multiobjetivo, normalmente no existe una solución global única sino que se pretende obtener un conjunto de puntos que se ajusten a una definición predeterminada para un óptimo. El concepto de punto Pareto óptimo [13] es el predominante en la definición de lo que es un punto óptimo en un problema de optimización multiobjetivo.

Definición 1.1. *Un punto x^* es Pareto óptimo cuando $\nexists\, x \in X \;/\; F(x) \leq F(x^*)$ y además $F_i(x) < F_i(x^*)$ para alguna función F_i.*

La frontera del espacio alcanzable $\mathcal{Z}$ es el lugar en donde se encuentran todos los puntos Pareto óptimos [14, 15]. Sin embargo, la mayoría de las soluciones que nos proporcionan los diferentes algoritmos de resolución no son Pareto óptimas aunque pueden satisfacer otros criterios como por ejemplo, ser débilmente Pareto óptimas, siendo muy significativas para aplicaciones prácticas.

Definición 1.2. *Un punto x^* es débilmente Pareto óptimo cuando $\nexists\, x \in X \;/\; F(x) < F(x^*)$.*

Todo punto encontrado para el cuál no existe ningún otro que mejore todas las funciones objetivo de forma simultánea se dice que es débilmente Pareto óptimo. Por contra, si no existe ningún punto que mejore al menos una función objetivo sin detrimento de otra, entonces se tiene un punto Pareto óptimo. Evidentemente, todo punto Pareto óptimo es débilmente Pareto óptimo pero el recíproco no se cumple.

1.3.2. Eficiencia y dominancia.

Otro concepto básico en optimización multiobjetivo es el de eficiencia, que en algunos casos se entiende del mismo modo que la admisibilidad o no inferioridad [16].

Definición 1.3. *Un punto $x^* \in X$ es eficiente cuando $\nexists\, x \in X \;/\; F(x) \leq F(x^*) \wedge$ $\wedge\; F_i(x) < F_i(x^*)$ para alguna función F_i. En otro caso, x^* es ineficiente.*

A partir de esta definición, se puede definir también el concepto de frontera eficiente.

Definición 1.4. *La frontera eficiente es el conjunto de todos los puntos eficientes.*

En algunos casos, podemos encontrarnos bibliografía en la que se habla de puntos no dominados. Según [16] se pueden definir los puntos dominados y no dominados como:

Definición 1.5. *Un vector de funciones objetivo $F(x^*) \in \mathcal{Z}$ es no dominado cuando $\nexists\, F(x) \in \mathcal{Z} \;/\; F(x) \leq F(x^*) \;\wedge\; F_i(x) < F_i(x^*)$ para alguna función F_i. En otro caso, $F(x^*)$ es dominado.*

Las definiciones 1.3 y 1.5 son equivalentes para fines prácticos. Sin embargo, la dominancia hace referencia a un vector de funciones en el espacio alcanzable mientras que la eficiencia hace referencia a un vector de variables en el espacio factible. Las definiciones de punto Pareto óptimo y de punto eficiente son similares y habitualmente un punto no dominado se considera lo mismo que un punto Pareto óptimo en el espacio alcanzable.

1.3.3. Metodologías de resolución

Como ya se mencionó anteriormente las metodologías de resolución de los problemas de optimización multiobjetivo son muy diversas. Vamos a centrarnos en este apartado en las diferentes metodologías que hemos usado en esta tesis.

Método de las ε-constraints.

El metodo de las ε-constraints fue introducido por Haimes [17] en 1971. El método se basa en la optimización de uno de los objetivos del problema, introduciendo el resto de objetivos como restricciones paramétricas. La formulación general del método de las ε-constraints es la siguiente:

$$
\begin{aligned}
&\min_{x \in X} F_i(x) \\
&s.a. \\
&\qquad x \in \mathcal{S} \\
&\qquad F_j(x) \leq \varepsilon_j, \quad j \neq i
\end{aligned}
\tag{2}
$$

De este modo, realizando una variación sistemática de ε_j se obtendrá un conjunto de soluciones que son Pareto óptimas [18] y que formarán lo que denominaremos la Frontera de Pareto del problema (Figura 1.2). No obstante, hay que tener cuidado a la hora de elegir el ε_j puesto que una mala elección puede derivar en un problema infactible. Goicoechea [19], Cohon [20], Stadler [21] y Carmichael [22] presentan distintos métodos para la selección de los valores de ε que reflejan preferencias.

En el caso en el que la formulación de las ε-restricciones tenga solución, ésta va a ser débilmente Pareto óptima [23], y todo punto débilmente Pareto óptimo puede ser obtenido si las funciones objetivo son explícitamente cuasi-convexas y la región factible es convexa [24]. Si se tiene que la solución es única, entonces es Pareto óptima [23]. Evidentemente, probar la unicidad es muy difícil aunque si $F_i(x)$ es estrictamente convexa y el problema es convexo, entonces la solución es necesariamente única[25].

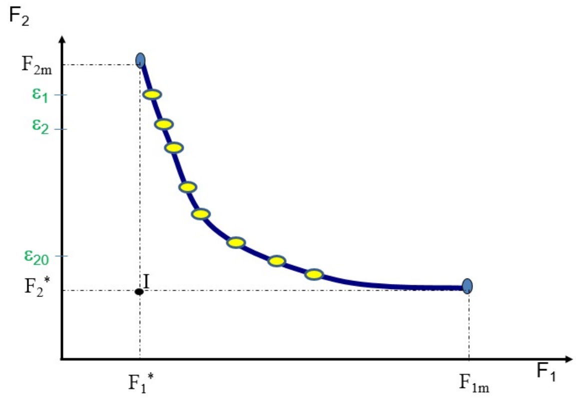

Figura 1.2: Ejemplo de una Frontera de Pareto para un problema biobjetivo

1.3.4. Fuzzy Linear Programming. Weighted Additive Model.

Fuzzy linear programming fue propuesto por primera vez por Zimmermann [26] en 1978. La metodología consiste en funciones objetivo fuzzy y restricciones fuzzy que pueden ser reformuladas de manera que se puede resolver un problema de programación lineal normal. El uso de esta metodología permite determinar una solución única, en lugar de una colección de soluciones potenciales.

Existen muchos modelos diferentes de fuzzy linear programming. En esta tesis, se ha usado un weighted additive model, basado en la formulación propuesta por Tiwari [27] pero con alguna ligera modificación. La formulación general del modelo es la siguiente:

Se tienen I objetivos lineales $\min f_i(x)$, J restricciones lineales fuzzy $g_j(x) \sim b_j$ (es decir, con cualquier tipo de relación) y otras K restricciones $h_k(x) \sim c_k$.

Para un determinado $i \in I$ se denota z_i^- y z_i^+ al valor de la función objetivo en la solución óptima de los modelos 3 y 4 respectivamente:

$$\begin{aligned} &\min F_i(x) \\ &s.a. \\ &\qquad g_j(x) \le b_j \\ &\qquad h_k(x) \le c_k \\ &\qquad x \ge 0 \end{aligned} \qquad (3) \qquad\qquad \begin{aligned} &\max F_i(x) \\ &s.a. \\ &\qquad g_j(x) \le b_j \\ &\qquad h_k(x) \le c_k \\ &\qquad x \ge 0 \end{aligned} \qquad (4)$$

Se pueden definir entonces las membership functions $\mu_{f_i}(x)$ del objetivo i (Figura 1.3), $\mu_{g_j}(x)$ de la restricción j de tipo menor o igual y $\mu_{g_j}(x)$ de la restricción j de tipo mayor o igual respectivamente (Figura 1.4) como:

$$\mu_{f_i}(x) = \frac{z_i^+ - f_i(x)}{z_i^+ - z_i^-},\ \mu_{g_j}(x) = \frac{(b_j + d_j) - g_j(x)}{d_j} \text{ y } \mu_{g_j}(x) = \frac{g_j(x) - (b_j - d_j)}{d_j}$$

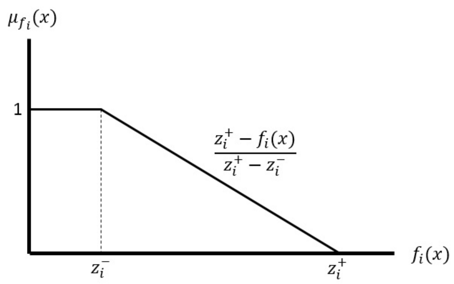

Figura 1.3: Membership function para funciones objetivo

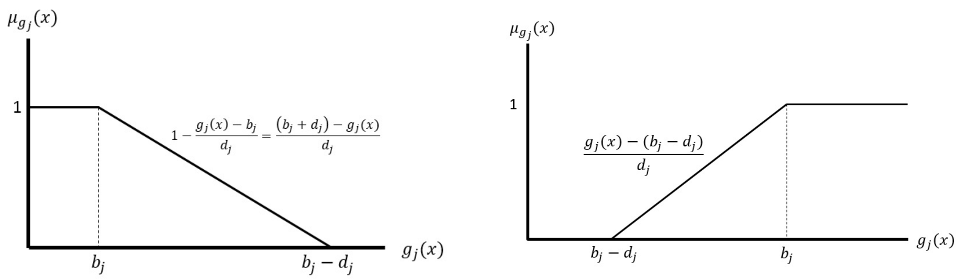

Figura 1.4: Membership functions para restricciones menor o igual y mayor o igual

En el caso de tener una restricción de igualdad estricta, ésta la habría que desdoblar en dos restricciones, una del tipo menor o igual y otra del tipo mayor o igual, dando lugar en este caso a dos membership functions.

Una vez que se obtienen todas las membership functions asociadas a los objetivos y las restricciones, el siguiente paso es obtener la membership function de todos ellos. Esto es, realizar la intersección de todas las membership functions obtenidas, dando lugar a:

$$\mu_s(x) = \left(\bigcap_{i=1}^{I} \mu_{f_i}(x)\right) \bigcap \left(\bigcap_{j=1}^{J} \mu_{g_j}(x)\right) = \text{mín}\{\min_{i\in I}\{\mu_{f_i}(x)\}, \min_{j\in J}\{\mu_{g_j}(x)\}\}$$

De este modo, la solución buscada es aquella que hace máxima dicha intersección dando lugar al modelo:

$$\begin{aligned}
&\text{máx} \sum_{i=1}^{I} \omega_i \lambda_i + \sum_{j=i}^{J} \omega_j^* \gamma_j \\
&s.a. \\
&\qquad \lambda_i \leq \frac{z_i^+ - f_i(x)}{z_i^+ - z_i^-} \ \forall\ i = 1, \ldots, I \\
&\qquad \gamma_j \leq \frac{(b_j + d_j) - g_j(x)}{d_j} \ \forall\ j \in J/ \text{ la restricción } j \text{ es de tipo } \leq \\
&\qquad \gamma_j \leq \frac{g_j(x) - (b_j - d_j)}{d_j} \ \forall\ j \in J/ \text{ la restricción } j \text{ es de tipo } \geq \\
&\qquad h_k \leq c_k \ \forall\ k = i, \ldots, K \\
&\qquad \lambda_i,\ \gamma_j \in [0, 1] \\
&\qquad x \geq 0
\end{aligned} \tag{5}$$

donde ω_i y ω_i^* son unos pesos que van a ponderar adecuadamente los λ_i y γ_j.

1.3.5. Analytic Hierarchy Process.

El Analytic Hierarchy Process (AHP) [28] fue diseñado en los años 70 por Thomas L. Saaty. Este método, permite tomar decisiones para priorizar las diferentes alternativas que se plantean cuando se consideran múltiples criterios. El proceso permite a los decisores estructurar de manera jerárquica o mediante niveles problemas complejos. En cada uno de los niveles todos los elementos son del mismo orden de magnitud y se pueden relacionar con algunos o todos los elementos del siguiente nivel. Una jerarquía contiene normalmente al menos tres niveles: el objetivo, los criterios y las alternativas (Figura 1.5). Por lo general, el nivel más alto de una jerarquía focaliza el objetivo.

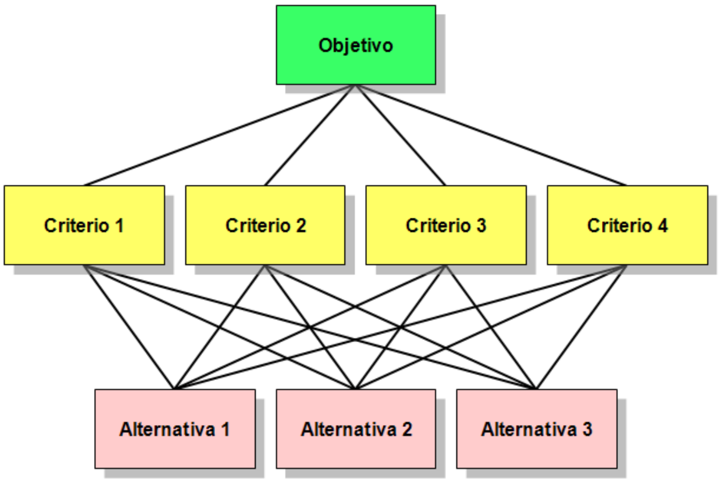

Figura 1.5: Niveles de un AHP

Una vez establecidos los niveles jerárquicos del problema se realizan comparaciones 2 a 2 de los criterios con el fin de definir los pesos ω_i asociados a cada uno de estos criterios que reflejen la importancia relativa entre cada uno de ellos. El procedimiento se basa en la construcción de una matriz M de tal manera que $m_{ij} > 0 \ \forall i, j$, $m_{ji} = \dfrac{1}{m_{ij}} \ \forall i, j$ y $m_{ii} = 1 \ \forall i$, donde los $m_{i,j} = \{1, 3, 5, 7, 9\}$ determinan la importancia que tiene el criterio i sobre el criterio j en base a la tabla siguiente (Tabla 1.1):

No obstante estos valores han evolucionado a lo largo de los años de manera que también se consideran todos los valores naturales intermedios entre ellos.

Uno de los mayores problemas que se suele encontrar a la hora de implementar

Valor	*Descripción*
1	Igual importancia.
3	Importancia moderada.
5	Importancia fuerte.
7	Importancia muy fuerte.
9	Importancia extremadamente fuerte.

Tabla 1.1: Escala de medidas

esta metodología cuando el número de criterios posibles va aumentando es conseguir que las matrices de comparación que van a usarse sean consistentes. Obviamente, conseguir una consistencia perfecta no puede ser exigible, pero si que es necesario que las valoraciones tengan cierta consistencia, es decir, si se tiene que el criterio i es más importante que el j y se tiene que j es más importante que k, es absolutamente necesario que el criterio i sea más importante que j.

Supongamos que tenemos una matriz $M \in \mathcal{M}_n$ donde n es el número de criterios a estudiar. Se calcula el polinomio característico de dicha matriz $p(\lambda) = |M - \lambda I|$, y de sus valores propios se escoge λ_{max}, es decir, el mayor valor propio real que haya sido obtenido. A partir de este valor λ_{max} calculamos $IC = \dfrac{\lambda_{max} - n}{n-1}$. Diremos entonces que la matriz M es aceptablemente consistente si el cociente $RC = \dfrac{IC}{RI(n)} \leq 0{,}1$ donde $RI(n)$ para $n > 2$ (Tabla 1.2) es la tabla de índices calculada por Saaty siguiente:

n	3	4	5	6	7	8	9	10
RI(n)	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49

Tabla 1.2: Índices calculados por Saaty

Una vez demostrado que la matriz M es consistente, se calcula el autovector asociado al valor propio escogido, y los pesos ω_i se corresponderán con la normalización de los valores obtenidos en dicho autovector.

En el caso en el que la matriz M obtenida no sea consistente, existe una técnica para la modificación de dicha matriz hasta obtener una que sea consistente. En primer lugar hay que calcular el valor m_{ij} más "inconsistente". Para ello, se calcula la matriz M' en la que cada elemento es de la forma $m'_{ij} = w_i/w_j$ y se compara con la matriz M de manera que para cada elemento se halla el cociente m_{ij}/m'_{ij}. El cociente que más alejado esté de 1 será el elemento más "inconsistente" y por tanto en la matriz original se efectuará el cambio $m_{ij} = m_{ij} - 1$ si $m_{ij}/m'_{ij} > 1$ o $m_{ij} = m_{ij} + 1$ en otro caso.

Una vez que los pesos de los criterios están calculados, se pasa al siguiente nivel y así sucesivamente hasta llegar al último de ellos. Finalmente, cuando se tienen todos los pesos del problema calculados se crea una tabla que se denomina tabla de decisión de manera que las alternativas se corresponderán con cada una de las filas de la tabla, las columnas serán los elementos que están conectados en la jerarquía con las alternativas, los pesos de los elementos conectados con cada alternativa se asocian a cada columna y los valores obtenidos por cada alternativa en la matriz asociada al criterio de cada columna son los valores que van en dicha columna de la tabla. Por último, la alternativa que mayor peso haya obtenido será la escogida.

En muchas ocasiones, el número de alternativas que han de ser evaluadas es elevado por lo que la evaluación para cada criterio del último nivel se realiza definiendo varias categorías propias, estableciendo matrices de comparación dos a dos para cada una de ellas en lugar de valorar cada alternativa para cada criterio. En este caso, la tabla de decisión se calcula utilizando el "ratings mode", que pese a ser menos exacto que el método clásico, es mucho más rápido y las aproximaciones son buenas.

Group AHP

Por lo general, los pesos asociados a los diferentes niveles de un AHP no son decisión de un único experto, sino que intervienen un conjunto T de ellos. En estos casos, existen varias opciones para el cálculo de dichos pesos, destacando las dos siguientes:

- Por un lado está el voto consensuado. Para esta metodología, todos los expertos han de reunirse con el fin de generar una única matriz M. Es claro, que a mayor número de expertos, mayor complejidad a la hora de poder llegar a un acuerdo sobre la matriz M.
- La segunda de las opciones es el uso de la media geométrica. En este caso, cada uno de los expertos del grupo diseña una matriz de prioridades $M_t = \begin{pmatrix} m_{11}^t & \cdots & m_{1n}^t \\ \vdots & \ddots & \vdots \\ m_{n1}^t & \cdots & m_{nn}^t \end{pmatrix}$. La matriz de consenso M^* será la resultante de realizar la media geométrica de cada m_{ij}.

El principal inconveniente del Group AHP es la dificultad que conlleva que no exista mucha disparidad entre las matrices M_t puesto que en este caso la matriz de consenso M^* prodría no ser representativa. Para lidiar con este problema Bryson [29] diseño un procedimiento para medir el grado de consenso entre los vectores ω_t de cada experto y el vector de consenso final ω_{GM}.

En primer lugar se define una función de similitud s entre los vectores ω_i y ω_j. Aunque se pueden definir distintas funciones (se han propuesto el seno, el coseno, la norma $L-1$,...) en este caso vamos a definirla con la función seno, de manera que:

$$s(\omega_i, \omega_j) = 1 - \sin(\omega_i, \omega_j)$$

que toma valores en el intervalo $[0, 1]$ de manera que a mayor valor de s mayor es la similitud.

En segundo lugar, se definen unos ratios de fuerte similitud y fuerte disimilitud. El ratio de fuerte similitud (*Group Strong Agreement Quotient*) de un vector frente al vector ω_{GM} del grupo se define como:

$$GSAQ_\alpha = \frac{\sum\limits_{i \in T} \Gamma(\omega_i, \omega_{GM})}{T}, \text{ donde } \Gamma(\omega_i, \omega_j) = \begin{cases} 1, \text{ si } s(\omega_i, \omega_j) \geq \alpha \\ 0, \text{ en otro caso} \end{cases}$$

mientras que el ratio de fuerte disimilitud (*Group Strong Disagreement Quotient*) de un vector frente al vector ω_{GM} del grupo se define como:

$$GSDQ_\delta = \frac{\sum\limits_{i \in T} \Phi(\omega_i, \omega_{GM})}{T}, \text{ donde } \Phi(\omega_i, \omega_j) = \begin{cases} 1, \text{ si } s(\omega_i, \omega_j) \leq \delta \\ 0, \text{ en otro caso} \end{cases}$$

Por último se analizan los ratios para los valores α y δ elegidos que indican si dos vectores son razonablemente similares o no. Para que exista el consenso, al menos una proporción $GSAQ_\alpha$ de los T miembros (por ejemplo el 75 %) ha de tener una fuerte similitud con el vector ω_{GM} resumen del grupo, y como mucho una proporción $GSDQ_\delta$ (por ejemplo el 20 %) puede tener una fuerte disimilitud con el vector ω_{GM} del grupo.

Fuzzy AHP

La selección de las comparaciones que un decisor ha de realizar en una matriz de prioridades entre diferentes criterios cuantificando dichas comparaciones con un único valor puede resultar poco realista. Una forma de paliar este problema es usando la metodología Fuzzy-AHP.

En primer lugar, cada experto define una matriz crisp comparando los diferentes criterios dos a dos. Una vez que se tienen dichas matrices, se chequea su consistencia y se modifica como ya se vio anteriormente toda aquella matriz no consistente hasta obtener una que lo sea. Posteriormente, estas matrices se "fuzzyfican" con números triangulares en arreglo a la siguiente lógica: el número 1 se "fuzzyfica" como $< 1, 1, 2 >$; el número 9 como $< 8, 9, 9 >$; y cualquier otro número $i \in \{2, 3, \ldots, 8\}$ como $< i - 1, i, i + 1 >$.

Una vez "fuzzyficadas" las matrices, se pasan a una matriz de consenso M donde el elemento en la posición (i, j) de la matriz se obtiene hallando la media geométrica de los componentes izquierdo, central y derecho de los valores que cada experto ha dado en su matriz en dicha posición. Además, dado el elemento $m_{ij} =< l_{ij}, m_{ij}, u_{ij} >$ obtenido en la matriz de consenso, el elemento $m_{ji} =< u_{ij}^{-1}, m_{ij}^{-1}, l_{ij}^{-1} >$. Esta matriz de consenso se comprueba que es consistente transformándola a una matriz crisp utilizando el método propuesto por Kwong y Bai [30] en el que cada elemento se calcula según la fórmula $m_{ij} = \dfrac{(l_{ij} + 4m_{ij} + u_{ij})}{6}$.

A continuación, para calcular los pesos se utiliza el "fuzzy synthetic extent" en el que para cada fila i de la matriz M_{ij} se calcula:

$$S_i = \sum_{j=1}^{n} M_{ij} \otimes \left[\sum_{k=1}^{n} \sum_{j=i}^{n} M_{kj} \right]^{-1}$$

donde la suma de dos números triangulares se define como
$< l_1, m_1, u_1 > + < l_2, m_2, u_2 >=< l_1 + l_2,\ m_1 + m_2,\ u_1 + u_2 >$ y el producto como $< l_1, m_1, u_1 > \otimes < l_2, m_2, u_2 >=< l_1 \cdot l_2,\ m_1 \cdot m_2,\ u_1 \cdot u_2 >$

Posteriormente, se calculan los "degree of possibility" entre cada $S_i =< s_i^-, s_i, s_i^+ >$ en base a la fórmula:

$$V(S_i \geq S_j) = \begin{cases} 1 & \text{si } s_i \geq s_j \\ \dfrac{s_i^+ - s_j^-}{(s_i^+ - s_i) + (s_j - s_j^-)} & \text{si } (s_i < s_j) \wedge (s_i^+ \geq s_j^-) \\ 0 & \text{si } (s_i < s_j) \wedge (s_i^+ < s_j^-) \end{cases}$$

Finalmente, se calcula el "degree of possibility" general de cada criterio como el mínimo de los "degree of possibility" calculados previamente entre los S_i.

$$d(C_i) = \min_{j \neq i} \{V(S_i \geq S_j)\}$$

El vector de pesos de los criterios es $\omega = [d(C_1), \ldots, d(C_n)]$ que una vez normalizado dará los pesos finales asociados a la matriz de consenso M.

Capítulo 2

Objetivos

El diseño de redes logísticas ha sido tratado tradicionalmente desde el objetivo de la minimización de los costes del sistema en estudio. Dado el interés actual por el impacto sobre el medio ambiente de este tipo de actividades, el efecto de cierto tipo de riesgos sobre la cadena logística así como la necesidad de reducir los desperdicios, especialmente de los productos alimenticios, que se generan, parece adecuado incorporar todos estos objetivos en el diseño de las redes. En esta tesis, se aborda el problema del diseño de redes logísticas multiobjetivo con el fin de estudiar simultáneamente estos objetivos y sus conflictos. Las metodologías de resolución serán fundamentalmente técnicas de optimización de tipo multicriterio.

Como consecuencia de la presentación de la tesis como compendio de publicaciones, en el apéndice A se pueden encontrar los tres trabajos a los que se hace referencia en esta sección y las posteriores. A continuación se realizará un resumen de los objetivos de cada uno de estos artículos que componen el cuerpo principal de la tesis. Además, en el apéndice C, se puede encontrar un último trabajo finalizado en diciembre de 2016 y que se encuentra aún en revisión por lo que no se incluye como parte principal de la misma pero forma parte de las investigaciones realizadas en esta tesis.

2.1. Bicriteria Optimization Model for Locating Maritime Container Depots: Application to the Port of Valencia

El objetivo de este primer artículo es el diseño de una red de depósitos de contenedores en un hinterland con dos objetivos: la minimización del coste total de la red y la minimización del impacto medioambiental de la misma. Para ello, se ha diseñado un modelo basado en el propuesto por Gendron et. al [31] diferenciándose principalmente en que en nuestro problema, además de los clientes y los depósitos de contenedores intervienen también los terminales de los puertos, pero sobre todo, en que su modelo es un modelo mono-objetivo mientras que en este trabajo se incluye una segunda función objetivo con el fin de minimizar el impacto medioambiental que genera el transporte y almacenaje de contenedores.

Se parte de un conjunto de potenciales depósitos y el problema consiste en decidir cuáles de ellos han de ser seleccionados para el almacenaje de los contenedores vacíos que se usan en las operaciones de importación y exportación llevadas a cabo por los clientes a través de las terminales de los puertos. Se consideran por tanto tres tipos de nodos en la red: el conjunto de terminales (T), el conjunto de depósitos (D) y el conjunto de clientes (S).

Al diseñar el modelo, se ha tenido en cuenta que no necesariamente se han de dar todas las relaciones entre depósitos, terminales y clientes, aunque exista esa posibilidad. Hay que notar que este modelo es de carácter estático y por tanto se supone que a largo plazo es estable. Por esa razón, se supone que debe de haber un equilibrio en el número de contenedores que circulan por el sistema, y por tanto, ese equilibrio se produce en cada elemento: terminal, depósito y cliente. También se ha de tener en cuenta que los terminales pueden actuar también como depósitos pero no serán considerados en las funciones objetivo, ya que en ningún caso se considera la opción de cerrar un terminal, se da por hecho que éstos están siempre en funcionamiento.

El primer objetivo del problema es la minimización total de los costes, que incluye los costes fijos de operación de los depósitos y los costes de transporte de los contenedores entre terminales, depósitos y clientes. El segundo objetivo de este problema es la minimización del impacto ambiental generado tanto por las operaciones llevadas a cabo en los depósitos como por las operaciones de transporte de los contenedores. Para cuantificar el impacto ambiental generado por las operaciones de transporte se han tenido en cuenta las cinco principales externalidades que suelen asociarse en la literatura a éste: la congestión del tráfico, la accidentabilidad, la contaminación atmosférica, la contaminación acústica y la contaminación visual. Para la cuantificación del impacto generado por los propios depósitos, se ha tenido en cuenta el impacto generado por la puesta en marcha del depósito, el impacto visual generado en el entorno y la contaminación generada por las operaciones que se llevan a cabo en dichos depósitos. A partir de esta división se solicitó a un conjunto de expertos el diseño de una matriz de comparaciones y se aplico la metodología AHP para obtener los pesos asociados a cada externalidad.

Como metodología de resolución se utilizó el método de las ε-constraints con el fin de obtener la frontera de Pareto del problema.

2.2. A decision-making model to design a sustainable container depot logistic network: the case of the Port of Valencia

En el artículo anterior se observó que para el cálculo de la función objetivo que determina el impacto medioambiental era necesario utilizar una parámetro λ de manera que se buscase un equilibrio entre el impacto generado por las operaciones de transporte y el impacto generado por la apertura y operación de los propios depósitos. Para evitar la utilización de este parámetro se diseñó un nuevo modelo que considerase los impactos medioambientales de transporte, y de apertura y operación de los depósitos por separado, surgiendo así un modelo con tres objetivos: la minimización del coste total del sistema, la minimización del impacto medioambiental generado por las operaciones de transporte y la minimización del impacto medioambiental generado por los propios depósitos.

Además de esto, para ampliar los objetivos abordados en el anterior trabajo, se incluyeron varias modificaciones con el fin de buscar un modelo que se pudiese ajustar lo más posible a una situación real. En este sentido, al igual que puede pasar con la demanda en cualquier modelo, que puede no considerarse una “hard constraint”, la capacidad de los depósitos se ha considerado una restricción fuzzy, ya que siempre existe una cierta holgura dependiendo de la colocación de los contenedores dentro del depósito. Por otro lado, se elaboró una nueva metodología de resolución para el problema, usando una modificación del “Weighted Additive Model” en la que se considera un modelo “preemptive goal programming” como se detalla en el artículo. También se ha modificado el cálculo de los pesos asociados tanto al impacto medioambiental generado por las operaciones de transporte como para el generado por la apertura y operación de los depósitos, transformando las matrices de decisión generadas por los expertos en unas matrices fuzzy, y utilizando la metodología Fuzzy-AHP para obtener los valores de dichos pesos.

Por último, los resultados obtenidos para este nuevo modelo con esta nueva metodología, se compararon con los obtenidos en el primer artículo como se podrá ver en las siguientes secciones.

2.3. Effects of dynamic pricing of perishable products on profit and residues

El interés en reducir los desperdicios, especialmente de los productos alimenticios, ha aumentado no sólo por su importancia económica, sino también por su impacto social y medioambiental. Las estrategias dinámicas de precios, es decir, ofreciendo unidades cercanas a su fecha límite a un precio más bajo que las unidades frescas, son una manera eficaz de reducir los desperdicios, ya que los clientes son alentados a exigir unidades menos frescas pero más baratas. Existe el riesgo, sin embargo, de que si la reducción de precios es demasiado pronunciada o si la elasticidad-precio de la demanda es demasiado baja, la estrategia de dinámica de precios puede conducir a un menor ingreso total.

Con el fin de medir y cuantificar los efectos de estos y otros factores (como el perfil de edad inicial del inventario o la sensibilidad de la demanda a la edad del producto) sobre las ventas, los ingresos y los desperdicios, se ha propuesto un modelo matemático de tiempo continuo que permite estudiar el agotamiento de un inventario inicial dado. El objetivo de este modelo es investigar los efectos que una política de precios variable en función del tiempo de vida restante de un producto, es decir, del tiempo que lleva ya en la tienda, tiene sobre los beneficios y los residuos generados. La hipótesis que se ha planteado es que la reducción del precio para los productos que se encuentren cerca de su caducidad aumentará la demanda de los mismos y por tanto la cantidad de ellos que han de ser desechados será menor. Por otro lado, también se ha estudiado los efectos que esta reducción de precio tiene sobre los ingresos de la compañía. Se ha diseñado un modelo matemático determinista considerando un enfoque paramétrico, bi-objetivo, con el objetivo de estimar los "trade-offs" existentes entre los ingresos y los desperdicios.

Inicialmente se ha supuesto que la vida útil máxima de un producto perecedero es L y se ha definido el inventario del producto que tiene una edad $a \leq L$ en un instante $t \leq L$ como $I(a, t)$. Se parte de un stock inicial de productos frescos $I(0, 0)$ que junto con el resto del stock en el instante $t = 0$, $I(a, 0)$, define la edad del stock inicial del producto (Ver Figura 2.1). Se asume una demanda sin ninguna reposición de producto, ya que, se ha estudiado lo que ocurre con todo el stock inicial, es decir, los ingresos obtenidos y los residuos generados. Se ha supuesto que las demandas son deterministas y continuas por lo que el análisis se realizará desde el instante inicial $t = 0$ hasta el instante final $t = L$, donde todos los productos han sido vendidos o han caducado.

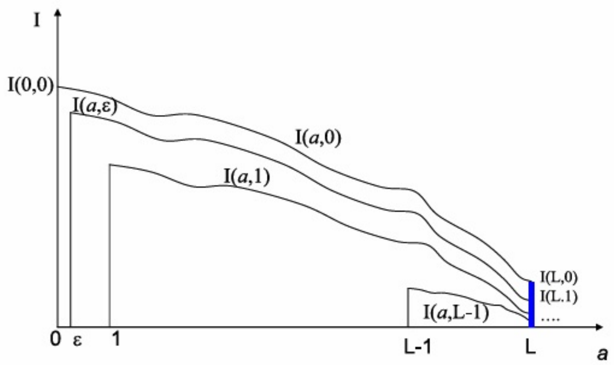

Figura 2.1: Evolución del inventario a lo largo del tiempo.

La demanda se supone que ha de depender del precio y de la edad del producto, es decir, los productos más caros tendrán menor demanda al igual que los más antiguos. Por su parte, se supone que el precio de los productos disminuirá a medida que el producto a vender es más antiguo. Por lo tanto, hay tres parámetros que han de regir la demanda y el precio: uno para ver la influencia que el precio tiene en la demanda (α); otro para ver la influencia que la antigüedad de los productos tiene en la demanda (β); y un último parámetro para ver la influencia que la antigüedad de los productos tiene en el precio (γ).

En base a estas variables y parámetros se han establecido las ecuaciones que definen los desperdicios y los ingresos y se han realizado experimentos con distintos valores de los parámetros para ver la influencia que estos tienen sobre los ingresos y los desperdicios.

Capítulo 3

Resultados

En este capítulo se realizará un breve resumen de los resultados obtenidos en cada uno de los artículos realizados.

3.1. Bicriteria Optimization Model for Locating Maritime Container Depots: Application to the Port of Valencia

Para comprobar la eficacia del modelo diseñado en este artículo, se aplicó al caso real del Puerto de Valencia. Desde la Fundación Valenciaport se proporcionaron los datos necesarios para llevar a cabo la implementación del modelo. De este modo se ha trabajado con la demanda de contenedores de una muestra de 357 clientes y con las capacidades de flujo y almacenamiento aproximadas de cada uno de los 8 depósitos operativos para dicha muestra. Además de estos depósitos, se han propuesto otras 11 nuevas ubicaciones para potenciales depósitos a tener en cuenta en el modelo teniendo en cuenta la zonas con mayor tráfico de contenedores según la demanda de los clientes.

Los costes para los depósitos se han estimado proporcionalmente a su tamaño según las indicaciones de un experto de la Fundación Valenciaport. Para obtener los datos acerca del impacto que provoca el transporte generado por la localización de un depósito se ha contado con la opinión de 6 expertos logísticos sobre sus preferencias entre los 5 criterios de medición del impacto: la contaminación atmosférica, la contaminación acústica, la contaminación visual, la congestión del tráfico y la accidentabilidad. Con el uso de la metodología Group-AHP definida en la introducción de esta tesis se obtuvieron los respectivos vectores de pesos de la función objetivo ω_d y υ_d.

El modelo de optimización biobjetivo definido se resolvió utilizando el método de las ε-restricciones. Dado que este método calcula la frontera de Pareto, en particular incluye la solución de coste mínimo. Por lo tanto, el enfoque multiobjetivo propuesto produce la solución de coste mínimo (como si se calculase con un enfoque mono-objetivo) más otras soluciones alternativas adicionales que representan diferentes compensaciones entre las dos funciones objetivo consideradas.

Para estudiar el efecto de los posibles valores de λ en la segunda función objetivo (es decir, la importancia de los impactos de transporte medidos a través de los coeficientes ω_d, frente al impacto del propio depósito medido con los coeficientes υ_d), se realizaron algunos ensayos previos observando que los valores cercanos a $\lambda = 10$ hacen que ambos tipos de impacto alcancen valores similares en la segunda función objetivo. Se decidió entonces, para analizar el comportamiento del modelo según la variación de λ, resolver el modelo para nueve valores diferentes de λ agrupados en tres casos:

a) Caso 1: valores para los cuales los impactos generados por las operaciones de transporte tienen mucho más peso que los impactos generados por los depósitos ($\lambda = \{1,\ 2,\ 4\}$).

b) Caso 2: valores para los cuales el peso de ambos impactos es similar

($\lambda = \{8,\ 10,\ 12\}$).

c) Caso 3: valores para los cuales los impactos generados por los depósitos tienen mucho más peso que los impactos generados por las operaciones de transporte ($\lambda = \{16,\ 18,\ 20\}$).

Así pues, se han resuelto tres casos distintos que incluyen nueve valores distintos de lambda. Para cada uno de ellos se ha obtenido la frontera de Pareto y se han representado gráficamente para comprender mejor su comportamiento (Ver Figura 3.1).

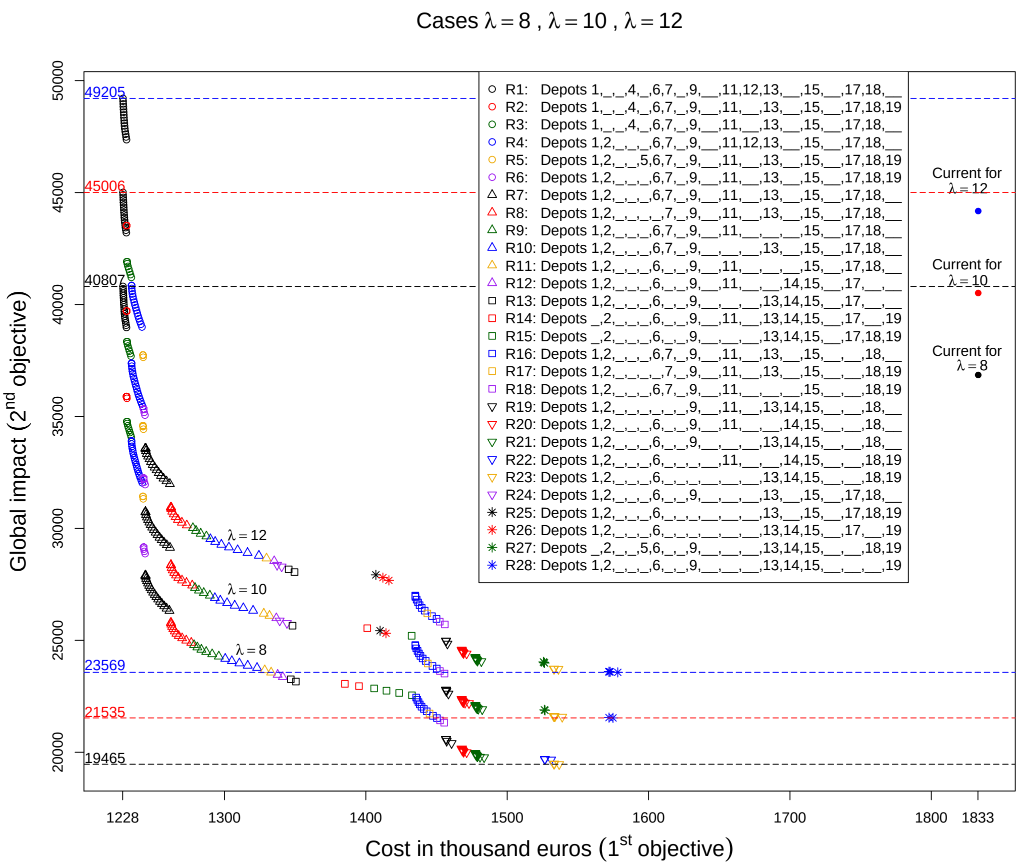

Figura 3.1: Fronteras de Pareto para el Caso 2.

Se ha observado que la amplitud del rango del coste del sistema va disminuyendo en términos relativos a medida que se va aumentando el valor de λ. De este modo, el coste máximo entre las soluciones de la frontera de Pareto pasa de un 147 %

(sobre la solución de coste mínimo) cuando $\lambda = 1$ a un 128 % cuando $\lambda = 20$. Del mismo modo, para el segundo objetivo, también se obtiene una disminución en términos relativos al aumentar el valor λ pasando de un 221 % para el caso $\lambda = 1$ a un 208 % para el caso $\lambda = 20$. Es decir, el rango de variabilidad de las soluciones de Pareto se reduce cuanto mayor es la importancia que se le da al impacto de los depósitos frente al del transporte.

Por otro lado, si se realiza una comparación entre cualquiera de las soluciones de las 9 fronteras de Pareto con la situación actual (los depósitos operativos son del 1 al 8) se puede observar que tanto el coste como el impacto obtenidos son muchos menores. Más aún, la situación actual no forma parte del conjunto de 82 soluciones diferentes que se han encontrado para los 9 valores distintos de λ. Se ha obtenido que el coste actual es aproximadamente un 40 % más elevado que el obtenido para soluciones con un impacto similar mientras que para soluciones con coste parecido al actual se obtiene una reducción a la mitad del impacto ambiental. Estos resultados, se deben principalmente al hecho de que los depósitos 3 y 8 no se abren en ninguna de las 82 soluciones obtenidas. Por contra, uno de los depósitos potenciales planteados (el 15), está operativo para todas las soluciones que se han encontrado.

3.2. A decision-making model to design a sustainable container depot logistic network: the case of the Port of Valencia

Para la aplicación práctica de este modelo, se utilizó el mismo conjunto de datos que la Fundación Valenciaport había proporcionado para el trabajo anterior. De este modo, se podría hacer una comparación de los resultados obtenidos en ambos trabajos utilizando distintos modelos y metodologías de resolución.

En este trabajo, se consideró que la capacidad de los depósitos era una restricción fuzzy y además, las matrices de comparación proporcionadas por los expertos se "fuzzyficaron" usando la metodología Fuzzy-AHP para la obtención de los pesos ω_d y υ_d asociados a los impactos de las operaciones de transporte y de los propios depósitos respectivamente.

En primer lugar, se calcularon el máximo y el mínimo de los tres objetivos. El coste mínimo obtenido para la red diseñada es de 1212,98 (en miles de euros) y el coste máximo de 9614,51. En cuanto a los impactos ambientales, el valor mínimo y máximo para las operaciones de transporte fue de 10305,11 y 48854,9 respectivamente, y para la puesta en marcha y operación de los depósitos de la red fueron 774,13 y 3820,06 respectivamente. Estos valores definen las "membership functions" de nuestro modelo (Ver Figura 3.2).

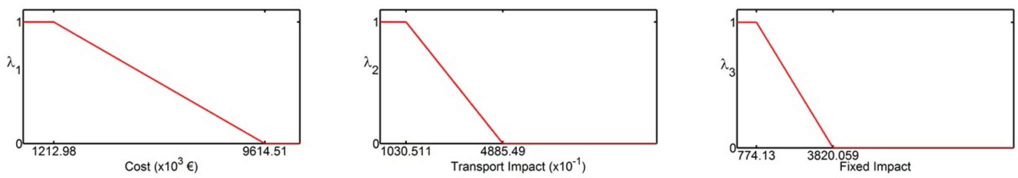

Figura 3.2: Membership functions de cada uno de los objetivos.

Con el fin de analizar en profundidad el comportamiento del modelo, se consideraron cinco casos, dependiendo de la importancia dada a las tres "membership functions".

- Caso 1: En este caso se considera la situación actual en el hinterland de Valencia, es decir, se impuso que los depósitos abiertos sean los ocho depósitos existentes $(1-8)$.
- Caso 2: No se ha considerado restricción alguna sobre la importancia de las tres funciones objetivo, es decir, se considera que los tres objetivos tienen la misma importancia.
- Caso 3: El problema se ha resuelto dando más importancia a la función de coste que a las funciones de impacto. Se consideran seis situaciones

diferentes en función de la relación entre los tres objetivos; el coste más importante que el impacto del transporte (IT) y que el impacto fijo (IF), el coste más importante que IT e IT más importante que IF, el coste más importante que IF e IF más importante que IT, el coste 2 veces más importante que IT e IF, el coste 3/2 veces más importante que IT e IT 3/2 más importante que IF y el coste 3/2 veces más importante que IF e IF 3/2 veces más importante que IT.

- Caso 4: Se ha resuelto el problema dando más importancia al impacto medioambiental generado por las operaciones de transporte que al coste y a la puesta en marcha y mantenimiento de los depósitos. Nuevamente se consideran seis situaciones diferentes (cambiando en la descripción anterior los roles de coste e IT).

- Caso 5: Se ha dado más importancia al impacto medioambiental generado por la puesta en marcha y mantenimiento de los depósitos que al coste y al impacto de las operaciones de transporte. De nuevo se consideran seis situaciones diferentes (cambiando en la descripción del Caso 3 los roles de coste e IF).

Al resolver todos estos casos se ha observado que cuando a una de las funciones objetivo se le da mucho más peso que a las otras dos, se obtiene el mejor valor para dicha función objetivo comparándola con las obtenidas en el resto de los experimentos, pero esto ocurre a costa de una gran penalización en los otros dos objetivos. Por lo tanto, esta opción es sólo viable en el caso en el que realmente uno de los objetivos produce mucho más interés que el resto. De hecho, si se compara estos subcasos con el caso 1, la solución obtenida en ellos no domina a la actual.

Atendiendo a las soluciones no dominadas obtenidas en los diferentes casos y descartando las soluciones que alcanzan el mejor valor para una de las funciones objetivo, debido a la penalización en los otros dos objetivos, sólo se han encontrado dos soluciones en término de depósitos abiertos. Estas soluciones, se componen de un conjunto de depósitos que incluye tres de los depósitos actuales y cinco de los potenciales. Además, todas las soluciones encontradas en estas condiciones, dominan completamente a la solución para el caso actual especialmente en lo que respecta a sus impactos ambientales, que se pueden mejorar hasta en un 50 %.

Cabe señalar que sólo en el caso en que se da más importancia al impacto medioambiental generado por los depósitos que a los otros dos objetivos, se seleccionan más depósitos de los actuales que depósitos nuevos. Esto se debe al hecho de que los depósitos actualmente abiertos están en grandes áreas industriales, por lo que su IF es menor que otros que se pueden abrir en otras áreas más pobladas.

En cuanto a las soluciones obtenidas en el artículo anterior, cuando se evalúan con este nuevo modelo, se obtiene que el coste total actual del sistema puede reducirse entre un 16, 4 % y un 19, 4 %, el IT entre un 44, 34 % y un 47, 54 % y el IF entre un 39, 78 % y un 44, 03 %. Hay que notar que una de las cinco soluciones no dominadas obtenidas con los resultados de dicho artículo abre sólo dos de los ocho depósitos operativos actuales, mientras que abre hasta seis de los nuevos sitios potenciales. También se puede observar que estas soluciones logran mejores resultados de coste que la solución no dominada encontrada en los cinco casos estudiados, pero sin embargo, son peores en términos de sus valores de IF.

3.3. Effects of dynamic pricing of perishable products on profit and residues

Para estudiar en detalle los efectos de la estrategia de precios dinámica propuesta, tanto en los ingresos totales como en los residuos totales, se ha llevado a cabo una serie de experimentos que consideran diferentes combinaciones de parámetros α. β, γ. Para la elasticidad precio de la demanda se consideraron siete valores diferentes $\alpha \in \{1/3; 1/2; 2/3; 1; 3/2; 2; 3\}$. Para cada valor de α se han definido 21 valores diferentes e igualmente espaciados para el parámetro de velocidad de descuento en el precio γ que se encuentran entre los valores 0 y $1/\alpha$, lo que nos permite evaluar en detalle el efecto de este influyente parámetro. Para el caso del parámetro β, se han estudiado 3 valores distintos $\beta \in \{1,\ 2,\ 5\}$. Estos valores se han elegido para representar tres niveles diferentes para este factor: $\beta = 1$ representa una reducción lineal de la demanda debido al envejecimiento del producto, mientras que los otros dos valores representan una reducción no lineal de la demanda.

Con respecto al perfil de edad del inventario inicial, se han considerado tres escenarios (Ver Figura 3.3). En el primero de ellos (Caso I) se asume una selección aleatoria de las unidades por los clientes, lo que puede dar lugar a una distribución uniforme del número de unidades de cada edad que se tiene en stock. El segundo escenario (Caso II) se compone de una selección inicial aleatoria hasta el instante $L/2$, y luego una disminución lineal hasta el instante L. Por último, el tercer escenario (Caso III) es el caso opuesto al Caso I, es decir, se corresponde con la situación probablemente más común en la que el número de unidades más viejas en inventario disminuye con la edad. Los tres patrones pueden ser vistos como casos especiales de un patrón único con inventario constante hasta una cierta edad (0 para el Caso I, $L/2$ para el Caso II y L para el Caso III) y luego una tendencia decreciente lineal para alcanzar el stock cero en L. En los tres casos, el número total de unidades en el inventario inicial se fijó en el mismo valor (300 unidades), a efectos comparativos.

Estos tres perfiles de inventario inicial son sólo ejemplos que se consideran para ilustrar y evaluar la efectividad del uso de reducciones en los precios para reducir el desperdicio sin sacrificar los ingresos. La metodología utilizada para evaluar la eficacia funciona independientemente de un perfil de inventario

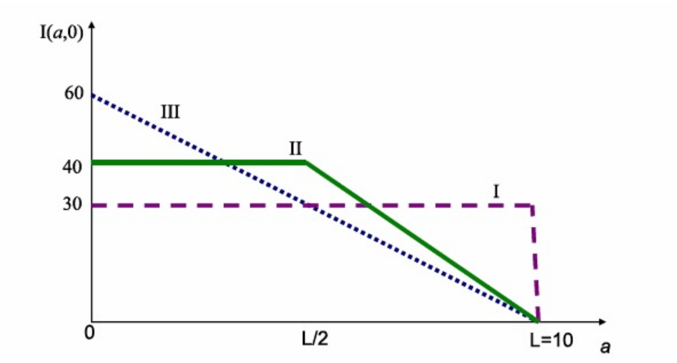

Figura 3.3: Perfil de edad del inventario inicial.

inicial determinado. Cualquiera que sea el perfil de inventario inicial, es decir, para cualquier perfil de inventario inicial arbitrario, el enfoque propuesto puede calcular empíricamente/numéricamente las ventas y los ingresos en cada período de tiempo y para todo el horizonte temporal.

Los valores específicos utilizados para los parámetros han sido $L = 10$ unidades temporales y $p_0 = 5$ unidades monetarias. Con el fin de fijar el valor del parámetro de demanda D_0, se han realizado algunos experimentos preliminares para evaluar la cantidad de desperdicio generado en cada caso. Finalmente se ha seleccionado como valor $D_0 = 15$ ya que el desperdicio que resulta tras los experimentos iniciales es similar a este valor (alrededor del 15 %) que coincide con los valores encontrados en la literatura relacionada. Con estos valores iniciales, los resultados obtenidos se pueden analizar según las perspectivas siguientes:

- **Pérdida de ingresos frente a reducción de desperdicios.**
  Aunque las reducciones de desperdicio están garantizadas con una estrategia dinámica de precios, los ingresos totales pueden caer. En ese caso, el enfoque propuesto permite ver los trade-offs entre ambas magnitudes. En el Caso I, los ingresos totales primero aumentan ligeramente pero después de alcanzar un máximo, disminuyen si se realizan mayores descuentos de precios. El Caso I es el que genera el mayor desperdicio mientras que el Caso III genera el menor. La disminución del desperdicio a medida que γ aumenta

es significativa, llegando a cero residuos totales en los Casos II y III. Dado que en el Caso I existe inicialmente un inventario con una vida útil próxima a cero, no es posible reducir el desperdicio total a cero. En cuanto a los ingresos, debido a la alta elasticidad-precio del escenario $\alpha = 3$ los aumentos de los mismos son más significativos en los Casos I y II porque implican más desperdicio que en el Caso III.

Los casos I y II conducen a un desperdicio mayor en el escenario sin descuento $\gamma = 0$. Sin embargo, independientemente del escenario, el desperdicio total se reduce siempre cuando γ aumenta. En cuanto a los ingresos totales, si bien para las elasticidades de precios elevados puede aumentar, para las elasticidades de precios más bajos los ingresos disminuyen según aumenta γ, porque los aumentos de la demanda inducidos por los descuentos de precios no son lo suficientemente grandes para compensar el menor precio unitario.

- **Ventas e ingresos en función de la edad y el tiempo.**

  El enfoque propuesto nos permite estudiar los patrones de distribución para cualquier escenario de precios dinámicos. Para el escenario correspondiente a $\alpha = 1$, $\beta = 2$ y $\gamma = 0{,}5$, aunque hay poca diferencia en la edad media de las unidades vendidas entre los tres casos (5,09, 5,16 y 4,79 para los Casos I, II y III respectivamente), se observa que los Casos I y II implican una mayor proporción de unidades envejecidas y una menor proporción de unidades más frescas que el Caso III. En cuanto a la contribución de ingresos de las unidades de diferentes edades, las unidades más viejas se venden a un menor precio y por lo tanto su contribución relativa de ingresos disminuye con la edad.

  En cuanto a la evolución de las ventas y los ingresos con el tiempo, se observa que las ventas y los ingresos en el tiempo cero, son los mismos para los tres perfiles iniciales de inventario. Esto se debe al hecho de que estos dos valores no dependen del perfil de inventario inicial.

- **Efectos de la elasticidad de la demanda en los ingresos totales**

  Para medir el efecto de la elasticidad de la demanda, se ha considerado la reducción de los ingresos totales correspondiente a una reducción del 50 % en los desperdicios. Se ha observado que la pérdida de ingresos totales depende claramente de la elasticidad de la demanda α, aunque esa dependencia es menor a medida que β aumenta. Además, las pérdidas totales de ingresos generalmente existen para elasticidades de la demanda por debajo de 1,5. Por encima de ese umbral, los ingresos totales se mantienen o incluso aumentan ligeramente. Curiosamente, para valores grandes de α, las mejoras en los ingresos totales son más grandes cuando β decrece.

  Los escenarios en los que el impacto económico (negativo) de la reducción de los desperdicios son mayores, corresponden a una demanda inelástica (es decir, $\alpha < 1$). Esto se debe a que cuando la demanda es inelástica, la efectividad de los descuentos de precios, como un medio para lograr aumentos de la demanda, es bastante limitada. De hecho, cuando α disminuye por debajo del umbral de unidad, la pérdida en el ingreso total aumenta a una tasa exponencial. Este comportamiento ocurre para los tres perfiles de inventario inicial, aunque es algo menos agudo para el caso III.

Capítulo 4

Conclusiones

En esta tesis se ha abordado el problema del diseño de redes logísticas trabajando con múltiples objetivos, profundizando de esta manera en un problema que tradicionalmente se ha abordado únicamente desde un punto de vista económico, es decir, tratando de minimizar los costes (o en su defecto, maximizar los beneficios). Los diferentes trabajos efectuados se han centrado en el estudio de redes logísticas multiobjetivo sostenibles, así como aquellas cuyos riesgos sobre la cadena logística ponen en peligro el correcto funcionamiento de las mismas. Se ha analizado asimismo el papel de las políticas de precios a la hora de reducir los desperdicios en esas redes.

En el primero de los trabajos realizados se ha analizado la mejor ubicación de los depósitos de contenedores en un hinterland, teniendo en cuenta el coste total del sistema así como el impacto ambiental que se genera debido a las operaciones de transporte y la puesta en marcha y utilización de dichos depósitos. De este modo, se ha formulado un problema de optimización biobjetivo minimizando ambas características. Este enfoque era algo completamente nuevo, ya que hasta el momento no se había realizado ningún trabajo previo que incluyese el estudio del impacto ambiental en este ámbito.

En el estudio realizado se ha presentado un caso de aplicación real, correspondiente al Puerto de Valencia. De este modo, se han podido realizar comparaciones entre los resultados obtenidos con el modelo, y la actual red de depósitos existente en el hinterland de Valencia.

Las soluciones obtenidas muestran que el impacto generado en toda la red podría mejorarse hasta un 47 % en comparación con la situación actual para soluciones con costes aproximadamente un 15 % inferiores al actual. Por otro lado, si nos fijamos en soluciones que tenga un impacto aproximado al actual, se ha podido mejorar el coste en hasta un 40 %. Esto muestra, que con el modelo que se ha diseñado, se obtienen significativas mejoras en los costes respecto de los actuales, incluso después de considerar los impactos ambientales como un nuevo objetivo.

También se ha podido concluir que la ubicación actual de los depósitos parece basarse principalmente en su proximidad a las instalaciones portuarias en lugar de en el entorno de los clientes. Esta decisión, suele aumentar el impacto ambiental de las operaciones logísticas de los contenedores e incluso los costes en función de las características de la ubicación de los clientes. El estudio ha mostrado que se pueden encontrar mejores soluciones en ambos objetivos y que uno no debe tener miedo de incurrir en costes adicionales sólo por ser responsable con el medioambiente.

Por otro lado, el hecho de integrar los impactos ambientales de las operaciones de transporte y de los propios depósitos en una misma función objetivo pierde en parte la visión realista del problema al tener que usar un parámetro de peso λ para realizar una compensación entre dichos impactos. Una de las posibles soluciones que se podrían considerar es separar en dos funciones objetivo este impacto. Esto eliminaría la necesidad de este parámetro, pero haría más difícil la visualización de las fronteras de Pareto obtenidas como solución, algo que es una clara ventaja del enfoque de optimización bicriterio propuesto. Además de esto, incluir la incertidumbre en algunos de los datos puede ser más realista, considerando que algunos de ellos, como las capacidades de flujo de los depósitos y terminales, son difusos. En ese caso, en lugar del método de las ε-constraints un enfoque multiobjetivo difuso podría ser más apropiado.

Teniendo en cuenta todos estos puntos se ha realizado un segundo trabajo en el que se ha diseñado una red de depósito de contenedores para la que se ha definido un modelo de optimización de tres objetivos datos difusos para encontrar la mejor ubicación para depósitos de contenedores vacíos en un hinterland. En este trabajo, para la obtención de los datos acerca del impacto ambiental se utilizó la metodología F-AHP en lugar del AHP. Además, como algunos de los datos necesarios tienen un cierto grado de incertidumbre, se han utilizado en el modelo restricciones difusas para las capacidades de flujo de los depósitos.

En todos los casos estudiados al menos uno de los objetivos mejoró la situación actual. Además, se encontraron algunas soluciones que mejoran la situación actual en los tres objetivos. En estas soluciones la función de coste puede lograr alrededor de un 17 % de mejora, el impacto medioambiental generado por las operaciones de transporte (IT) en torno al 45 % de mejora y el impacto medioambiental generado por los propios depósitos (IF) sobre un 50 % de mejora.

Respecto a los resultados obtenidos imponiendo qué depósitos deben estar abiertos, se encontró que sólo cinco de las 25 soluciones obtenidas en el trabajo anterior no están dominadas. Estas soluciones pueden mejorar la actual para cada objetivo en un 17 %, 45 % y 40 % respectivamente. Por lo tanto, al resolver el problema con "fuzzy multiobjectivo optimization" reduce el número de alternativas en comparación a las obtenidas en la frontera de Pareto con el método de las ε-constraints. De esta manera, podemos reducir las 25 soluciones encontradas en el trabajo anterior a sólo siete soluciones que dominan la situación actual: cinco obtenidas en el anterior trabajo más dos nuevas soluciones obtenidas en éste.

En el tercero de los trabajos elaborados para esta tesis se propone un modelo matemático de tiempo continuo que permite estudiar en función de políticas de descuento, el agotamiento de un inventario inicial dado. En este trabajo, además de las ventas y los ingresos totales, también se puede calcular y analizar la distribución por edad correspondiente. Más aún, no sólo se pueden calcular las ventas totales y los ingresos para todo el horizonte sino también el valor de esas magnitudes en cada período de tiempo. Se ha demostrado que una política de descuento de precios dependiente de la edad, como la que se considera, siempre reduce el número de unidades deterioradas/desperdiciadas, de modo que cuanto mayor es la tasa de descuento, menor es el número de unidades que alcanzan el fin de su vida útil. Además, este efecto es más evidente a medida que aumenta la elasticidad precio de la demanda.

Se han realizado un gran número de experimentos considerando muchos escenarios diferentes. Uno de las principales puntos a tener en cuenta es que el comportamiento es diferente dependiendo del escenario considerado. Por otro lado, en todos ellos se ha obtenido que la estrategia dinámica de precios reduce significativamente los desperdicios totales. Aún así, el efecto que se produce en los ingresos totales con dicha estrategia no siempre es positivo. Existen algunos escenarios con alta elasticidad precio de la demanda y grandes desperdicios potenciales, en los que los ingresos totales se pueden incrementarse ligeramente si se realiza un descuento en el precio. En otros escenarios, los ingresos totales se mantienen más o menos constantes, siempre que la velocidad de descuento de precios no sea demasiado alta. Y en otros escenarios, generalmente con elasticidad baja en los precios, una demanda insensible a la edad o un inventario inicial no demasiado viejo, puede derivar en una pérdida sustancial de ingresos que aumenta a medida que el descuento de precio se realiza más rápido.

Se ha observado que los efectos sobre los ingresos al realizar un descuento en los productos a medida que se aproximan a su fecha de caducidad depende en gran medida de la elasticidad de la demanda. Se puede esperar que la política de precios dinámica sea muy efectiva para reducir los desperdicios sin grandes reducciones en los ingresos totales (o incluso con pequeños incrementos) para una gran fracción de posibles escenarios de demanda y comportamiento del consumidor, excluyendo los casos con una elasticidad precio baja, especialmente cuando se combina con insensibilidad de la demanda a la edad del producto. En esos casos desfavorables, debe buscarse otra alternativa, diferente de los descuentos de precios.

Por todo esto, se puede considera que esta investigación es un primer paso para probar que lo mejor de ambos objetivos (más ingresos y menos desperdicios) se puede lograr a través de esta estrategia de precios dinámicos.

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Apéndices

Apéndice A

Artículos publicados

Netw Spat Econ (2016) 16:331–348
DOI 10.1007/s11067-013-9205-7

Bicriteria Optimization Model for Locating Maritime Container Depots: Application to the Port of Valencia

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Published online: 11 September 2013

Abstract Since the location of container depots has an impact on maritime logistics costs, the container depot location problem is usually treated as a cost minimization problem. But the location of the container depots also has a serious environmental impact, given the heavy traffic load inherent to these operations and the setting up and maintenance of the depots. In this paper a bicriteria optimization model for designing a network of depots in a hinterland is proposed and its application to the Port of Valencia, Spain is reported. The two objectives considered are (1) the total cost of the network and (2) the environmental impact of the container depots and the transport operations associated with them. An Analytic Hierarchy Process (AHP) has been used to determine the environmental impact of each depot, and the ε-constraint method to obtain the optimal Pareto set of the problem. The results clearly show that trade-offs are possible between both objective functions and that, for our case study, the proposed approach can obtain solutions that are more cost-effective and have lower environmental impacts than those currently existing.

Keywords Maritime transportation · Container depots · Cost minimization · Environmental impact · Bicriteria optimization

1 Introduction

Maritime container transportation has undergone significant growth worldwide. Since competition is intense, efficient inland operations are essential. One of the issues that

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must be dealt with is the storage of empty containers. Furió et al. (2005) list several reasons that may make it necessary to store empty containers. Among them are: a) The world container fleet is nearly double the total capacity of container ships; b) The lack of balance between import and export operations requires the repositioning of large amounts of equipment used for import and export; c) The difficulties reported for triangulations (i.e. coordinating import and export operations) require the storage of equipment once emptied until it is used again in a 'match back' operation; d) The variability in the load and the inability to match quantity, location and time between supply and demand, requires that carriers and leasing companies have stocks of equipment available to satisfy the demands of the different regions in which they operate.

As the storage capacity of port terminals is limited and expensive (Holguín-Veras and Jara-Díaz 2006) it becomes necessary to have other places available for storing the empty containers. Container depots are where empty containers are stored after being used and are waiting to be taken for exportation. Furthermore, the containers require intermediate operations before being reused, such as inspection, cleaning and/or repair. Container depots usually offer these services, taking advantage of the empty containers passing through their facilities.

It can thus be concluded that deciding on the location of depots in the different hinterlands is a decision of particular importance in maritime logistics operations. Since the location of container depots has an impact on maritime logistics costs, the container depot location problem is usually treated as a cost minimization problem. However, the location and operation of container depots also has an important environmental impact, defined as any change or modification in the environment with negative (or positive) effects produced as a result of the activities, products and services of any organization. Container depots, due to the amount of daily movements performed by trucks, generate a lot of traffic. This is one of the main reasons why container depots have a sizable environmental impact (e.g. traffic congestion; traffic accidents; atmospheric, noise and visual pollution). In addition to the impact caused by heavy transport operations associated with container depots, the environmental impact generated by the existence of the depots themselves should also be considered (e.g. construction of the depot, visual impact, pollution due to the internal operations of the depot).

1.1 Problem Introduction

This paper considers the problem of designing a network of container depots in a hinterland. The starting point for our research is the Multicommodity Capacitated Location Problem with Balancing Requirements (MCLB) initially proposed by Crainic et al. (1989). This model assumes that once a ship reaches a port and is unloaded, the incoming containers are delivered to the consignees and, once unloaded, have to be transported to a depot or a terminal to be stored. These containers then remain in the depot until shippers request them for shipping their own products.

Gendron et al. (2003) consider limited capacities at depots, where the capacity of a depot is represented by an estimate of the number of empty containers that can be handled there. The problem is defined as finding the best location for the depots to satisfy the demand for empty containers and minimize operating costs. Several methods have been proposed for efficiently solving the MCLB problem, mainly based on branch and bound (Crainic et al. 1993a; Gendron and Crainic 1995, 1997) as well as on tabu search (Crainic et al. 1993b; Gendron et al. 2003).

However, although cost minimization is of course a primary objective, the growing importance of environmental responsibility makes it necessary to include also environmental impacts in formal decision models. This is sometimes done by incorporating impacts as explicit objective functions, thus giving rise to multi-objective approaches (e.g. Harris et al. 2009, 2011) or as constraints that bound acceptable environmental impact levels (e.g. Ghaddar and Naoum-Sawaya 2011). We have taken the former path, i.e. considering a bi-objective optimization model.

Our approach differs from existing ones in that many different impacts are considered and not just CO_2 emissions – which has become the main type of global impact considered in the literature on green logistics. Thus, as mentioned above, not only atmospheric but also noise and visual impacts, and accidents and congestion, will be considered. This has led us to use experts' opinions on the importance and magnitude of these impacts for the different depot locations. To that end, the well-known Analytic Hierarchy Process (AHP) methodology (Saaty 1980) has been used.

The proposed procedure thus consists of augmenting the Multicommodity Capacitated Location Problem with Balancing Requirements (MCLB) of Crainic et al. (1989) with the environmental impacts that result from the transport associated with the depots and to the setting up and maintenance of the depots themselves. It has been applied to the Port of Valencia, which is the largest container port in Spain, using as the solution methodology the ε-constraint method (Haimes et al. 1971; Miettinen 1999).

The structure of the paper is as follows. In section 2 the proposed approach is presented. Section 3 reports the results of the application of the proposed approach to the hinterland of the Port of Valencia. Finally, in section 4, the summary and conclusions of this study are presented.

2 Proposed Approach

As indicated above, when solving a container depot location problem, both the costs and the environmental impact of the logistics network are relevant. Therefore, the aim of our bicriteria optimization problem is to find the Pareto set considering both goals. To generate this Pareto optimal set we opted to solve a sequence of single-objective optimization problems using the ε-constraint method. This method, introduced by Haimes et al. (1971), selects one of the objective functions as primary. The first step is to minimize this primary objective function (the costs function in our case). After that, the second objective (i.e. the environmental impact) is introduced into the optimization model as a constraint, such that the value of the impact has to be lower than the impact value obtained in the previous step. This is repeated iteratively until the environmental impact bound reaches the minimum impact value that the logistics network can achieve. The advantage of using the ε-constraint method is that the solution obtained is always weak Pareto optimal.

Note that since the ε bound is varied in small but finite step sizes; the sampling of the Pareto front is not continuous, which means that the ε-constraint method gives an incomplete Pareto front. It is incomplete in the sense that, although all solutions found are (weak) Pareto optimal, the method may miss some Pareto optimal solutions. Of course, this is not significant as the step size used to vary the value of the ε bound is usually rather small.

The bicriteria optimization model proposed in this article is based on the MCLB problem by Gendron et al. (2003) The most important differences between their model and ours are the simplification of some variables, the use of port terminals and of course the fact that we consider two objective functions instead of one. The second objective function considered quantifies the environmental impact generated by the heavy transport operations associated with the depots, and the environmental impact generated by the setting up and maintenance of those depots.

Therefore, we assume that there is a set of potential depots, and the problem is to decide which of them should be finally selected for the storage of the empty containers used for the export/import operations conducted by the shippers/consignees through port terminals. There are three types of nodes in our network: shippers/consignees (set S), depots (set D) and terminals (set T).

It is assumed that from each terminal t∈T, a subset of shippers S(t)⊆S can be supplied, and in the same way each terminal t can work with a subset of depots D(t)⊆D. Analogously, each consignee s∈S can send its empty containers to a subset of depots D(s)⊆D. All these relations are bidirectional, so that there also exist the sets T(s)⊆T, T(d)⊆T and S(d)⊆S that identify the terminals working with shipper s∈S, with depot d∈D, and the shippers working with depot d∈D. The notation used is shown in Table 1.

The model proposed is:

$$\min \sum_{d} f_d \delta_d + \sum_{s} \sum_{t \in T(s)} c_{st}(x_{st} + x_{ts}) + \sum_{t} \sum_{d \in D(t)} c_{td}(x_{td} + x_{dt}) + \sum_{s} \sum_{d \in D(s)} c_{sd}(x_{sd} + x_{ds}) \tag{1}$$

$$\min 2 \sum_{d} w_d \left(\sum_{s \in S(d)} x_{sd} + \sum_{t \in T(d)} x_{td} \right) + \lambda \sum_{d} C_d v_d \delta_d \tag{2}$$

s.t.

$$\sum_{s \in S(t)} x_{st} + \sum_{d \in D(t)} x_{dt} + \sum_{s} E_{st} = \sum_{s \in S(t)} x_{ts} + \sum_{d \in D(t)} x_{td} + \sum_{s} I_{st} \quad \forall t \in T \tag{3}$$

$$\sum_{s \in S(d)} x_{sd} + \sum_{t \in T(d)} x_{td} = \sum_{s \in S(d)} x_{ds} + \sum_{t \in T(d)} x_{dt} \quad \forall d \in D \tag{4}$$

$$\sum_{t \in T(s)} x_{st} + \sum_{d \in D(s)} x_{sd} = \sum_{t \in T(s)} I_{st} \quad \forall s \in S \tag{5}$$

$$\sum_{t \in T(s)} x_{ts} + \sum_{d \in D(s)} x_{ds} = \sum_{t \in T(s)} E_{st} \quad \forall s \in S \tag{6}$$

Table 1 Notation for model parameters and variables

Notation	Description
S	Set of shippers
T	Set of terminals
D	Set of depots
s	Index for shippers
t	Index for terminals
d	Index for depots
S(t), D(t)	Shippers and depots working with terminal t
S(d), T(d)	Shippers and terminals working with depot d
D(s), T(s)	Depots and terminals working with shipper s
I_{st}	Containers imported by consignee s through terminal t every year
E_{st}	Containers exported by shipper s through terminal t every year
K_d	Flow capacity limit of depot d
K_t	Flow capacity limit of terminal t
C_d	Storage capacity of depot d
f_d	Fixed operation cost of depot d
c_{st}	Cost per transport unit between shipper/consignee s and terminal t
c_{sd}	Cost per transport unit between shipper/consignee s and depot d
c_{td}	Cost per transport unit between terminal t and depot d
w_d	Environmental impact per flow unit from/to depot d
v_d	Environmental impact per stored unit in depot d
x_{st}, x_{ts}	Container flow between shipper/consignee s and terminal t, and between terminal t and the shipper
x_{sd}, x_{ds}	Container flow between shipper/consignee s and depot d, and between the depot and the shipper
x_{td}, x_{dt}	Container flow between terminal t and depot d, and between the depot and the terminal
δ_d	Binary variable that indicates if depot d opens or not
λ	Weighting factor between depot impact and transport impact

$$\sum_{s\in S(t)} x_{st} + \sum_{d\in D(t)} x_{dt} + \sum_{s\in S(t)} x_{ts} + \sum_{d\in D(t)} x_{td} \le K_t \quad \forall t\in T \tag{7}$$

$$2\left(\sum_{s\in S(d)} x_{sd} + \sum_{t\in T(d)} x_{td}\right) \le K_d \delta_d \quad \forall d\in D \tag{8}$$

$$\delta_d \in \{0,1\} \quad \forall d\in D \;\; ; \;\; x_{st}, \;\; x_{ts}, x_{sd}, x_{ds}, x_{td}, x_{dt} \ge 0 \quad \forall t\in T \;\; \forall d\in D \;\; \forall s\in S \tag{9}$$

The first objective function represents the total system cost, including the fixed cost of open depots, the cost of container flow between shippers/consignees and terminals, the cost of container flow between terminals and depots, and the cost of container flow between shippers/consignees and depots. The second objective function corresponds to the total environmental impact generated by the depots, including the total impact generated by heavy transport operations associated with the depots, and the total impact generated by the open depots themselves (i.e. their construction and maintenance). The parameter λ weights these two different sources of environmental impacts. Since this parameter multiplies the second term of the objective function it represents the relative weight of the impacts of the depots' construction and operation with respect to the impacts of the transport flow in and out of the depots. The first term of the second objective function is multiplied by two for the same reason as that in constraint (8), i.e. because the sum of the input and output movements are exactly double the number of input movements, as constraint (2) shows.

Regarding the constraints, (3) ensures that the number of containers arriving at a terminal is exactly the same as those leaving the terminal. Thus, the first two terms on the left hand side correspond to the number of empty containers that arrive to terminal t from either the shippers or the depots.

Similarly, the first two terms on the right hand side represent the number of empty containers sent from the terminal to the shippers and to the depots. This empty container flow to/from the terminal t balances itself with the total net exports and imports $\sum E_{st}$ -$\sum I_{st}$ so that if, for example, there are more imports than exports then a number of empty containers are assumed to have been specifically exported by the terminal (i.e. repositioned to other ports) to make up for the difference. In other words, to maintain the equilibrium and to balance the number of containers that enter and leave the system through imports and exports, a corresponding matching flow of empty containers to places outside the system (i.e. to other ports) needs to be assumed and that is the meaning of constraint (3).

Constraint (4) ensures that the number of containers arriving at a depot are exactly equal to those that go out. Constraint (5) ensures that all the containers imported and emptied by a consignee are to be stored at a depot or at a terminal. Analogously, constraint (6) ensures that all the empty containers required by a shipper are supplied from a depot or terminal. In other words, whenever a shipper needs a container to load with items for export, the corresponding empty container must come from either the terminals or the depots. Thus, the sum of all those empty containers (that are required for loading) must match the total exports of that shipper through all the terminals.

Constraint (7) ensures that the movements of empty containers that are processed in a terminal do not exceed the available operating capacity (discounting the full container movements) of that terminal. Constraint (8) ensures that the total number of containers that move into or from a depot does not exceed the operating capacity of that depot. Recall that, according to constraint (2), the sum of the input and output movements is exactly double the number of input movements.

Note also that this model is static and assumes that the system is at equilibrium. This means that the container flow through the system is balanced, and that a balance occurs in each node of the network: terminal nodes (constraint 1), depots (constraint 2) and shippers/consignees (constraints 3 and 4).

The total number of constraints is 2(t+s+d) and the number of variables is d+2(st+dt+sd) of which d are binary. Note that, in this respect, the solutions obtained are all integer because when the depots to open are fixed (i.e. for a given value of the binary variables δ_d) the resulting subproblem is a minimum cost flow network problem (see, for example, Gendron et al. 2003, whose precise use of a tabu search heuristic solves that subproblem in each iteration).

2.1 Impact Estimation

In the proposed model it is necessary to gather the environmental impact per flow unit from/to depot d and the environmental impact per stored unit in depot d (w_d and v_d respectively). Measuring environmental impacts and aggregating them is a complex issue that is being heavily researched into in the Life Cycle Assessment (LCA) realm. The approach adopted in this paper is innovative and relies on subjective opinions from experts. What we propose is to use a well-known multicriteria method such as AHP to assess the aggregate environmental impact of the different depot locations. It is a structured technique for organizing and analyzing complex decisions (see, for example, Ishizaka and Labib 2011), and it is particularly suited for group decision making (Tsyganok et al. 2012).

Thus, experts provide a qualitative assessment of the level of impact of each depot location along each criterion. These experts also provide the pairwise comparison matrix from which to extract the criteria weights. In the end, AHP computes a normalized, aggregated environmental impact per flow unit for each depot.

Therefore, the environmental impact w_d generated per transport unit at each potential depot location can be quantified by considering the different possible levels for each externality. To assess it, a group of experts could be asked for their assessment of the environmental impact generated by the depots and their associated container traffic, with regard to five externalities: atmospheric pollution, noise pollution, visual pollution, traffic congestion and likelihood of accidents.

This methodology can also be used for estimating the environmental impact v_d generated by the setting up and maintenance of a depot in each potential location. In that case, three criteria should be considered: the setting up, visual contamination and operations contamination. With the data provided by the experts, the procedure introduced by Bryson (1996) can be used to check the degree of consensus between those experts, by determining the weighting assessed by each expert. To obtain the final decision table, a "ratings mode" procedure seems suitable to consider three categories (low, medium, high) for each externality. In our case, all the AHP calculations were performed using MATLAB.

In other words, the approach adopted in this paper for assessing the environmental impact of operating the container depots is innovative and relies on subjective opinions from experts. What we propose is to use a well-known multicriteria method such as AHP to evaluate the aggregate environmental impact of the different depot locations. Thus, experts provide a qualitative assessment of the level of impact of each depot location along each criterion. The experts also provide the pairwise comparison matrix from which to extract the criteria weights. Finally, AHP computes a normalized, aggregated environmental impact per flow unit for each depot. Using the same procedure, but with fewer impact categories, a normalized fixed impact per unit capacity in each depot is also computed.

Therefore, these indexes of the environmental impact of each depot (coefficient w_d and v_d in the model) are relative and aggregated. Moreover, they are further aggregated in the form of the objective function (2). However, since one corresponds to the recurrent impact due to the traffic in and out of the depot (and is therefore proportional to the traffic level) while the other corresponds to the one-time impact due to the construction (and is therefore proportional to depot capacity but independent of traffic), that is why adding these two different sources of environmental impact has been done using parameter λ so that different weightings can be considered.

Summarizing this point, the proposed approach estimates environmental impacts per unit of traffic in/out of each depot and per unit of storage capacity of each depot. The former is therefore multiplied by the traffic in/out of the depots while the latter is multiplied by the capacity of the depot and then both sources of environmental impact are added using weighting parameter λ.

3 Application to the Port of Valencia

This section reports the results of the application of the proposed approach to the Port of Valencia, the largest container port in Spain. Its traffic reached 4.21 million TEUs (Twenty-foot Equivalent Unit containers, the capacity unit of a standard container of 20 ft) in 2010. Of these TEUs, 1.04 million were loaded, 1.01 million were unloaded and 2.16 million were for transit. Regarding the number of containers, in 2010 the port of Valencia had 2,776,910 container movements (Valenciaport Annual Report 2010). Given the overall size of the problem, we decided to take a sample of the 357 largest shippers in the surrounding Valencia and Murcia regions and scale that sample to the rest of the data. This number of shippers/consignees was chosen because it corresponds to those that move a minimum of four containers annually, considering the others as occasional shippers.

In the hinterland of the port of Valencia, there are currently eight container depots (see Fig. 1), each with a different flow capacity. Considering the location of the shippers and consignees, in addition to these depots, another 11 potential new depot locations have been proposed to be considered by our model. Given the average figures in this hinterland, we assigned to these potential new depots a maximum flow capacity of 95,000 annual container movements and a storage capacity of 8,800 containers. The new locations that have been considered are also shown, not circled, in Fig. 1.

Regarding costs, it will be recalled that the model considers two types: the fixed operating costs of depots, and the cost per unit flow between all combinations of shippers/consignees, depots and terminals. The fixed operating cost is estimated at 1,000,000 € for a depot of 250,000 annual movements, taking in our case proportional values according to the capacity of each depot. To calculate the cost per flow unit, we have calculated the distances (km) between each node and multiplied the distance by the unit cost per km of a standard container transport vehicle, which can be estimated as approximately 1.152 €/km according to Spanish Ministry of Infrastructures (2012).

Note that in the proposed approach, the fixed operation cost is different for each depot. For those depots that are not currently open, this fixed operation cost should take into account the corresponding annual amortization (using the expected depot's

Fig. 1 Currently open depots in Valencia's hinterland (numbered 1–8, *circled*) and potential new sites (numbered 9–19)

useful life) of opening the site and, therefore, those cost coefficients would be larger for the new locations than the existing ones. However, in the case study we have carried out, we have assumed that the fixed operation cost is the same for all potential locations without differentiating between existing and potential locations. The research idea is to see what would have been the optimal locations selected if the proposed approach had initially been applied, i.e. before establishing the actual current depots. We would not have been able to answer that question properly if we had considered a lower fixed operation cost for the existing depots. In any case, this does not mean, from a competitive location perspective, that fixed operation costs of new locations should, in general, be higher than for already existing ones.

The corresponding impacts per flow unit are shown in Table 2 for transportation, and in Table 3 for setting up and maintenance.

3.1 Results

After obtaining all the necessary data to perform the experiments, the bi-objective optimization model defined above was solved using the ε-constraint method and LINGO 10 optimization software, running on an Intel® Core™ i7-3770 K CPU at 3.50 GHz, 16 Gb RAM memory. Since we considered a sample of the 357 largest shippers/consignees in the hinterland of Valencia, 19 depots and a terminal, the model had a total of 754 constraints and 14,337 variables, of which 19 are binary.

Since the ε-constraint method used computes the whole Pareto front, in particular it includes the minimum cost solution. Thus, the proposed multi-objective approach produces the minimum cost solution computed by the existing single objective approaches plus additional alternatives that represent different trade-offs between the two objective functions considered.

To study the effect of the possible values of λ in the second objective function (i.e. the importance of the transport impacts measured through the coefficients w_d, against the impact of the depot itself measured with the coefficients v_d), some previous tests

Table 2 Normalized impact per flow unit for each depot

	Atmospheric (0.122)		Noise (0.528)		Visual (0.060)		Traffic (0.129)		Likelihood of accidents (0.161)		Total impact
Depot 1	M	0.464	M	0.333	M	0.464	H	1.000	M	0.333	0.443
Depot 2	L	0.215	M	0.333	M	0.464	L	0.215	L	0.111	0.276
Depot 3	H	1.000	H	1.000	H	1.000	H	1.000	H	1.000	1.000
Depot 4	H	1.000	H	1.000	H	1.000	H	1.000	H	1.000	1.000
Depot 5	H	1.000	H	1.000	H	1.000	H	1.000	H	1.000	1.000
Depot 6	M	0.464	M	0.333	L	0.215	L	0.215	H	0.333	0.327
Depot 7	H	1.000	H	1.000	H	1.000	H	1.000	H	0.333	0.893
Depot 8	H	1.000	H	1.000	H	1.000	H	1.000	H	0.333	0.893
Depot 9	M	0.464	M	0.333	M	0.464	H	1.000	H	0.333	0.443
Depot 10	M	0.464	M	0.333	M	0.464	H	1.000	H	0.333	0.443
Depot 11	M	0.464	M	0.333	L	0.215	H	1.000	H	0.333	0.428
Depot 12	H	1.000	H	1.000	H	1.000	H	1.000	A	1.000	1.000
Depot 13	M	0.464	M	0.333	M	0.464	H	1.000	H	0.333	0.443
Depot 14	M	0.464	M	0.333	L	0.215	M	0.464	H	0.333	0.359
Depot 15	M	0.464	M	0.333	M	0.464	L	0.215	H	0.333	0.342
Depot 16	M	0.464	M	0.333	M	0.464	M	0.464	H	0.333	0.374
Depot 17	H	1.000	H	1.000	H	1.000	H	1.000	A	1.000	1.000
Depot 18	M	0.464	M	0.333	L	0.215	M	0.464	H	0.333	0.359
Depot 19	M	0.464	M	0.333	M	0.464	M	0.464	H	0.333	0.374

L low, *M* medium, *H* high

Table 3 Normalized fixed impact per stored unit in each depot

	Setting up (0.20)		Visual impact (0.08)		Operations impact (0.72)		Total impact
Depot 1	L	0.215	M	0.464	M	0.333	0.320
Depot 2	H	1.000	L	0.215	L	0.111	0.297
Depot 3	H	1.000	H	1.000	H	1.000	1.000
Depot 4	L	0.215	M	0.464	H	1.000	0.800
Depot 5	M	0.464	H	1.000	H	1.000	0.893
Depot 6	M	0.464	M	0.464	M	0.333	0.370
Depot 7	M	0.464	H	1.000	H	1.000	0.893
Depot 8	M	0.464	H	1.000	H	1.000	0.893
Depot 9	M	0.464	M	0.464	M	0.333	0.370
Depot 10	H	1.000	M	0.464	M	0.333	0.477
Depot 11	H	1.000	L	0.215	M	0.333	0.457
Depot 12	M	0.464	H	1.000	H	1.000	0.893
Depot 13	L	0.215	H	1.000	M	0.333	0.363
Depot 14	H	1.000	L	0.215	M	0.333	0.457
Depot 15	H	1.000	L	0.215	M	0.333	0.457
Depot 16	H	1.000	L	0.215	M	0.3333	0.457
Depot 17	M	0.464	H	1.000	H	1.000	0.893
Depot 18	H	1.000	M	0.464	M	0.333	0.477
Depot 19	M	0.464	L	0.215	M	0.333	0.350

L low, *M* medium, *H* high)

were carried out observing that values close to $\lambda=10$ make both types of impact achieve similar values in Eq. (2). It was then decided, in order to analyze the model behaviour as λ varies, to solve the model for nine different values of λ grouped into three cases: a) Case 1: values for which the impacts generated by the heavy transport operations have much more weight than the impacts generated by the depots ($\lambda=\{1,2,4\}$); b) Case 2: values for which the weight of both impacts are similar ($\lambda=\{8,10,12\}$); c) Case 3: values for which the impacts generated by the depots have much more weight than the impacts generated by the heavy transport operations ($\lambda=\{16,18,20\}$).

Results for Case 1 The initial solution obtained by solving the model minimizing only the cost objective function (solution S1 in Fig. 2, R1 in Fig. 3 and P1 in Fig. 4), consists of 11 depots, four of them (1, 4, 6 and 7) currently open and the other seven (9, 11, 12, 13, 15, 17 and 18) selected among the potential new ones. Although the cost is the same for all λ (1.228 million €), the corresponding weighted impacts are $I_{\lambda=1}$=26,111.60, $I_{\lambda=2}$=28,211.81 and $I_{\lambda=4}$=32,409.81, respectively (see Fig. 2).

Next, an ε-constraint is added to the single-objective optimization model to impose that the impact value given by Eq. (2) has to be lower than or equal to $\alpha\cdot I_\lambda$, i.e. the impact value obtained in the initial solution multiplied by a value $\alpha\in(0,1]$. The value of parameter α is iteratively decreased ($\alpha_{t+1}=\alpha_t-\Delta$, with $\Delta=0.0025$) until infeasible solutions are obtained. A fine-grain exploration of solutions corresponding to consecutive α for which changes in the open depots were obtained, is performed using Δ=0.0005. Obviously, the total system cost obtained increases as the upper bound on the impact value decreases, thus obtaining the three optimal Pareto sets, one for each value of λ. Thus, Fig. 2 shows the Pareto optimal set for Case 1 (λ={1,2,3}). Note that the different solutions found correspond to just 27 ways of selecting the depots to open. These 27 solutions, labelled S1 to S27, are shown in the panel on the upper part of that figure. The number of iterations for each value of parameter λ, as well as the minimum value of parameter α before infeasibility occurs and the total computation time, are shown in Table 4.

Figure 2 also shows the points that correspond to the current solution (i.e. only depots 1 to 8 opened), which has a cost of 1.833 million € and a weighted impact that is slightly different for each value of λ. It can be seen that the current solution is completely dominated by the solutions obtained with our model for any of the three λ values, achieving cost improvements up to 33 %. Note that the impact generated by the initial solution (S1) is higher than the impact generated by the current solution by 8.6 %, 9.1 % and 9.8 % for the three λ values, respectively. Of course, for the successive ε-constraint solutions of the Pareto optimal set, the corresponding impacts are lower. Thus, considering the lowest impact solution that is obtained for each of the three λ values, the generated impact (corresponding to solution S20) represents a

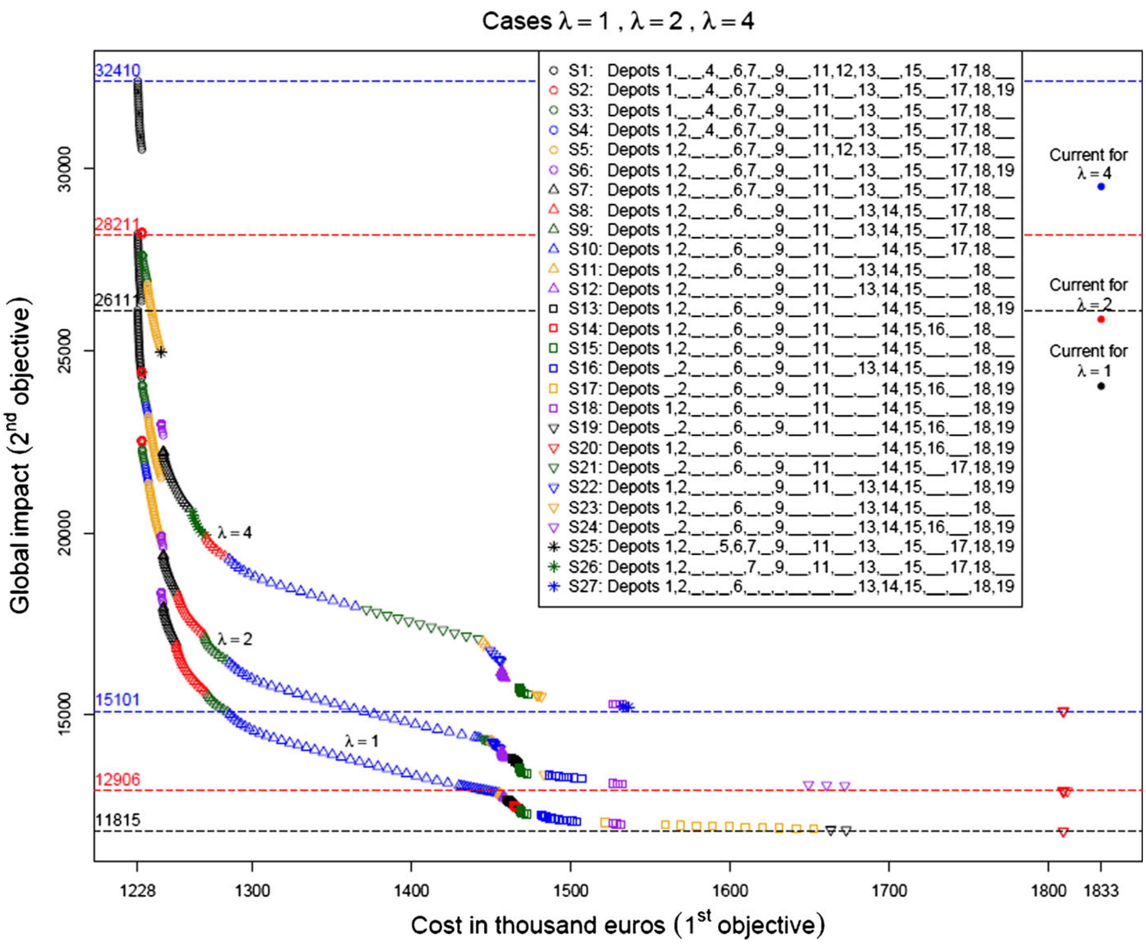

Fig. 2 Pareto optimal set for Case 1 (λ={1,2,3}). For the current existing network, cost (1.833 million €) and impacts (for the three values of λ) can be seen on the right

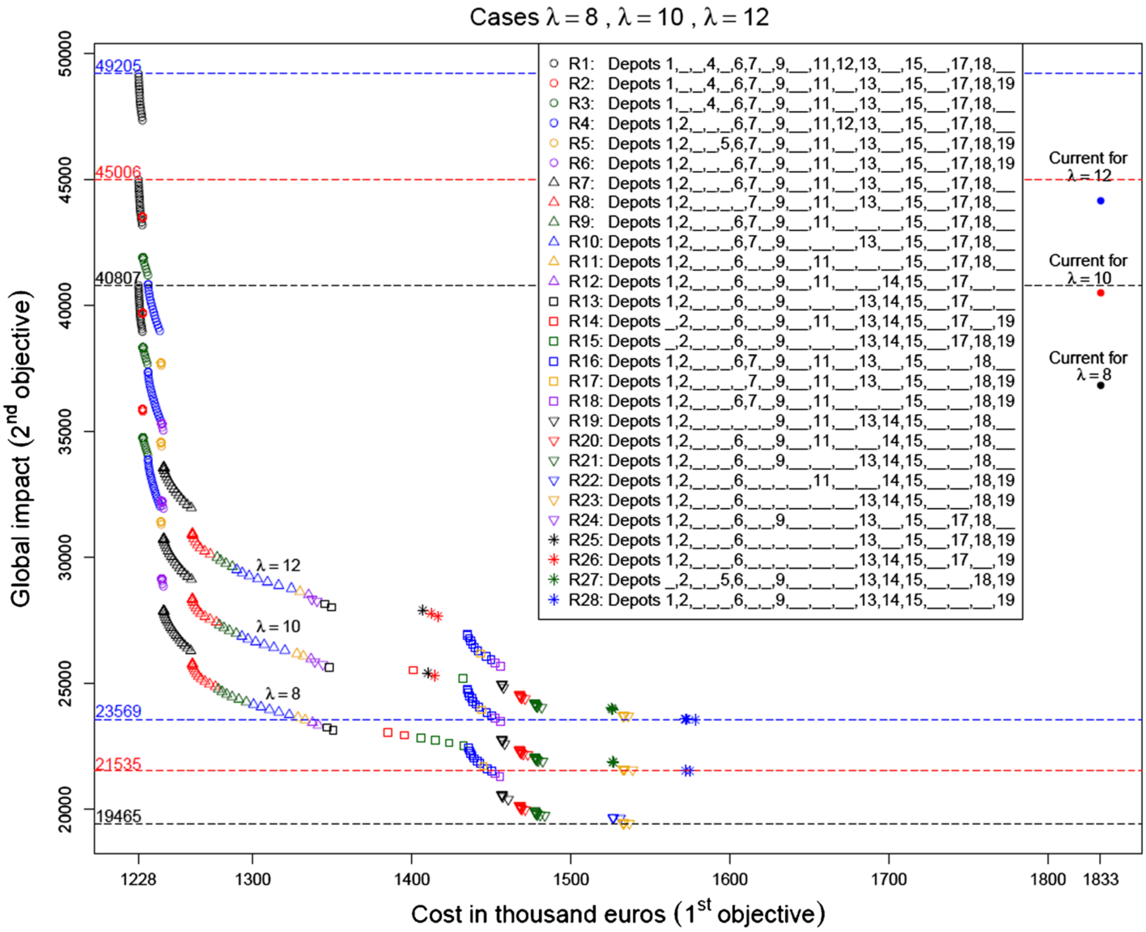

Fig. 3 Pareto optimal set for Case 2 (λ={8,10,12}). For the current existing network, cost (1.833 million €) and impacts (for the three values of λ) can be seen on the right

reduction of approximately 50 % with respect to the impact generated by the current solution for the three values of λ, while still obtaining a similar cost.

It can be observed that two of the new depots, namely 15 and 18, are open in all the solutions in the Pareto optimal sets, while depots 3, 8 and 10, two of which are currently open, are closed in all the Pareto optimal solutions obtained.

Results for Case 2 In this case, with λ∈{8, 10, 12}, the impacts generated by the heavy transport operations and by the setting up and maintenance of the depots have approximately the same weight. By repeating the iterative ε-constraint process, the Pareto optimal set for each value of λ can be obtained, as shown in Fig. 3. In this case, the different solutions of the Pareto optimal set correspond to 28 ways of selecting the depots to open. These 28 solutions, labelled R1 to R28, are shown in the panel on the upper part of that figure. It can be seen that the initial solution (R1) has more impact than the current solution for any of the three values of λ and that the lowest impact solution obtained in this case for the three values of λ improves the environmental impact of the current solution by 47 %, in addition to further reducing its cost between 14 % and 16 % approximately. It can be seen again that depot 15 is open in all solutions of the Pareto optimal set while depots 3, 8, 10 and 16 remain closed for all the Pareto optimal solutions.

Results for Case 3 The last case corresponds to values of λ ∈{16,18,20}, giving more weight to the impact generated by the setting up and maintenance of the depots than

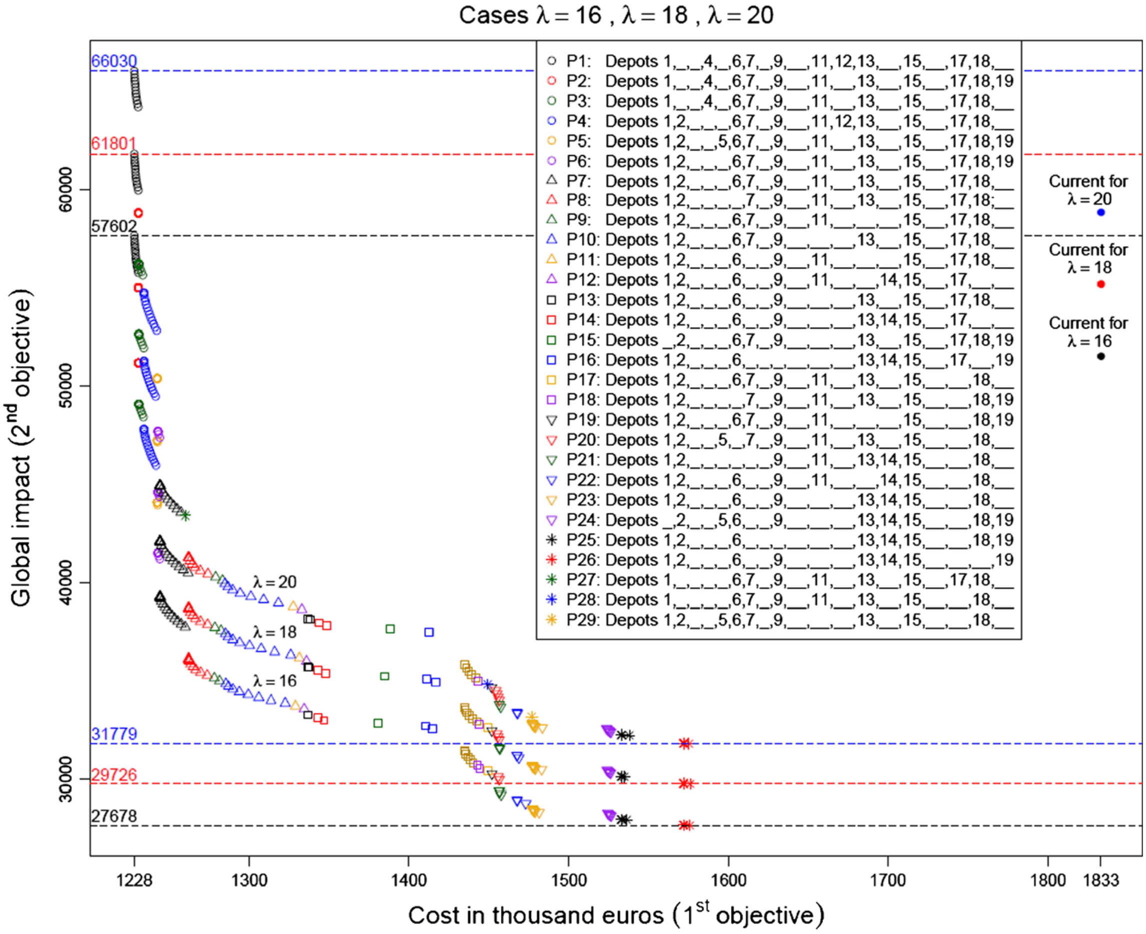

Fig. 4 Pareto optimal set for Case 3 (λ={16,18,20}). For the current existing network, cost (1.833 million €) and impacts (for the three values of λ) can be seen on the right

to the impact generated by the heavy transport operations. The corresponding results are shown in Fig. 4. In this case, the different solutions of the Pareto optimal set correspond to 29 ways of selecting the depots to open. As before, these 29 solutions, labelled P1 to P29, are shown in the panel on the upper part of that figure. The initial

Table 4 Number of iterations corresponding to each λ value, impact of the initial solution (i.e. for α=1.0), minimum α-value before infeasibility occurs and computational burden

λ	Number of iterations	I_λ	Minimum α	Total CPU time (min.)
1	296	26,111.60	0.4525	85
2	302	28,211.81	0.4575	129
4	282	32,409.81	0.4675	150
8	247	40,807.42	0.4770	154
10	244	45,006.22	0.4785	135
12	243	49,205.03	0.4790	149
16	240	57,602.64	0.4805	166
18	239	61,801.44	0.4810	173
20	238	66,000.24	0.4815	178

solution (P1) generates more impact units than the current solution for the three values of λ. The lowest impact solution found for all three values of λ improves the impact of the current solution by approximately 46 %, while also reducing its cost by approximately 14 %. Once more, depot 15 is open for all the Pareto optimal solutions while depots 3, 8, 10 and 16 are not selected for any of them.

3.2 Discussion

Analysing globally all the solutions that have been obtained, it can be observed in Fig. 5 that as λ increases, the solutions in the Pareto optimal sets have a reduced cost range. Thus, the maximum cost among the Pareto optimal solutions goes from 147 % (over the minimum cost initial solution) for λ=1, to 128 % for λ=20. Analogously, the impact range also decreases, in relative terms, as λ increases. Thus, the maximum impact among the Pareto optimal solutions goes from 221 % (over the minimum impact solution) for λ=1 to 208 % for λ=20. In other words, giving more importance to the depots' impact (versus the transport impact), reduces the range of variability of the Pareto optimal solutions' objective function values.

Comparing the current situation (i.e. only depots 1 to 8 open) with the Pareto optimal solutions found, it can be observed that for all λ values both the cost and the impact of the current solution are much higher than those of the alternative solutions found. None of the 82 different solutions obtained in the Pareto optimal sets for the 9 λ values considered coincides with the current situation. In general, the current cost is

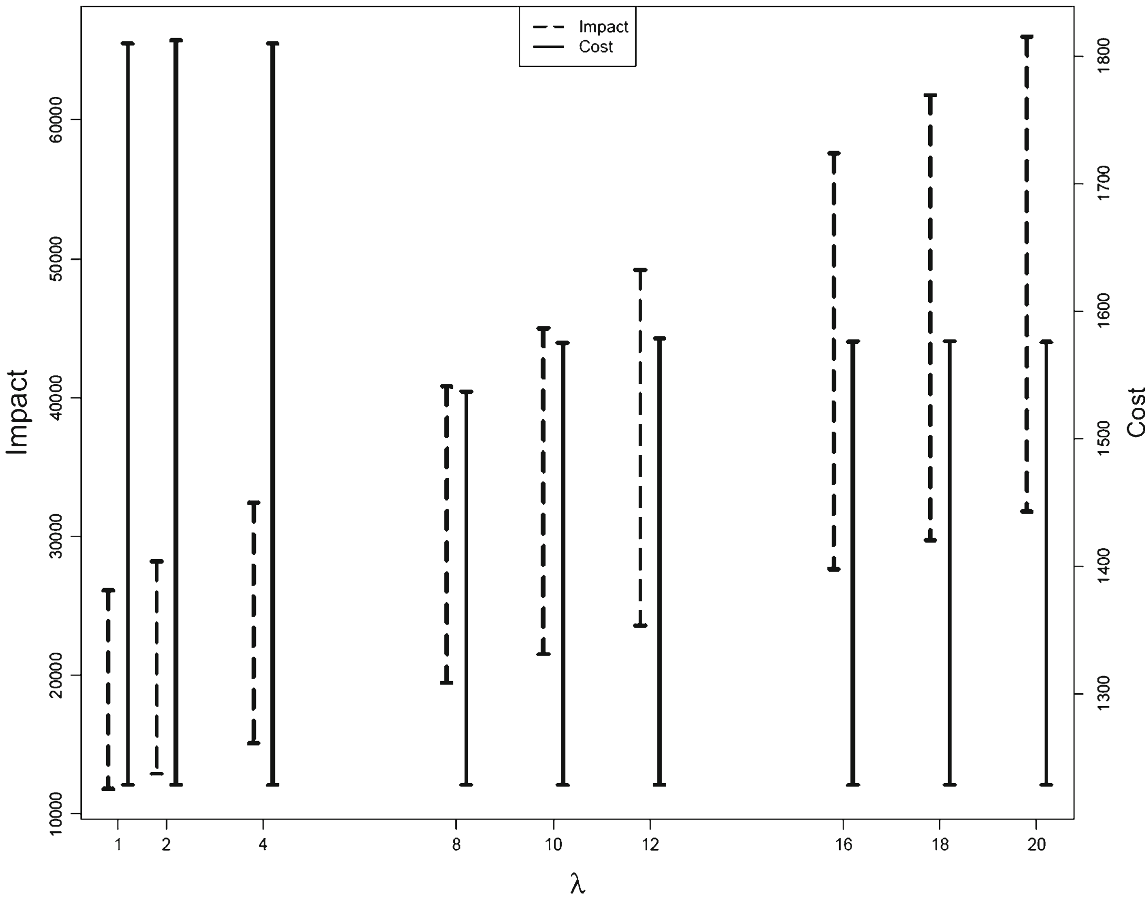

Fig. 5 Evolution of the ranges of total costs and impacts in the Pareto set as a function of λ

around 40 % higher than that of the similar-impact solutions found, and, in addition, the impact of the current solution is around twice the impact of the similar-cost solutions found. These results are thought-provoking and call for a reassessment of the need to maintain those depots that are currently open.

One may ask why the current situation is so inefficient in terms of the environmental impact criteria. The explanation can be ascertained from the examination of the depots that define each solution. Two of the current depots (3 and 8) are not open in any of the Pareto optimal solutions. These are depots that are close to port facilities (Valencia and Cartagena), which used to be an important factor when deciding where to open a depot. The rationale was that depots were needed because the cost of land in the harbour was too expensive, so it seemed logical that the depots should be close to the place where they would be located naturally. However, being so close to urban areas, the environmental impact of those depots is very high. The opposite occurs with depot 15. It is open in all the 82 Pareto optimal solutions. The reason is simple: its impacts are small for both the transport and the depot itself, and there is an important number of shippers/consignees in its vicinity.

4 Conclusions

This article analyses the location of container depots in a hinterland, considering not only the cost of operating these facilities and the cost of the transport of containers between shippers/consignees, depots and terminals, but also the environmental impact generated by the heavy transport operations and the setting up and maintenance of the depots. Therefore a bi-objective optimization model has been formulated with the aim of minimizing both the cost and environmental impacts of the container depots' operations. This means a new approach to the container depot location, since no previous work has included these environmental impacts. As shown in the case study presented corresponding to the Port of Valencia, trade-offs are possible between both objectives. Moreover, the current network of depots can be compared with selected depots by the proposed approach, to better understand what were the managerial drivers involved in the current solution, and the potential improvement gap.

The results obtained show that the impact caused by the currently open depots could be improved by about 47 % for solutions, with costs approximately 15 % lower than the current cost. For solutions with an impact similar to the current one, the cost can be improved by around 40 %. Therefore, with this model, significant cost improvements are obtained with respect to the current situation, even after giving consideration to the resulting environmental impacts.

From the analysis carried out, it can be concluded that the current location of the depots seems to be mainly based on their proximity to harbour facilities instead of clients' surroundings. This decision usually increases the environmental impact of the containers' logistics operations and, depending on the characteristics of the customers' location, also the operating costs.

As said before, incorporating environmental impacts into the analysis is vital if we ever to expect the decisions to be sensitive to sustainability issues (Szeto et al. 2013). Otherwise, the decisions will only take into account, as has been mainly the case in the past, the costs aspects. Thus, the proposed multi-objective approach highlights existing trade-offs. Moreover, the case study reported clearly shows that better solutions in both objectives can be found and that one should have no fear of incurring additional costs just for being environmentally responsible.

The current study has a number of limitations that should be taken into account. Although a panel of experts has been used to determine the environmental impact and the aggregation weights of the different types of externalities, this may still be considered to be a subjective assessment. A more objective method, such as Life Cycle Assessment (see, e.g. Guinée 2002), could be tried although this would probably involve a protracted and expensive process. Also, since the proposed approach requires assessing the environmental impact of each candidate site, it is clear that the effort greatly increases with the number of potential locations.

With respect to further research, there are several topics that can be considered. One is a different way of integrating the environmental impacts of the transport operations and of the depots themselves. For example, instead of using a weight parameter λ, two separate objective functions could be considered. This would eliminate the need for this parameter but would make it more difficult for the visualization of Pareto optimal sets, something which is a clear advantage of the proposed bicriteria optimization approach. Another line of research that may be interesting is to include uncertainty in some of the data. The proposed approach assumes that all the data are known with certainty but it may be more realistic to consider that some of them, such as the depots' and terminals' flow capacities, are fuzzy. In that case, instead of the ε-constraint method, a fuzzy multi-objective approach might be more appropriate. Also, including routing decisions (Toyoglu et al. 2012) makes the problem more accurate but also much more complex.

Acknowledgments Research funded by the Spanish Ministry of Science and FEDER, grant DPI2010-16201. The authors are also grateful to the reviewers and editor for their constructive comments and suggestions.

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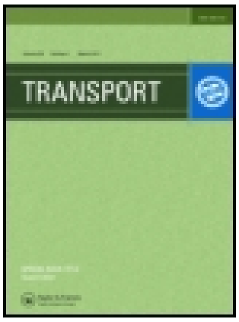

Transport

ISSN: 1648-4142 (Print) 1648-3480 (Online) Journal homepage: http://www.tandfonline.com/loi/tran20

A decision-making model to design a sustainable container depot logistic network: the case of the Port of Valencia

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TRANSPORT
ISSN 1648-4142 / eISSN 1648-3480
Article in press
doi:10.3846/16484142.2015.1107621

A DECISION-MAKING MODEL TO DESIGN A SUSTAINABLE CONTAINER DEPOT LOGISTIC NETWORK: THE CASE OF THE PORT OF VALENCIA

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Submitted 20 June 2014; resubmitted 28 August 2014, 24 October 2014; accepted 18 November 2014; first published online

Abstract. In this paper, the design of a maritime container depot logistic network in a hinterland is studied. Containers are a basic tool in multimodal product transportation and all related operations have an impact on the environment due to different externalities such as noise, atmospheric and visual pollution. A three objective optimization model is used to minimize the total network cost, the environmental impact generated by the road transport operations associated with the depots (TI) and the environmental impact generated by the setting up and maintenance of the depots (FI). To determine the environmental impacts of each depot, Fuzzy Analytic Hierarchy Process (F-AHP) is used in both cases. In addition, a fuzzy multiobjective optimization approach has been used to solve the problem. The application case study is based on the Port of Valencia (Spain).

Keywords: environmental impact; sustainable supply chain management; reverse logistics; maritime transportation; container depots; fuzzy multiobjective optimization.

Introduction

Import and export operations have grown considerably in the last decades. Maritime containers have become a basic tool for these multimodal operations. In addition, containers are very useful due to their characteristics, such as standardization, flexibility and possibility of reuse. The latter is probably the most interesting characteristic of containers and what adds complexity to its management.

Before a container is reused, it needs some intermediate operations and a place to be stored. Since the storage capacity of ports is limited and, in many cases, the ports are far away from the shippers, it is necessary to store the empty containers somewhere so as to minimize time and costs of delivering the empty containers to the shippers who need them (Furió *et al.* 2013). However, in addition to cost effectiveness, there are other reasons for empty containers storage; for example, the import and export operations are not balanced or that the number of available containers in the world is double the total capacity of container vessels (Furió *et al.* 2006). For all these reasons, it is generally necessary to store empty containers in container depots.

Container depots are generally large ground extensions near ports or industrial areas where empty containers are stored waiting to be distributed to shippers. In addition, in these facilities different activities are performed, such as the cleaning and repairing of containers. These operations, as well as the container transport operations between shippers/consignees and depots, imply costs that companies try to minimize.

The concern for the environment, the inclusion of several factors in trying to estimate environmental impacts and the necessity to search for more sustainable networks, make the design of a logistic network more and more complex. For this reason, Decision Support Systems (DSSs) are increasing their importance as a suitable solution in this field. Thus, several researchers have designed DSSs for the operation, planning or design of container terminals (Murty *et al.* 2005; Harit *et al.* 1997; Van Hee, Wijbrands 1988). DSSs try to find out what would happen when making a series of decisions and then provide decisions or suggestions to managers. The main architecture of a DSS is similar to the 3-tier architecture of an Information System. This architecture was named DMM – Data, Dialog, Model – by Sprague and Watson (1995). We are going to focus our DSS de-

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scription on the intelligence component, i.e. the model tier, which is the base for helping the user to make more informed and effective decisions. Therefore, our aim is to model the design of a container depot network in a hinterland, by trying to decide the best location for each depot, and taking into account not only cost-related objectives but also the environmental impacts generated by the location and operation of the depots.

With regard to those environmental impacts, all the activities carried out in a depot as well as the containers' transportation have an impact on the surrounding area due to the factors such as greenhouse gas emissions, noise, wastewater (resulting from container cleaning) and other externalities. Thus, the setting up of a depot requires the use of heavy equipment that generates noise and atmospheric pollution, and increases the traffic congestion of the area. Moreover, a container depot logistic network generates a large amount of traffic due to the transportation trucks. Trucks' engines generate greenhouse gases with consequent effects on health and ecosystems, among other factors (Figliozzi 2011). But the main externalities generated by the road transport are: traffic congestion at peak times (which decreases overall productivity); the likelihood of accidents (road traffic causes over 1.2 million deaths each year worldwide (Toroyan, Peden 2009)); atmospheric pollution; noise pollution generated by the heavy traffic (which is partly responsible for the fact that nearly 80 million people in the European Union are exposed to noise levels exceeding the acceptable level of 65 dB (EC 1996)); visual pollution that alters the aesthetics of the rural and urban landscape, etc.

Obtaining data about the environmental impact generated by the transport operations and setting up and maintenance of the depots is a particularly difficult task. An alternative could be to use estimations of the marginal external costs of the transportation activity, such as those collected by Maibach *et al.* (2008) and Korzhenevych *et al.* (2014) under the auspices of the European Commission. These estimations could be included in a cost-based model, analysing the whole behaviour of the system. In this paper, however, a multiobjective optimization approach that makes the tradeoffs between the objectives more visible and explicit is proposed. Therefore, to handle these environmental impacts, a feasible way that could fit our goal, having so many different impact sources, has been found to be the use of a Fuzzy Analytic Hierarchy Process (F-AHP). In that way, the opinion of a number of experts is taken into account, summarizing all those heterogeneous effects.

It is noted that the flow capacity of a depot (i.e., the number of container movements it can handle per year) is an important factor when estimating the environmental impact generated by the transport operations carried out, and by the setting up and maintenance of the depot itself. It is as well a very important factor affecting the facility competitiveness. Do Ngoc and Moon (2011) developed a model for the decision of expanding a depot capacity, assuming the importance of operating at the correct size. Due to the difficulty of obtaining exact values for these flow capacities when designing a general network, we decided to consider them as fuzzy data. In this way, the flow capacity of depots is considered as a fuzzy constraint within the fuzzy multiobjective optimization approach used to solve the problem.

Summarizing, in this paper, a three objective fuzzy optimization approach based on the Multicommodity Capacitated Location Problem with Balancing Requirements (Crainic *et al.* 1989) is proposed. In order to identify the best container depot logistic network in a hinterland we aim not only to minimize the total cost of the network but also to minimize the total environmental impact generated by the transport operations associated with the depots network (TI) and the total environmental impact generated by the setting up and maintenance of those depots (FI).The proposed approach is applied to the case of the hinterland of the port of Valencia, Spain.

A previous work by the authors (Palacio *et al.* 2014) dealt with this type of container depot location problem by considering the environmental impacts on a single objective function. In that work, the authors used deterministic (i.e. without uncertainty) information both about the environmental impacts and depots' flow capacity. Under such circumstances the problem can be solved using the ε-constraints method and giving a Pareto frontier as a solution. This research improves upon that work by separately considering the environmental impacts of the setting up and maintenance of a depot from those of its operation, thus removing the need to aggregate them (something which required the use of a parameter for weighing the values of both impacts). In addition, uncertainties in the estimation of the environmental impact and low capacities data have been taken into account, thus increasing the realism and applicability of the solution approach. Finally, the use of a fuzzy multiobjective optimization approach leads to determining a single solution instead of a collection of potential solutions (Zimmermann 1978).

1. Literature Review

The depot location problem appears when deciding what to do with empty containers once consignees have downloaded their wares from the containers that have arrived from a port. This problem, known in the literature as the Multicommodity Capacitated Location Problem with Balancing Requirements (MCLB), was initially studied by Crainic *et al.* (1989). The following authors used several techniques to solve the problem such as branch and bound (Crainic *et al.* 1993a; Gendron, Crainic 1995, 1997; Bourbeau *et al.* 2000), tabu search (Crainic *et al.* 1993b) or goal programming (Badri 1999). Crainic *et al.* (1993a) did not find an optimal solution in a reasonable time using branch-and-bound and showed that standard methods are not efficient for this problem.

Similarly, Gendron *et al.* (2003a) showed that problems with a large number of variables of the MCLB could not be solved by mixed-integer programming solvers at that time. They combined slope scaling and tabu search and obtained good solutions. Representing N as the set of nodes and A as the set of arcs, they considered a network $G = (N, A)$ with two kind of nodes, the customers and the depots, with the arcs representing the existence of flows between these nodes. They minimized the total cost of the problem, satisfying the demand of each node. Gendron *et al.* (2003b) used a parallel hybrid heuristic for solving the MCLB problem.

More recently, Palacio *et al.* (2014) designed a model to find the best location for a container depot by considering the minimization of the total environmental impact as an additional objective function. They solved the problem using the ε-constraints method, obtaining a Pareto frontier, but they could not determine to what extent the environmental impact generated by the depots themselves is relevant for the final location within the network.

Apart from the above container depot location papers, there are a number of research works on empty container management in the literature. Thus, for example, Li *et al.* (2004) showed that there exists an optimal (U, D) policy for the management of empty containers in a port with stochastic demand. If there are fewer than U containers they are imported up to U but if there are more than D they are exported down to D. They also used multi-ports applications. Similarly, Dong and Song (2009) considered multi-vessel, multi-port and multi-voyage shipping systems with uncertain and unbalanced demands. They used Genetic Algorithms and Evolutionary Strategies to solve their problem. Other authors (Mittal *et al.* 2013) focused on the demand uncertainty characteristic of the problem when locating depots, while Boile *et al.* (2008) applied their model for location of new container depots and the repositioning of empty containers to the New York-New Jersey port region, based on the idea of building them close to customer clusters. Braekers *et al.* (2011) presented a good review about planning models for the empty container repositioning problem, focusing not only on strategic and tactical decisions (what was the most common approach in the first researches), but also on planning models dealing at strategic, tactical and operational levels.

It is important to note that all these papers only consider one objective, namely the minimization of the total cost of the logistic network. In this paper two additional objective functions are considered: the environmental impact generated by the setting up and maintenance of the depots (TI) and the impact generated by the transport operations associated with the depots (FI).

2. Problem Modelling

As mentioned before, the goal of this work is to design a container depot logistic network that minimizes the total cost of the system, the environmental impact generated by the transport operations associated to this network, and the environmental impact generated by the setting up and maintenance of the depots in the network. In this way, a crisp optimization model can be designed by extending the model proposed by Gendron *et al.* (2003a, 2003b) by introducing two new objective functions and considering three kinds of nodes instead of two: depots, terminals and shippers/consignees. The decision variables are a set of binary variables (that determine whether to open a depot) plus some continuous variables (to define the empty container flows). The notation for this model is shown in Table 1.

Table 1. Notation for model parameters and variables

Data	
T –	set containing all terminals in the system under study
D –	set containing all depots in the system under study
S –	set containing all shippers in the system under study
R –	set containing all consignees in the system under study
$S(t)$ –	subset of shippers that can be supplied from terminal t
$R(t)$ –	subset of consignees that can send empty containers to terminal t
$D(t)$ –	depots that work with terminal t
$S(d)$ –	subset of shippers that can be supplied from depot d
$R(d)$ –	subset of consignees that can send empty containers to depot d
$T(d)$ –	terminals that work with depot d
$D(r)$ –	depots where consignee r can send its empty containers
$T(r)$ –	terminals where consignee r can send its empty containers
$D(s)$ –	depots that can send empty containers to shipper s
$T(s)$ –	terminals that can send empty containers to shipper s
I_{rt} –	containers imported by consignee r through terminal t every year
E_{st} –	containers exported by shipper s through terminal t every year
K_d –	flow capacity limit of depot d
K_t –	flow capacity limit of terminal t
C_d –	storage capacity of depot d
f_d –	fixed operation cost of depot d
c_{rt} –	unit transport cost between consignee r and terminal t
c_{ts} –	unit transport cost between terminal t and shipper s
c_{rd} –	unit transport cost between consignee r and depot d
c_{ds} –	unit transport cost between depot d and shipper s
c_{td} –	unit transport cost between terminal t and depot d
w_d –	environmental impact per unit flow from/to depot d
v_d –	environmental impact per stored unit in depot d
Decision variables	
x_{rt} –	container flow from consignee r to terminal t
x_{ts} –	container flow from terminal t to shipper s
x_{rd} –	container flow from consignee r to depot d
x_{ds} –	container flow from depot d to shipper s
x_{td} –	container flow from terminal t to depot d
x_{dt} –	container flow from depot d to terminal t
δ_d –	binary variable that indicates if depot d opens or not

$$\min \sum_d f_d \delta_d + \sum_r \sum_{t \in T(r)} c_{rt} x_{rt} + \sum_t \sum_{s \in S(t)} c_{ts} x_{ts} +$$
$$\sum_t \sum_{d \in D(t)} c_{td} \left(x_{td} + x_{dt} \right) +$$
$$\sum_r \sum_{d \in D(r)} c_{rd} x_{rd} + \sum_d \sum_{s \in S(d)} c_{ds} x_{ds}; \quad (1)$$

$$\min 2 \sum_d w_d \left(\sum_{r \in R(d)} x_{rd} + \sum_{t \in T(d)} x_{td} \right); \quad (2)$$

$$\min \sum_d C_d v_d \delta_d \quad (3)$$

subject to:

$$\sum_{r \in R(t)} x_{rt} + \sum_{d \in D(t)} x_{dt} + \sum_s E_{st} =$$
$$\sum_{s \in S(t)} x_{ts} + \sum_{d \in D(t)} x_{td} + \sum_r I_{rt} \ \forall t \in T; \quad (4)$$

$$\sum_{r \in R(d)} x_{rd} + \sum_{t \in T(d)} x_{td} =$$
$$\sum_{s \in S(d)} x_{ds} + \sum_{t \in T(d)} x_{dt}, \ \forall d \in D; \quad (5)$$

$$\sum_{t \in T(r)} x_{rt} + \sum_{d \in D(r)} x_{rd} =$$
$$\sum_{t \in T(s)} I_{rt}, \ \forall r \in R; \quad (6)$$

$$\sum_{t \in T(s)} x_{ts} + \sum_{d \in D(s)} x_{ds} =$$
$$\sum_{t \in T(s)} E_{st}, \ \forall s \in S; \quad (7)$$

$$\sum_{r \in R(t)} x_{rt} + \sum_{d \in D(t)} x_{dt} + \sum_{s \in S(t)} x_{ts} +$$
$$\sum_{d \in D(t)} x_{td} \le K_t, \ \forall t \in T; \quad (8)$$

$$2 \left(\sum_{r \in R(d)} x_{rd} + \sum_{t \in T(d)} x_{td} \right) \le K_d \delta_d, \ \forall d \in D \quad (9)$$

$\delta_d \in \{0,1\}$, $\forall d \in D$ all other variables non-negative. (10)

The total cost of the network is considered in the first objective function: the first term is the setting up and maintenance cost of the depots; the second term is the total cost of the container movements between each shipper/consignee and terminal; the third term is the total cost of the container movements between each terminal and depot, and the last term is the total cost of the container movements between each shipper/consignee and depot. In the second objective function the total impact associated with the container movements from/to each depot is considered. The coefficient (2) comes from the fact that, as imposed by constraints (5), the total number of movements of empty containers into a depot is equal to the total number of movements out of that depot. Hence, the sum of inward and outward movements is two times the number of inwards movements. The last objective function is associated with the total impact generated by the maintenance and setting up of each depot.

Regarding the seven blocks of constraints, constraints (4) and (5) guarantee that the number of containers arriving at a terminal or depot is equal to the number of containers that leave that same terminal or depot; constraints (6) and (7) ensure that each container imported or exported by a consignee/shipper is stored or received from a depot or a terminal; constraints (8) and (9) guarantee that the number of container movements in a terminal or a depot does not exceed the container movement capacity of that terminal or depot. Note that constraints (9) use a coefficient 2 for the same reason that objective function (2), i.e. because the total flow into/from a depot is two times the inward flow. Finally, constraint (10) imposes that variables δ_d are binary.

Regarding constraint (9), we note that the flow capacity of a depot is not actually an exact number so that a parameter τ is needed that determines by how much the capacity of a depot can potentially be increased from its nominal value. In that way and to use a fuzzy multiobjective optimization approach, a new constraint is introduced to replace constraint (9). Thus, constraint (9′) imposes that there cannot be container movements to/from a depot when it is not open:

$$2 \left(\sum_{r \in R(d)} x_{rd} + \sum_{t \in T(d)} x_{td} \right) \le \tau K_d \delta_d, \ \forall d \in D. \quad (9')$$

A reasonable value for parameter τ may be, for example, τ=1.15; that means the flow of each depot can rise up to a limit 15% above its nominal capacity.

Let λ_1 be the cost membership function, λ_2 the environmental impact generated by the transport operations membership function and λ_3 the environmental impact generated by the setting up and maintenance of the depots membership function. Denoting the three objective functions (1) to (3) as $f_i(x,\delta)$, $i = 1, 2, 3$ the proposed fuzzy multiobjective model is:

$$\max \sum_{i=1}^{3} \lambda_i \quad (11)$$

subject to:

$$\lambda_i \le \frac{z_i^+ - f_i(x,\delta)}{z_i^+ - z_i^-}, \ \forall i = 1, \ldots, 3; \quad (12)$$

$$\gamma_d \le \frac{\tau K_d - g_d(x,\delta)}{(\tau - 1) \cdot K_d}, \ \forall d. \quad (13)$$

Constraints (4)–(8), (9′), (10):

$\delta_d \in \{0,1\}$, $\forall d$;

$\lambda_i, \gamma_d \in [0,1]$, $\forall i$, $\forall d$ and all variables non-negative, (14)

where: $g_d(x,\delta)$ is the left hand side of constraint (9’); z_i^- is the optimal objective function value of the model min $f_i(x,\delta)$ subject to (4)–(8), (9’), (10) for i = 1, …, 3; z_i^+ is the optimal objective function value of the model max

$f_i(x,\delta)$ subject to (4)–(8), (9'), (10) for $i = 1, \ldots, 3$. In other words, z_i^- and z_i^+ are, respectively, the minimum and maximum values of the i-th objective function when it is optimized separately. Note that in this model the three objectives have been assigned the same importance. To assign different importance to the objectives some constraint prioritizing the membership functions λ_i can be introduced. For example, if cost minimization is given no less importance than the other two objectives, then these constraints should be added $\lambda_1 \geq \lambda_2$ and $\lambda_1 \geq \lambda_3$.

The optimal solution of the above model $\left(x^*,\delta^*,\lambda_1^*,\lambda_2^*,\lambda_3^*,\gamma^*\right)$ has an associated cost $f_1\left(x^*,\delta^*\right)$, an associated environmental impact generated by the transport $f_2\left(x^*,\delta^*\right)$ and an environmental impact generated by the setting up and maintenance of the depots $f_3\left(x^*,\delta^*\right)$. With these three values and changing in the model above the objective function $\max\sum_{i=1}^{3}\lambda_i$ by $\max\sum_{d}\gamma_d$ and replacing constraints (12) by new constraints imposing that the values of the three objectives cannot be worse than those computed before, i.e. $f_i\left(x,\delta\right) \leq f_i\left(x^*,\delta^*\right)$, the model is solved again giving the final solution. This second phase, once the optimal objective function values have been determined, aims at maximizing the membership function values of the different flow capacity constraints. This makes the solution to balance the empty container flows so that these exceed the nominal capacity of the depots at the minimum.

3. Application to the Hinterland of Valencia

The above model was developed for the port of Valencia, one of the largest ports on the Mediterranean Sea and the most important container port in Spain. It offers a network of regular, transoceanic and regional connections with major ports around the world and in 2010 its maritime container traffic reached 4.21 million TEUs (Twenty-foot Equivalent Unit, the capacity unit of a standard container of 20 feet) (Valenciaport 2010).

Currently, the logistic network of the hinterland of Valencia includes eight empty container depots. These depots have a flow capacity between 50000 and 125000 container movements per year and a storage capacity between 1000 and 14000 containers. To improve the design of this logistic network an additional set of potential depot locations have been considered. Thus, based on the distribution of the shippers/consignees that must be serviced, 11 potential new depot locations have been selected. As experimental data for these potential depots, a nominal flow capacity of 95000 container movements per year and a storage capacity of 8800 containers was designed (Table 2).

Another factor to consider in the problem is the fixed cost of each depot and the cost per flow unit. Considering raw data coming from the real port used in this research, it was estimated that a depot with a flow capacity of 250000 containers per year has an operating cost of €1000000. Therefore, in this case study, proportional values according with the flow capacities of each

Table 2. Depot data

Depot	Location	Capacity	% of shippers within 50 km	Road distance to port [km]
1	Riba-Roja de Turia	125000	26.89	30.5
2	Náquera	50000	28.01	40.2
3	Alfafar	125000	30.53	12.5
4	Quart de Poblet	112500	29.13	15.7
5	Castellar	20000	29.97	6.5
6	Sagunto	95000	28.01	33.4
7	Port of Alicante	50000	18.21	172.0
8	Port of Cartagena	125000	7.56	273.0
9	Almussafes*	95000	32.49	25.7
10	Onda*	95000	12.32	75.0
11	L'Alcora*	95000	9.52	86.9
12	Albal*	95000	31.09	15.0
13	Villarreal*	95000	11.48	68.4
14	Novelda*	95000	17.65	155.0
15	Jumilla*	95000	3.36	161.0
16	Requena*	95000	3.08	77.2
17	Murcia*	95000	21.01	232.0
18	Ibi*	95000	24.37	126.0
19	Chiva*	95000	27.17	39.5

Note: * indicates potential location of depots not currently in operation, all of them with the same theoretical capacity.

depot are considered. Regarding the cost per flow unit, the distance between all the pairwise nodes has been calculated and multiplied by the unit cost per km of a standard container transport vehicle, which is estimated as 1.152 €/km (Ministerio de Fomento 2012).

4. Impact Estimation Using F-AHP

Due to the difficulty of obtaining quantitative environmental impact data, they have been estimated using F-AHP methodology. Triangular fuzzy numbers were used for making comparisons between each of the different alternatives considered, transforming the consensus fuzzy matrix into a crisp one by using the method proposed by Kwong and Bai (2003). This method is used to obtain the environmental impact data associated with the transportation operations w_d and with the setting up and maintenance v_d of each depot needed in the model. Five externalities associated with the environmental impact generated by the transport operations (atmospheric, visual and noise pollution, traffic congestion and likelihood of accident) have been considered. Six experts from the Port of Valencia were asked for their assessment of the environmental impact generated by the empty container transport.

The first step was to ask each expert to define a fuzzy matrix representing the pairwise comparisons of those five externalities. Matrices consistence was checked as well as the degree of consensus between those experts, using the procedure introduced by Bryson (1996). The consensus matrix was calculated using the geometric mean of each component of the triangular fuzzy numbers provided by each expert. Using the formulation proposed by Kwong and Bai (2003), this matrix was transformed into a crisp one, and to be sure that this transformation had not lost the matrix consistence, the final crisp matrix consistence was checked as well. Finally, to determine the normalized impact per flow unit generated by the transport operations of each potential depot location, three levels (low, medium, high) for each externality were considered and by using a 'ratings mode' the decision table was obtained. The calculation of this normalized impact per flow unit at each depot location is shown in Table 3.

On the other hand, for the impact generated by the setting up and maintenance of each depot, three externalities were considered: the setting up impact, the visual impact and the operations impact. Again, the normalized fixed impact per stored unit in each depot was calculated using the geometric mean of the expert assessments and the decision table using the 'ratings mode' as shown in Table 4.

5. Results

The model was programmed in LINGO. The maximum and minimum of the three objectives were previously calculated separately. The minimum cost of the network is 1212.98 (in thousand €) and the maximum

Table 3. Calculation of the normalized impact per flow unit for each depot

Depot	Atmospheric (0.1193)		Noise (0.5435)		Visual (0.0464)		Traffic (0.1247)		Likelihood of accidents (0.1661)		Total impact (w_d)
1	*M*	0.464	*M*	0.333	*M*	0.464	*H*	1.000	*M*	0.333	0.438
2	*L*	0.215	*M*	0.333	*M*	0.464	*L*	0.215	*L*	0.111	0.273
3	*H*	1.000	*H*	1.000	*H*	1.000	*H*	1.000	*H*	1.000	1.000
4	*H*	1.000	*H*	1.000	*H*	1.000	*H*	1.000	*H*	1.000	1.000
5	*H*	1.000	*H*	1.000	*H*	1.000	*H*	1.000	*H*	1.000	1.000
6	*M*	0.464	*M*	0.333	*L*	0.215	*L*	0.215	*H*	0.333	0.329
7	*H*	1.000	*H*	1.000	*H*	1.000	*H*	1.000	*H*	0.333	0.889
8	*H*	1.000	*H*	1.000	*H*	1.000	*H*	1.000	*H*	0.333	0.889
9	*M*	0.464	*M*	0.333	*M*	0.464	*H*	1.000	*H*	0.333	0.438
10	*M*	0.464	*M*	0.333	*M*	0.464	*H*	1.000	*H*	0.333	0.438
11	*M*	0.464	*M*	0.333	*L*	0.215	*H*	1.000	*H*	0.333	0.427
12	*H*	1.000	*H*	1.000	*H*	1.000	*H*	1.000	*H*	1.000	1.000
13	*M*	0.464	*M*	0.333	*M*	0.464	*H*	1.000	*H*	0.333	0.438
14	*M*	0.464	*M*	0.333	*L*	0.215	*M*	0.464	*H*	0.333	0.360
15	*M*	0.464	*M*	0.333	*M*	0.464	*L*	0.215	*H*	0.333	0.340
16	*M*	0.464	*M*	0.333	*M*	0.464	*M*	0.464	*H*	0.333	0.371
17	*H*	1.000	*H*	1.000	*H*	1.000	*H*	1.000	*H*	1.000	1.000
18	*M*	0.464	*M*	0.333	*L*	0.215	*M*	0.464	*H*	0.333	0.360
19	*M*	0.464	*M*	0.333	*M*	0.464	*M*	0.464	*H*	0.333	0.371

Notes: L – low, *M* – medium, *H* – high.

Table 4. Calculation of the normalized fixed impact per stored unit in each depot

Depot	Setting up impact (0.20)		Visual impact (0.08)		Operations impact (0.72)		Total impact (v_d)
1	*L*	0.215	*M*	0.464	*M*	0.333	0.320
2	*H*	1.000	*L*	0.215	*L*	0.111	0.297
3	*H*	1.000	*H*	1.000	*H*	1.000	1.000
4	*L*	0.215	*M*	0.464	*H*	1.000	0.800
5	*M*	0.464	*H*	1.000	*H*	1.000	0.893
6	*M*	0.464	*M*	0.464	*M*	0.333	0.370
7	*M*	0.464	*H*	1.000	*H*	1.000	0.893
8	*M*	0.464	*H*	1.000	*H*	1.000	0.893
9	*M*	0.464	*M*	0.464	*M*	0.333	0.370
10	*H*	1.000	*M*	0.464	*M*	0.333	0.477
11	*H*	1.000	*L*	0.215	*M*	0.333	0.457
12	*M*	0.464	*H*	1.000	*H*	1.000	0.893
13	*L*	0.215	*H*	1.000	*M*	0.333	0.363
14	*H*	1.000	*L*	0.215	*M*	0.333	0.457
15	*H*	1.000	*L*	0.215	*M*	0.333	0.457
16	*H*	1.000	*L*	0.215	*M*	0.3333	0.457
17	*M*	0.464	*H*	1.000	*H*	1.000	0.893
18	*H*	1.000	*M*	0.464	*M*	0.333	0.477
19	*M*	0.464	*L*	0.215	*M*	0.333	0.350

Notes: L – low, *M* – medium, *H* – high.

cost 9614.51. Regarding the environmental impacts, the minimum and maximum value for the transport operations were 10305.11 and 48854.9 respectively, and for the setting up and maintenance of the network were 774.13 and 3820.06 respectively. These values define the membership functions of our model (Fig. 1).

Once the three objective function membership functions have been determined, the fuzzy multiobjective optimization model of section 2 can be solved. In order to analyse the model performance more deeply, five cases were considered, depending on the different importance given to the three different objective function memberships:

- *Case 1:* The problem was run for the current situation in the hinterland of Valencia, i.e., we imposed that the open depots are just the existing eight depots (1–8). We can thus obtain the current cost and environmental impacts for further benchmarking.
- *Case 2:* The problem was solved without any restriction on the importance of the three objective functions, i.e., the three objectives are considered to have the same importance.
- *Case 3:* The problem was solved by giving more importance to the cost function than to the impact functions. Six different situations are considered depending on the relationship among the three objectives (cost more important than TI and FI; cost more important than TI and TI more important than FI; cost more important than FI and FI more important than TI; cost 2 times more important than TI and FI; cost 3/2 times more important than TI and TI 3/2 more important than FI; and cost 3/2 times more important than FI and FI (3/2) times more important than TI).
- *Case 4:* The problem was solved by giving more importance to the environmental impact generated by the transport operations than to the cost, and the setting up and maintenance impact. Again six different situations are considered (changing in the previous description the roles of cost and TI).
- *Case 5:* The problem was solved by giving more importance to the environmental impact generated by the setting up and maintenance of the depots than to the cost and transport operations impact. Again six different situations are considered (changing in the description of Case 3 the roles of cost and FI).

All the results can be seen in Table 5 and Fig. 2.

Results for Case 1. Considering the case that the currently operative depots are the only ones that are open, the solution computed by the model would have a cost of 1796.30 (in thousand €). The total impact generated by the transport operations would be 20584.66 and the total impact generated by the setting up and maintenance of the depots 1830.56. We are going to use this solution to make comparisons with the solutions found in every other case.

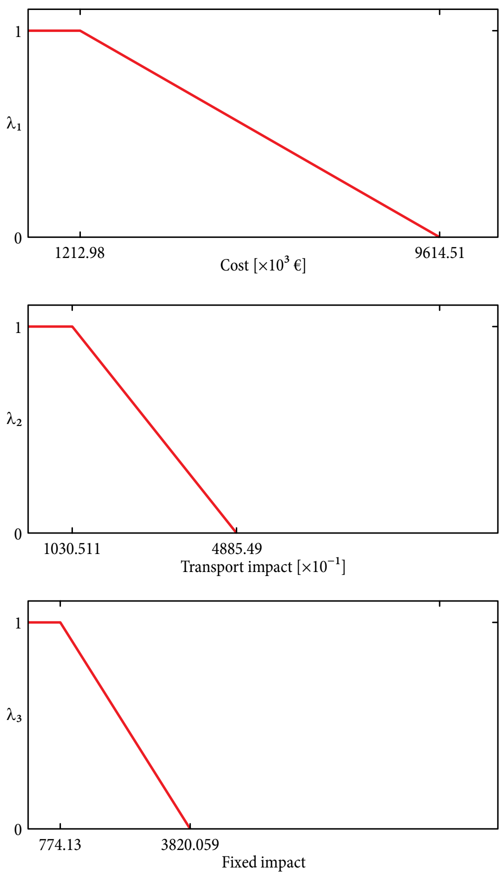

Fig. 1. Objective function membership functions

Results for Case 2. In this case all the objectives are considered with the same weight. This solution (Table 5) dominates the current situation, improving the cost by about 16% and TI and FI by about 50%. It opens new potential locations and closes some depots in the current situation.

Results for Case 3. In this case we consider that the cost objective has more importance than the other two objectives. Six subcases are explored (Table 5). The first two subcases have the same solution. This solution is similar to that of case 2, but opening depot 18 instead of depot 14. It is much better than the current situation, as it improves the three objective functions. The third subcase opens exactly the same depots as case 2 and also improves the current situation in all the objectives. The fourth subcase, in which the cost function is considered to be much more important than the other two, achieves the best cost value but obtains similar impact values as the current solution. Maintaining almost the same cost value of subcase 4, TI and FI can still be improved by about 16% in subcases 5 and 6 (Table 5).

Results for Case 4. Now, the most important objective is TI. In the first three subcases the solution obtained is the same as in case 2. The other three subcases open the same depots, but one of them dominates the other two. This solution improves the impact values of the current solution but almost doubles the cost value. It is important to note that this solution achieves the best possible transport impact values of all the solutions found.

Results for Case 5. In the last case of this study the most important objective is FI. The first three subcases

Table 5. Experimental results (dominated solutions by others in this set are shadowed; only 7 non-dominated solutions are found)

Sol. No.		Open depots 1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	Cost	Transport impact	Fixed impact	Objectives' importance
1	Case 1	1	1	1	1	1	1	1	1												1796.30	20584.66	1830.558	
2	Case 2		1				1	1		1				1	1	1				1	1515.58	11331.76	880.982	
3	Case 3		1				1	1		1				1		1			1	1	1490.22	11577.22	887.986	$\lambda_1>\lambda_2$; $\lambda_1>\lambda_3$
4			1				1	1		1				1		1			1	1	1490.22	11577.22	887.986	$\lambda_1>\lambda_2>\lambda_3$
5			1				1	1		1				1	1	1				1	1509.47	11665.51	880.982	$\lambda_1>\lambda_3>\lambda_2$
6		1	1		1			1		1		1	1	1		1		1	1		1212.98	25109.12	1981.064	$\lambda_1>2\lambda_2$; $\lambda_1>2\lambda_3$
7		1	1		1			1		1		1		1		1		1	1		1214.37	20825.47	1666.787	$\lambda_1>(3/2)\lambda_2;\lambda_2>(3/2)\lambda_3$
8		1	1		1			1		1		1		1		1		1	1		1214.37	20825.47	1666.787	$\lambda_1>(3/2)\lambda_3;\lambda_3>(3/2)\lambda_2$
9	Case 4		1				1	1		1				1	1	1				1	1515.58	11331.76	880.982	$\lambda_2>\lambda_1$; $\lambda_2>\lambda_3$
10			1				1	1		1				1	1	1				1	1515.58	11331.76	880.982	$\lambda_2>\lambda_1>\lambda_3$
11			1				1	1		1				1	1	1				1	1515.58	11331.76	880.982	$\lambda_2>\lambda_3>\lambda_1$
12			1				1					1			1	1	1		1	1	4111.82	10305.11	1077.079	$\lambda_2>2\lambda_1$; $\lambda_2>2\lambda_3$
13			1				1					1			1	1	1		1	1	3536.97	10305.11	1077.079	$\lambda_2>(3/2)\lambda_1;\lambda_1>(3/2)\lambda_3$
14			1				1					1			1	1	1		1	1	3788.81	10305.11	1077.079	$\lambda_2>(3/2)\lambda_3;\lambda_3>(3/2)\lambda_1$
15	Case 5		1				1	1		1				1	1	1				1	1509.50	11657.50	880.982	$\lambda_3>\lambda_1$; $\lambda_3>\lambda_2$
16			1				1	1		1				1	1	1				1	1509.50	11665.10	880.982	$\lambda_3>\lambda_1>\lambda_2$
17			1				1	1		1				1	1	1				1	1509.50	11657.50	880.982	$\lambda_3>\lambda_2>\lambda_1$
18		1	1			1	1	1		1				1						1	3390.70	14049.43	774.126	$\lambda_3>2\lambda_1$; $\lambda_3>2\lambda_2$
19		1	1			1	1	1		1				1						1	3616.43	14043.86	774.126	$\lambda_3>(3/2)\lambda_1;\lambda_1>(3/2)\lambda_2$
20		1	1			1	1	1		1				1						1	3176.32	14022.98	774.126	$\lambda_3>(3/2)\lambda_2;\lambda_2>(3/2)\lambda_1$

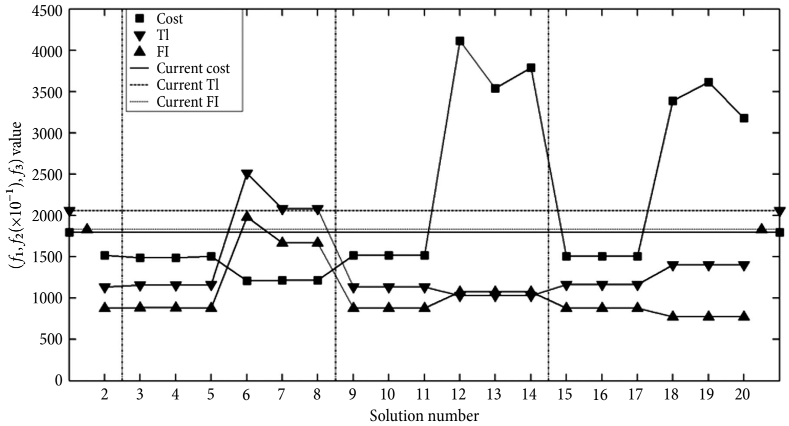

Fig. 2. Graphical representation of the objective function values of the 20 solutions found for the five cases considered

open the same depots. However, the second subcase is dominated by the other two, which have a lower TI value. This solution dominates the current one, with TI and FI values about 50% lower. The last three subcases also open the same depots but the last one dominates the other two. Moreover, this solution achieves the best possible FI function value of all the solutions found. This value improves the current fixed impact by 57.71% but with a big increase in the cost function value.

Regarding the question of which depots are open, note that depot 2 is always open in all the solutions found in these five cases while depots 3, 8 (both currently open) and 10 are not open in any solution. It is also important to mention that in the majority of the cases considered, the number of open depots is eight. Only the cases in which the cost function is considered much more important than the other two, is the number of depots opened increased to ten or eleven. This last case, in which eleven depots are open, is the one which achieves the best cost value for this case study.

As mentioned above, Palacio *et al.* (2014), using the ε-constraints method and considering just one aggregated environmental impact function and a more deterministic scenario, had computed different Pareto efficient sets of solutions. In order to compare the results from this paper with those solutions, we have taken their set of solutions corresponding to the parameter case in which the TI and the FI are similar and have evaluated it with the model of section 2. The results obtained are shown in Table 6.

Note that only 5 out of the 25 from Palacio *et al.* (2014) are non-dominated solutions. This reduction simplifies the decision making. If we compare these five solutions with the current situation, we obtain that they significantly improve the current one, as it can be seen from Table 7.

6. Discussion

From the results of the experiments, it has been observed that giving much more importance to one of the objectives than to the other two (subcases 4, 5 and 6) leads to the best value of the corresponding objective function at the expense of introducing a big penalty in the other two objective function values. In this way, if we pretend to obtain a balanced solution from the point of view of all three objectives, this option is not appropriate. Only if we truly want to focus our study on one main objective will this weighting scheme make sense. However, as the results of this case study show, these solutions do not generally dominate the current situation.

Attending to the non-dominated solutions obtained in the different cases and discarding the solutions that achieve the best value for one of the objective functions (due to the penalty in the other two objectives), only two depots selections were found to be solutions for the problem. These sets of open depots include three of the current depots (namely 2, 6 and 7) and five of the new potential sites (namely 9, 13, 14 or 18, 15 and 19). All these solutions completely dominate the current situation, clearly showing that it is inefficient especially as regards its environmental impacts, which can be improved by about 50%.

As mentioned above, considering all the non-dominated solutions, it has been found that depot 2 should always be open while depots 3, 8 and 10 should never be open. Regarding depots 3 and 8, the main reason for not being selected is because they have a very high fixed impact and the area where they are located also has a high TI value. On the other hand, depot 10 does not open because it is near depot 13 which is open for almost every solution and has a lower FI value. Depot 2 opens for every solution due to its good location and low TI and FI values.

It is worth noting that only in the case in which more importance is given to the environmental impact generated by the depots than to the other two objectives, more currently open depots than new depots are selected. This must be due to the fact that the currently open depots are in big industrial areas, so their FI is lower than others that can be opened in other, more populated areas.

As regards the solutions from Palacio *et al.* (2014), when evaluated with the model in section 2, we find that the current total cost of the system can be reduced by between 16.4% and 19.4%, TI between 44.34% and

47.54% and FI between 39.78% and 44.03%. It is interesting to note that one of the five non-dominated solutions obtained with the results of Palacio *et al.* (2014) opens just two of the eight current operative depots (namely 1 and 2) while it opens up to six of the new potential sites (namely 9, 11, 13, 14, 15 and 18). It can also be seen that these solutions achieve better cost results than the non-dominated solution found in the five cases studied. These solutions, however, are outperformed in terms of their FI values.

Table 6. Cost and impacts of the 25 solutions found by *Palacio et al.* (2014) evaluated with the model of section 2 (dominated solutions are shadowed)

Sol. No.	Open depots																			Cost	Transport impact	Fixed impact
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19			
*R*1	1			1		1	1		1		1	1	1		1		1	1		1566.39	11580.70	2099.40
*R*2	1			1		1	1		1		1		1		1		1	1	1	1562.66	11438.45	1908.35
*R*3	1			1		1	1		1		1		1		1		1	1		1551.19	11580.70	1785.13
*R*4	1	1				1	1		1		1	1	1		1		1	1		1553.09	11207.73	1733.59
*R*5	1	1			1	1	1		1		1		1		1		1	1	1	1561.37	11061.49	1578,25
*R*6	1	1				1	1		1		1		1		1		1	1	1	1553.37	11061.49	1542.53
*R*7	1	1				1	1		1		1		1		1		1	1		1537.89	11207.73	1419.31
*R*8	1	1					1		1		1		1		1		1	1		1524.39	11719.42	1289.08
*R*9	1	1				1	1		1		1				1		1	1		1537.08	11191.10	1291.50
*R*10	1	1				1	1		1				1		1		1	1		1542.71	11241.13	1258.36
*R*11	1	1				1			1		1				1		1	1		1527.08	11191.10	1255.79
*R*12	1	1				1			1		1			1	1		1			1500.17	11191.10	1248,79
*R*24	1	1				1			1				1		1		1	1		1532.71	11241.13	1222.65
*R*13	1	1				1			1				1	1	1		1			1505.79	11241.13	1215.65
*R*25	1	1				1							1		1		1	1	1	1606.53	10949.20	1215.65
*R*26	1	1				1							1	1	1		1		1	1581.63	10949.20	1208.64
*R*16	1	1				1	1		1		1		1		1			1		1522.69	11207.73	1105.03
*R*17	1	1					1		1		1		1		1			1	1	1526.08	11515.81	1098.03
*R*18	1	1				1	1		1		1				1			1	1	1535.20	11044.54	1100.45
*R*19	1	1							1		1		1	1	1			1		1447.88	11457.10	1100.04
*R*20	1	1				1			1		1			1	1			1		1464.47	10964.97	1102.46
*R*21	1	1				1			1				1	1	1			1		1471.86	11013.44	1069.32
*R*27		1			1	1			1				1	1	1			1	1	1498.54	10799.46	1048.93
*R*23	1	1				1							1	1	1			1	1	1502.91	10842.77	1062.32
*R*28	1	1				1			1				1	1	1				1	1501.71	11107.92	1024.59

Table 7. Percent improvement of the five non-dominated solutions with respect to the current situation

Sol. No.	Open depots																			Cost	%	Transport impact	%	Fixed impact	%
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19						
Case 1	1	1	1	1	1	1	1	1												1796.30	–	20584.66	–	1830.56	–
*R*19	1	1							1		1		1	1	1			1		1447.88	19.40	11457.10	44.34	1100.04	39.91
*R*20	1	1				1			1		1			1	1			1		1464.47	18.47	10964.97	46.73	1102.46	39.78
*R*21	1	1				1			1				1	1	1			1		1471.86	18.07	11013.44	46.50	1069,32	41.59
*R*27		1			1	1			1				1	1	1			1	1	1498.54	16.58	10799.46	47.54	1048.93	42.70
*R*28	1	1				1			1				1	1	1				1	1501.71	16.40	11107.92	46.04	1024.59	44.03

Conclusions

Designing a container depot network is a work that has not been widely addressed as a multiobjective problem. In this paper a three-objective, fuzzy optimization model is defined to find the best location for empty container depots in a hinterland. These objectives are the total cost of the network, the environmental impact generated by the transport operations associated with the depots, and the environmental impact generated by the setting up and maintenance of the depots. Due to the difficulty of obtaining impact data F-AHP was used to estimate, based on experts' judgement, the unit environmental impacts of the different depot locations. Also, as some of the data needed to have a certain degree of uncertainty, fuzzy constraints for the flow capacities of the depots were considered. The proposed approach was applied to the case of the hinterland of Valencia.

Regarding the results obtained in solving the multiobjective fuzzy optimization model without imposing which depots must be open, in all the cases studied at least one of the objectives improved the current situation. Moreover, a few solutions that improve the current situation in all three objectives were found. In these solutions the cost function can achieve around 17% improvement, the environmental impact generated by the transport operations (TI) around 45% improvement and the environmental impact generated by the depots themselves (FI) 50% improvement.

Regarding the results obtained imposing which depots must be open, it was found that only five of the 25 solutions from Palacio *et al.* (2014) are non-dominated. These solutions can improve the current one for each objective by around 17%, 45% and 40% respectively. Therefore, solving the problem with fuzzy multiobjective optimization reduces the number of alternatives than when obtaining the Pareto frontier with the ε-constraints method. In this way, we can reduce the 25 solutions found in Palacio *et al.* (2014) to only seven solutions that dominate the current situation: five from Palacio *et al.* (2014) plus two new solutions obtained by solving the model in section 2 without imposing which depots must be open.

Also, it can be seen that, in general, the solutions found tend to open more new locations than to preserve the currently open depots, indicating that the current container depot network in the hinterland of Valencia can significantly improve its overall performance.

It should be taken into account that this study has some limitations when talking about the estimation of the environmental impact. The opinions of the panel of experts consulted in order to obtain environmental impact data is a subjective method. Probably a method such as Life Cycle Assessment (see, e.g., Guinée 2002), is a more objective one to estimate the data but also involves an expensive and more difficult process. Also, multimodal transportation could be considered as a future research topic, adding higher complexity to the model. As indicated by one of the reviewers, the use of double container loads in the logistics of containers (e.g. Lai *et al.* 2013) is getting more and more common. It would be interesting to extend the proposed approach to this type operation.

Acknowledgements

This research was carried out with the financial support of the Spanish Ministry of Science Grant DPI2013-41469-P and the European Regional Development Fund (ERDF).

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Applied Mathematical Modelling 45 (2017) 148–164

Contents lists available at ScienceDirect

Applied Mathematical Modelling

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Effects of dynamic pricing of perishable products on revenue and waste

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ARTICLE INFO

Article history:
Received 20 January 2016
Revised 27 October 2016
Accepted 15 December 2016
Available online 23 December 2016

Keywords:
Perishable products
Dynamic pricing
Food spoilage
Waste reduction
Price elasticity

ABSTRACT

This paper deals with dynamic price strategies to reduce food and other perishable products spoilage. A deterministic mathematical model is proposed to study the influence of a number of factors, such as price elasticity of demand, age-sensitivity of demand and age profile of initial inventory, on revenue and spoilage. A parametric, bi-objective approach is considered with the aim of estimating the existing trade-offs between revenues and spoilage. The effects of price discounting are different in each scenario and also depend on the speed at which the price is reduced as it ages. Although a dynamic price strategy helps reduce spoilage, its effect on total revenue depends heavily on the scenario. In some specific cases identified below in the paper, total revenue can slightly increase or, at least, maintain its level. In other scenarios, the spoilage reduction comes as a loss in total revenue that can go from small to significant, depending on the scenario and the speed of the price discounting strategy. The proposed approach allows the quantification of the available trade-offs for each scenario. It also allows the analysis of the age distribution of units sold and their respective revenue contribution.

1. Introduction and motivation

In order to attract customers, large retailers are offering on their shelves a greater number of fresh products, allowing them to compete against the more traditional channels that usually specialize in those items [39]. Li et al. [35] report that more than 81% of the sales of the grocery retailing industry in the US in 2009 corresponded to food and beverages, and 63% of those were products with a limited shelf life, i.e. more than 50% of this sales channel are perishable units. Standard commercial products can be found anywhere, but perishable products are required on a daily basis and appreciated by customers looking for quality. These products introduce an additional complexity in the management of the stock. Thus, very often they require careful handling, and above all, their limited shelf life requires the implementation of some sort of strategy that avoids the spoilage of outdated units.

The problem of how to manage the inventory of perishable products has been extensively researched since the 1970s [43]. Depending on the lifetime of the products, models can be classified into three categories [45]: fixed lifetime, random lifetime, and models with a decaying lifetime. Everybody is accustomed to seeing on the shelves items marked with a fixed expiry date ("sell by" or "best before"), predetermined by the manufacturer to be valid under certain temperature, handling and storing conditions [33]. Theoretically a product is valid until that date, and many authors have considered

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http://dx.doi.org/10.1016/j.apm.2016.12.024

this case in taking pricing decisions (see [38]). In spite of that, the customer often sees less utility in some products as they become aged. Goyal and Giri [24] review different decay distributions that have been considered in the literature (exponential, Gamma, Weibull, etc.).

As periodic replenishment practices give rise to the presence on the shelves of units with different expiry dates but the same price, the customer prefers to select the fresher units which provide a higher perception of quality [15]. According to Chung and Li [16], 88% of consumers frequently check expiry dates when buying. It is clear that adjusting the price to the product characteristics, instead of adopting a fixed price along its whole shelf life, could increase sales and as a consequence perhaps the revenues gained by the retailer. That is to say, instead of posting a fixed price for a long period, the seller can dynamically change the price, thus balancing supply and demand based on information such as inventory shelf life and price elasticity of demand.

For instance, when the expiry date draws near, the retailer can post a lower price as, for the same price, the client may prefer a product with a longer shelf life because it is considered to be of higher quality [47]. In addition to reducing spoilage, this measure can produce a revenue loss, although not always because the price discount can be compensated for by an increase in sales. Note that in the case of food products (which are typically perishable items), they are price inelastic, with demand elasticities in the range 0.3–0.8 for common products [7]. It would therefore be interesting to explore how elasticity can influence demand so as to compensate for the suggested dynamic price reductions.

From a historical point of view, the interest in revenue management started in the early 1970s, focusing on airline and hotel overbooking [12], industries in which capacity is difficult to change in the short term and variable costs are small. The interest was not initially in intervening in the prices by looking for higher revenues, but in the capacity, by opening or closing certain fare classes as demand evolved in a segmented market. It was in the 1990s that pricing policies became a hot research topic, with the publication of some seminal works in the field (e.g. [23]). Applications moved from the hotel and airline business to many other industries (retail, energy, etc.), also to perishable products, price-sensitive demand and finite horizons [12]. However, the quantification of the benefits of dynamic pricing over a fixed price strategy has not been extensively studied. This is mainly due, according to Sen [50], to the difficulty of efficiently calculating optimal policies, and the high operational cost of changing prices on the shelves.

In spite of that, according to Elmaghraby and Keskinocak [19], there are three main reasons for the increased interest in these policies that differentiate price by expiry date: a higher level of data availability by the retailers (evidently it is necessary to know your customers very well to make good decisions); better Decision Support Systems (DSSs) are available; and a better technology that makes changing prices on the shelves less cumbersome. Some authors [32,39] have researched how traceability technology such as RFID can help to monitor and control time-sensitive perishables, providing data such as temperature, humidity, stock, expiry dates, or even demand trends, that help to make more founded decisions. Technology is, therefore, reducing operational costs and facilitating the implementation of this type of policy.

All these studies consider the sellers as revenue maximizers [19]. However, an inefficient stock rotation causes spoilage of expired units representing, in addition to billions of dollars of cost, an important problem in the short shelf life supply chain, with tons of items taken out of the stream and discarded [32]. Ferguson and Ketzenberg [22] report that in retailing, in some cases, up to 15% of perishables are disposed of due to spoilage or damage. Some other studies show different spoilage rates depending on the country, the channel and the product (e.g. [5]).

In any case, while the poverty rate in Europe is increasing due to the economic crisis and more people need to go to Food Banks to collect products for covering their daily necessities [49], at the same time millions of tons of edibles are landfilled in European countries every week [6,20]. This is a concern for governments, NGOs and society at large. In fact many retail companies have included waste reduction as one of their operational targets and performance indicators [14]. Therefore, not only does a severe financial problem exist around perishable products management at the retailer level, but there also exists an environmental (and social) impact as well, which should be included in the decision framework.

Keeping this in mind, one main issue is considered in this research that has not previously been considered in detail. Here the spoilage of expired products is not to be considered as being included in part of the cost function, but as a goal in itself, given the environmental and social issues involved. Therefore, we are not using here a single, cost-based objective function, but a bi-objective approach that considers, as another objective in the decision making process, the reduction in the number of units that are discarded because they have reached their expiry date and can no longer be sold nor safely consumed.

Thus, our goal is to gain insight and shed light on the relationship between revenue and wasted units when different dynamic pricing policies are implemented under different scenarios (i.e. products with different price elasticities and different aversions of customers to acquiring perishable products with shorter remaining shelf lives). By studying the effects of different parameters on the total revenue and total waste, we can better understand and quantify the overall effects of dynamic price-discount policies under different scenarios.

The approach proposed in this paper is rather general and applies to any perishable product (food, magazines, season tickets, etc.) for which a price reduction can stimulate demand for the aged units and thus help reduce waste/spoilage/unsold units. The idea, however, is to do this without harming sales revenue. The experiments carried out are aimed at showing that, depending on the scenario considered, this can generally be achieved.

Note that although we are considering a rather simplified model (e.g. we assume deterministic demand, continuous-time price markdown, etc.), it is still able to provide valuable insights into the relationship between dynamic pricing and revenue and waste, thus giving clues for managers to handle the day by day running of this type of operation. Furthermore, differently from existing research which approaches the issue from a strictly economic viewpoint, we propose a bi-objective approach, thus placing emphasis on the environmental and social impacts of the problem, and looking for ways of harmonizing profits and social responsibility.

The structure of the paper is the following. In Section 2 we review some of the existing literature, which will give us clues as to the parameters and factors that must be taken into account in our study. In Section 3 we present a mathematical model that incorporates those factors and parameters, and in Section 4 some formal analytical results based on the previous modeling. Later, in Section 5, we present and discuss the results of a number of experiments that have been carried out and finally, in Section 6, we summarize the conclusions of our study.

2. Relevant literature

When modeling products which, by their nature, are bound to become outdated, demand is conditioned (among other factors, see [18]) by the remaining shelf life of the item. Two initial assumptions can be made regarding knowledge of the demand function: uncertain demand (see for instance [35] for some comments regarding models under this assumption, or [48]) for deterministic demand.

Different models have been proposed considering the aging factor under deterministic demand. For instance, Rajan et al. [46] model this situation with a demand function which decreases as the price and age of the perishable units increase, deriving the optimal ordering cycle and price. Later Abad [3] extended this approach allowing backlogs.

Although most studies consider homogeneous units as not depending on their ages (see, for instance, [21,44]), in order to compensate for the reduction in demand, a dynamic pricing strategy appears as an interesting and cost-saving option [52]. Note that, although this is already quite a common practice in the retail industry, some stores are still reluctant to follow it as they are afraid that it could affect the company's image [35]. In some cases, in addition to the reputational risk, there is also a risk of selling already obsolete or damaged products that may put lives at risk and would require further compensation [28].

Liu et al. [39] define dynamic pricing as the assignment of different prices to items of the same category, considering their individual characteristics and changes to their status. Elmaghraby and Keskinocak [19] identify three characteristics to categorize the literature dealing with dynamic pricing: replenishment vs. no replenishment of inventory; dependent vs. independent demand; myopic vs. strategic customers (i.e. whether the customer purchases immediately when the price is acceptable, or looks forward to evaluating the price changes). Note that when the customer knows that the price will be marked down later on, additional factors have an influence on the demand for the product [51], such as delay in the buying decision (with the risk of the product being sold out), or creating the image of a lower quality product after the price has been reduced. Besanko and Winston [11] show that, in the case of potential myopic customers, it is better to set an initially high price and define a deeper decreasing price, while in the case of strategic customers a less steep decrease of prices works better.

In the literature discussions can be found about different factors affecting the modeling of the global demand and pricing alternatives [37]. As regards, for instance, the existence of salvage values, the presence of multiple liquidation channels where the seller can take a final decision on the remaining units (as well as the disposal costs in the case of many perishable products), makes it quite difficult to define a general framework for this variable.

Elmaghraby and Keskinocak [19] recognize the initial inventory decision as something very influential in the optimization of the pricing process. They mention especially questions such as how sensitive are the profits of optimal pricing policies to any deviation in the initial stock from optimal levels.

Most dynamic pricing approaches model the demand uncertainty by assuming it follows a specific distribution – estimated using historical data. However, some authors claim there is a risk in trusting those estimations, considering the observed fast technological and cultural changes and volatile market conditions, which can introduce serious errors in the solution [36]. These authors propose a fuzzy demand model where demand at period t given a price p_t is defined as a random fuzzy variable $\tilde{D}_t(p_t)$. Three different fuzzy programing models were considered for determining the best prices for period t.

Moreover, price markdown can be implemented in different ways depending on the moments in the product lifetime when the price is updated. Most of the models consider pricing policies with a continuous-time approach. However, from a realistic point of view it would be very difficult and costly to apply in practice, and periodic policies would be more convenient [13]. Chung and Li [16] consider two main procedures to put dynamic pricing into practice: a fixed-discount strategy, where the seller divides the product life into several stages and announces the initial and discounted prices at each moment; and a contingent strategy, which consists of fixing the initial price and defining a point in time at which the seller will announce the new price. According to Aviv and Pazgal [8], contingent strategies lead to lower expected revenues when dealing with strategic customers.

Since the aim of this paper is to show the compatibility of reducing waste with maintaining (or increasing) revenue, the assumption of reducing the price continuously with age is not vital and could alternatively be substituted by two or any finite number of price reductions. The results for a stepwise price reduction policy would be rather similar and, of course, would depend on the steepness of the price decreases.

In this regard, deciding the rate at which the price should be reduced is not a trivial decision. Tsiros and Heilman [53] studied the willingness of customers to pay as time passes for six perishable food products, and they observed that,

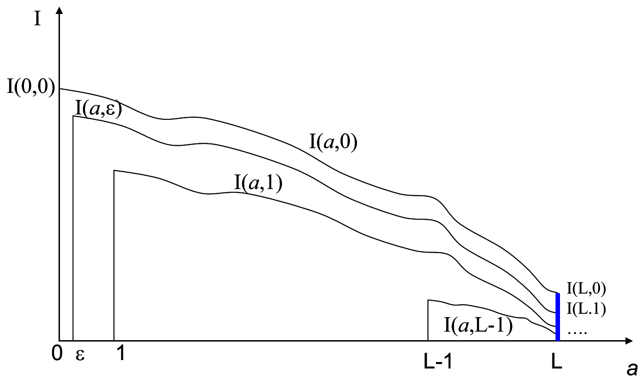

Fig. 1. Inventory evolution with time. As no replenishment is considered, $I(a,\ t)=0\ \forall a<t$. $I(L,\ t)$ represents the product wasted at instant $t\le L$.

depending on the product, the shape of the function changed, being linear for four of them and non-linear in the other two cases (incidentally meat products). Chung and Li [14] studied the most basic case, by considering a constant reduction rate for each remaining shelf life day. There are two main advantages to their assumption: this linear pattern simplifies the approach, making it simpler to implement, and the procedure results are more transparent for customers, which would stimulate consumption patterns. Actually, the goal in Chung and Li [14] was to better understand how dynamic pricing strategies would influence consumer behavior, after they observed that the usual policy of suddenly marking down the price when the expiry date was imminent was not appreciated by customers. According to a survey carried out by Chung and Li [16], a common practice in the Korean retail industry is to reduce the price of perishables by 30% when 30% of the product shelf life remains.

However Wang and Li [55] acknowledge that there can be some criticism of the assumption of a strictly linear demand function of the price, even though its wide use is based on an acceptable approximation of real demand. To respond to that criticism, and when the customers are aware of some deterioration through the age of the product, measured by its quality $q(t)$, they define the demand function as $D(t)=D_0-\alpha p(t)+\beta q(t)$, with α and β being two parameters measuring the influence on the demand of the price and the quality. All other factors such as competitors' prices, customers' perception, etc., are included in those parameters. This is the approach followed in the next section.

Throughout the research developed so far, the usual approach was to consider the spoilage as something undesirable due to its economic impact on the general cost function; however, we are considering a new point of view in which the spoilage is something to fight against independently of the cost. To reduce waste (mainly if we are talking about something so sensitive nowadays, such as food) is an objective in itself, when taking into account social and environmental factors. In this sense, this paper covers a new way of dealing with the problem, by acting on the demand via prices.

3. Modeling assumptions

3.1. Demand and price functions

Let us denote L as the maximum shelf life of a perishable product being studied, and let $I(a,\ t)$ be the inventory of the product having an age $a\le L$, in an instant $t\le L$. In order to estimate the effects of a dynamic pricing policy as the product ages, let us suppose there is an initial fresh product stock, $I(0,\ 0)$, which, together with the rest of the stock at instant 0, $I(a,\ 0)$, defines the age profile of the initial stock of the product (see Fig. 1). As mentioned above, this factor is considered to be relevant as it will have an influence both on sales and spoilage.

We assume a continuous-time, deterministic demand and no replenishment during the horizon L. Of course, in the real world, each time period the inventory may be renewed with replenished, zero-age units, will modify the inventory age profile at time t. The proposed approach can be adapted to that replenishment scenario but, in this paper, we are concerned with studying the depletion of the given initial stock and how that process may be influenced by adopting a dynamic pricing policy.

The evolution of the permanence in stock of the units available at instant 0 will depend on the scenario considered and on the dynamic pricing policy applied. Note that, at most, at time L, all the initial stock $I(a,\ 0)$ in the process would have been either sold or wasted. Those units that reach their maximum shelf life are retired and recorded as spoilage. The rest are sold units, but their contribution to revenue is not uniform since the sale price depends on the age of the product at the time of sale. The goal is to measure the effect on revenue and spoilage of a discount policy depending on the different factors considered.

We assume there is a pool of buyers that define an aggregate continuous-time demand function. As it usually happens in the case of perishable products, demand depends not only on the retailer price but also on the age of the product [3,55]. Thus, a product whose age is close to its maximum shelf life is not as appealing as a fresh one, and the customer prefers to pick up products with longer remaining shelf lives. The demand function considered takes into account this demand leakage.

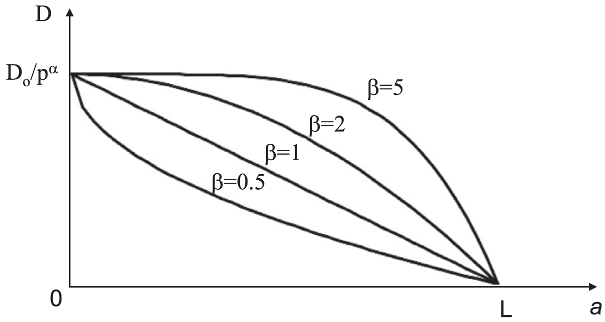

Fig. 2. Decreasing demand as the units age, depending on the β parameter.

It is implicitly done through a demand function that jointly depends on price and product age. Let $D(p, a)$ be the demand as a function of both variables, price (denoted p) and age (denoted a), with $a \leq L$. As we are proposing to explore the effects of including that client perception about aging into the price scheme, we therefore consider that the price depends on age, $p(a)$. As will be seen in the mathematical formulation, we consider three parameters in the model: α (for the price elasticity of demand), β (for the influence of aging on demand) and γ (for the influence of aging on price).

Regarding demand, we assume constant price elasticity of demand $\alpha > 0$, and, for a given price, a decreasing demand as the product loses freshness, controlled by parameter $\beta > 0$:

$$D(p, a) = D_0\left(\tfrac{p}{p_0}\right)^{-\alpha}\left[1 - (a/L)^{\beta}\right]. \tag{1}$$

Note that when $\beta = 1$ the decrease in demand is linear with age, with demand for a product decreasing to zero as its age reaches the maximum shelf life. Demand decreases less than linearly for $\beta > 1$ (see Fig. 2), i.e. the demand reduction with age is lower at first (so demand is not much lower for relatively fresh units, and only falls as the age of the unit approaches the maximum shelf life). Note that we shall not consider β values lower than 1 because that would mean that the demand reduction with age would be steep at first, which is not generally the case in practice.

Regarding the price discount policy, we propose that the price reduction due to aging (in case it is considered) should follow a similar pattern to the demand reduction, using a parameter $\gamma \geq 0$ to control the speed of the price reduction. Mathematically,

$$p(a) = p_o\left[1 - (a/_L)^{\beta}\right]^{\gamma}. \tag{2}$$

Note that the above equation assumes that for $a = L$ the retail price would be zero. Note also that $\gamma = 0$ means that no dynamic pricing is applied, while higher γ values accelerate the price reduction. The case with $\beta = \gamma = 1$ coincides with the basic linear markdown practice assumed by some authors [14].

Including in (1) the dependence of variable price with age, we arrive at the following demand function:

$$D(a) = D_o\left[1 - (a/_L)^{\beta}\right]^{1-\alpha\gamma}, \tag{3}$$

where the exponent of $1-\alpha\gamma$ now has a special importance: when $\gamma = 1/\alpha$, demand is constant for any age (i.e. marking down the price for older units compensates for a reduction in demand); when $\gamma < 1/\alpha$ demand still decreases with age; a scenario with $\gamma > 1/\alpha$ means that demand increases as the product is older, an extreme-discount scenario which will not be considered.

With respect to the justification of the functional forms assumed for the demand and the price discount policy considered, we should remember that in the classic economic theory, the simplest function relating demand and price is the linear approach, with many researches modeling the demand function in this way [17]; another very common approach is to assume a constant elasticity demand, already considered in classical texts such as Koutsoyiannis [34]. In fact many papers on supply chain management (including those dealing with perishable products) consider a constant price elasticity function of the type $D = D_0p^{-\alpha}$ (e.g., [1,4,30,31,41,42]). In order to keep some optimization properties [2], some of those papers consider elasticities $\alpha > 1$. However, in order to consider the most general case, as other authors do (e.g. [54]), we allow here the possibility of an inelastic demand.

Time is another major factor that can have an influence on demand. In addition to the “best before” case we deal with in this paper, some products change the demand pattern as the season passes, with higher rates at the beginning or at the end. As regards the use of a demand function that jointly depends on price and product age we can mention, among others [29,40,52]. Regarding the influence of time over demand, many authors assume a linear relationship (e.g. [17]), although a more general polynomial formulation was proposed by Barbosa and Friedman [10], $D = D_0t^r$ with $r > -2$. In our case, demand decreases with time, which would correspond to the case $r < 0$. However, as explained before, we are expecting a smaller decay rate at the beginning and a steeper one as time passes. Therefore the concave approach we have selected (with $\beta > 1$) was considered to be more appropriate. Researchers that have also considered a polynomial dependence of demand with age include [9,25–27].

3.2. Calculation of revenue and spoilage

As we assume that the inventory is not replenished in the time horizon [0, L], at time $t \le L$, there cannot be any inventory having age $a < t$, and the current inventory of age a corresponds to units that had age $(a-t)$ in the initial inventory. Of course, part of the inventory that initially had age $(a-t)$ must have been sold during the interval [0, t]. The other fraction remains in inventory and has age a at time t, i.e.

$$I(a,t) = \begin{cases} 0 & \forall a < t \\ \max\{0, I(a-t,0) - \int_0^t D(a-t')dt'\} & \forall a \ge t \end{cases}. \tag{4}$$

The wasted units are those units arriving at age L without being sold. Therefore, the waste generated at instant t is

$$W(t) = I(L,t), \tag{5}$$

and the total waste generated is

$$TW = \int_0^L W(t)dt. \tag{6}$$

Regarding the calculation of revenues, we need to calculate in advance the instant at which the inventory with age a runs out. Let us denote that instant as $\tau(a)$, i.e.

$$\tau(a) = \min\{t \in [0,L] : I(a,t) = 0\}, \tag{7}$$

i.e., I(a,$\tau(a)$) = 0, or, equivalently

$$I(a-\tau(a),0) = \int_0^{\tau(a)} D(a-t')dt'. \tag{8}$$

As there is no more inventory of age a after instant $\tau(a)$, we can therefore calculate the number of units of age a sold at instant t as

$$S(a,t) = \begin{cases} D(a) & \forall t \le \tau(a) \\ 0 & \forall t > \tau(a) \end{cases}. \tag{9}$$

The number of units sold at time t is

$$S(t) = \int_t^L S(a,t)\,da, \tag{10}$$

and the total sales is

$$TS = \int_0^L \int_t^L S(a,t)\,da\,dt = \int_0^L S(t)\,dt. \tag{11}$$

In a similar way, the revenue from selling products of age a at instant t is

$$R(a,t) = \begin{cases} p(a)\cdot D(a) & \forall t \le \tau(a) \\ 0 & \forall t > \tau(a) \end{cases}. \tag{12}$$

The revenue from units sold at time t is

$$R(t) = \int_t^L R(a,t)\,da, \tag{13}$$

and the total revenue is

$$TR = \int_0^L \int_t^L R(a,t)\,da\,dt = \int_0^L R(t)\,dt. \tag{14}$$

The above mathematical expressions allow us to compute total revenue (TR), total sales (TS) and total waste (TW). By the way, TS and TW are related in the sense that their sum is equal to the total initial inventory, i.e.

$$TS + TW = \int_0^L I(a,0)\,da. \tag{15}$$

Moreover, we can calculate the number of units of each age sold in the time horizon [0, L] as

$$\begin{aligned} \hat{S}(a) &= \int_0^L S(a,t)\,dt = \int_0^{\tau(a)} S(a,t)\,dt = \\ &= \int_0^{\tau(a)} D(a)\,dt = D(a)\cdot\tau(a). \end{aligned} \tag{16}$$

This leads to another way of computing total sales as

$$TS = \int_0^L \hat{S}(a)\,da = \int_0^L D(a)\cdot\tau(a)\,da. \tag{17}$$

Analogously, the amount of revenue obtained from the sale of units aged a along the horizon [0, L] can be computed as

$$\begin{aligned}\hat{R}(a) &= \int_0^a R(a,t)\,dt = \int_0^{\tau(a)} R(a,t)\,dt = \\ &= \int_0^{\tau(a)} p(a)\cdot D(a)\,dt = p(a)\cdot D(a)\cdot \tau(a).\end{aligned} \tag{18}$$

This allows an alternative expression for computing total revenue as

$$TR = \int_0^L \hat{R}(a)\,da = \int_0^L p(a)\cdot D(a)\cdot \tau(a)\,da. \tag{19}$$

Note also that the ratio $\hat{S}(a)/TS$ represents the percentage of the total units sold that had age a. Similarly, the ratio $\hat{R}(a)/TR$ corresponds to the percentage of the total revenue that comes from units of age a.

4. Some analytical results

Parameter γ controls the steepness of the price reduction. In fact, this is the only parameter that can be controlled by the decision maker (the other two, price elasticity and age sensitivity of demand, depend on consumers and cannot be changed by a manager's decision). Therefore it would be interesting for our analysis to know the relationship between γ and the relevant model outputs.

It is proven below that any price reduction policy will positively affect waste generation, reducing the number of spoiled units. In other words, there is an inverse relationship between the total waste generated TW, and the price reduction rate γ. Note that this means that when the price decreases at a faster rate, sales increase, thus reducing the number of units that reach their expiry dates.

Given that according to Eq. (15) the value TS+TW is a constant, stating that TW decreases when γ increases is equivalent to saying that when γ increases TS also increases. We should therefore prove that dTS(γ)/d(γ) is non-negative.

Proposition 1. $\partial \mathrm{TS}(\gamma)/\partial\gamma \geq 0$

Proof. Following the definition of TS in Eq. (11), and the definition of *S(t)* in Eq. (10), it holds that

$$\frac{\partial TS(\gamma)}{\partial\gamma} = \int_0^L \frac{\partial S(t,\gamma)}{\partial\gamma}dt = \int_0^L \int_t^L \frac{\partial S(a,t,\gamma)}{\partial\gamma}dt. \tag{20}$$

Also, by Eq. (9), it holds that

$$\frac{\partial S(a,t\gamma)}{\partial\gamma} = \begin{cases} -D_0\alpha\left[1-(a/L)^{\beta^{1-\alpha\gamma}}\right]\ln\left(1-(a/L)^{\beta}\right) & \text{if t} \leq \tau(a) \\ 0 & \text{if t} > \tau(a)\end{cases}. \tag{21}$$

Since the partial derivative in Eq. (21) has a non-negative value in any case, it holds by Eq. (20) that $\partial \mathrm{TS}(\gamma)/\partial\gamma \geq 0$. □

This result thus indicates that for the dynamic price policies considered, increasing the intensity of the price reduction (i.e. increasing γ) always leads to higher sales. Moreover, the positive effect of price reduction on waste reduction is higher the larger the price elasticity of demand, i.e., if $\alpha > \alpha'$ then $\partial \mathrm{TS}(\gamma,\alpha)/\partial\gamma \geq \partial \mathrm{TS}(\gamma,\alpha')/\partial\gamma$.

Proposition 2. $\partial(\partial \mathrm{TS}(\gamma)/\partial\gamma)/\partial\alpha \geq 0$

Proof. According to (20) and (21) it follows that

$$\frac{\partial}{\partial\alpha}\left(\frac{\partial TS(\gamma)}{\partial\gamma}\right) = \frac{\partial}{\partial\alpha}\left(\int_0^L\int_t^L \frac{\partial S(a,t,\gamma)}{\partial\gamma}da\,dt\right) = \int_0^L\int_t^L \frac{\partial}{\partial\alpha}\left(\frac{\partial S(a,t,\gamma)}{\partial\gamma\partial\alpha}\right)da\,dt, \tag{22}$$

i.e.,

$$\frac{\partial^2 S(a,t,\gamma)}{\partial\gamma\partial\alpha} = \begin{cases} -\mathrm{D}_0\ln\left(1-(a/L)^{\beta}\right)\left[1-(a/L)^{\beta}\right]^{1-\alpha\gamma}(1-\alpha\gamma) & \text{if } t \leq \tau(a) \\ 0 & \text{if } t > \tau(a)\end{cases}. \tag{23}$$

And, again, this second partial derivative is non-negative in any case, which confirms the proposition. □

This result thus states that the sales increase effect of the price reduction policy is more intense the larger the value of the demand elasticity. This means that products with elastic demand are the best candidates, i.e. those that will benefit more from, for implementing this type of dynamic pricing policy.

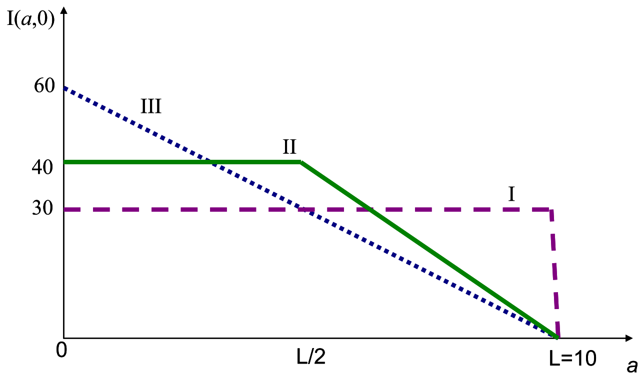

Fig. 3. Age profile of the initial inventory $I(a, 0)$ in the three cases considered, all with the same total initial stock.

5. Effects of dynamic pricing

In order to study in more detail the effects of the proposed dynamic price strategy both on total revenue and total waste, a series of experiments considering different combinations of parameters α, β and γ were carried out. The software used for all the calculations was MATLAB®, a well-known scientific computing environment. Seven different values ($\alpha \in \{1/3;\ 1/2;\ 2/3;\ 1;\ 3/2;\ 2;\ 3\}$) were considered for the price elasticity of demand. Note that these values consider different inelastic, unitarily elastic and elastic demand scenarios. For each value of α we explored 20 different, equally-spaced values for the price discount speed parameter γ varying from 0 to $1/\alpha$, allowing us to gauge in detail the effect of this influential parameter. The different γ values go from no price reduction ($\gamma = 0$) to the maximum reasonable price reduction intensity. Thus we do not consider extreme-discount policies involving $\gamma > 1/\alpha$. We also use one of three possible values for parameter $\beta = \{1;\ 2;\ 5\}$. These values have been chosen to represent three different levels for this factor: $\beta = 1$ represents a linear reduction in demand due to product aging, while the other two values represent a non-linear demand reduction, with the more significant effect occurring at a later date, the larger the value of β (see Fig. 2). Note that, because it is less realistic, we do not consider $\beta < 1$ which would correspond to a situation where the demand reduction with age would be steeper at first than later on.

Regarding the age profile of the initial inventory, we have considered three scenarios (see Fig. 3). The first one (labeled case I) implicitly assumes a random picking of units by customers, which can give rise to a uniform distribution of the number of units of each age kept in stock. The opposite case (labeled case III) corresponds to the more likely common situation in which the number of older units in inventory decreases with age (in our case, linearly). Case II is a mixture of the other two, with an initial random picking until instant $L/2$, and then a linear decrease. The three patterns can be seen as special cases of a single pattern with constant inventory until a certain age (0 for case I, $L/2$ for case II and L for case III) and then a linear decreasing trend to reach zero stock at L. No convex pattern for initial product age is considered. In all three cases the total number of units in the initial inventory, i.e. the area below the corresponding age profile, was fixed at the same value, namely 300 units, for the sake of comparison.

These three initial inventory profiles are just examples considered to illustrate and assess the effectiveness of using price reductions to reduce waste without sacrificing revenue. The methodology used to assess the effectiveness works independently of a given initial inventory profile. Actually, the initial inventory profile would be different from one company to another and, even for a given company, it would be different in different time periods. Whatever the initial inventory profile, i.e. for any arbitrary initial inventory profile, the proposed approach can empirically/numerically compute the sales and revenue in each time period and for the whole time horizon.

The specific values used for the parameters were $L = 10$ t.u. and $p_0 = 5$ m.u. In order to fix the value of the demand parameter D_0 we carried out some preliminary experiments to assess the amount of spoilage generated in each case. Fig. 4 shows the total waste and the total revenue for the no-discount scenario (i.e. $\gamma = 0$) and for $\alpha = 1$ and $\beta = 2$. Note that TW is highest for case I and lowest for case III (with case II in between). For TR the opposite occurs.

Note that all the points plotted in Fig. 4 lie on a straight line. That is not surprising, given that, according to (15), the sum of TW and TS is a constant, the same for all three initial inventory cases considered. And, since the results plotted in Fig. 4 correspond to a no-discount policy $\gamma = 0$, i.e. $p = p_0$, the total revenue TR is proportional to TS. Hence

$$\left.\begin{array}{r} TR = p_0 \cdot TS \\ TS + TW = c \end{array}\right\} \Rightarrow \frac{1}{p_0} \cdot TR + TW = c. \tag{25}$$

With respect to the value of D_0 chosen, in the end a value $D_0 = 15$ was selected so that the spoilage that results after the initial experiments (around 5%–10% depending on the case) is similar to the levels observed in practice and reported in the literature. For example, Chung and Li [14] report that disposal rates are on average 2%, sometimes reaching 10% while Ferguson and Ketzenberg [22] mention that spoilage rates may reach 15%.

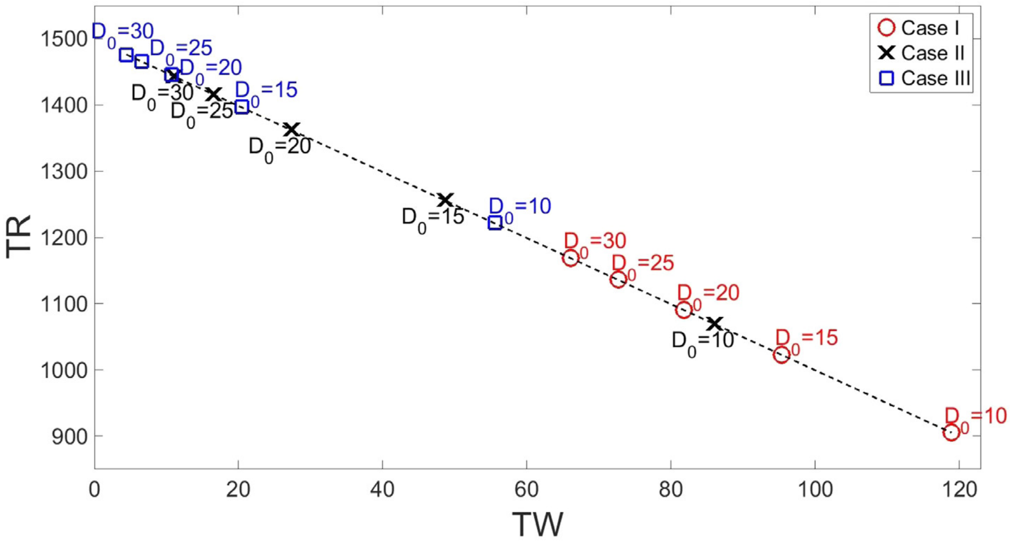

Fig. 4. Change in total revenue and total waste, for a no-discount scenario ($\alpha = 1$, $\beta = 2$, $\gamma = 0$), as D_0 increases.

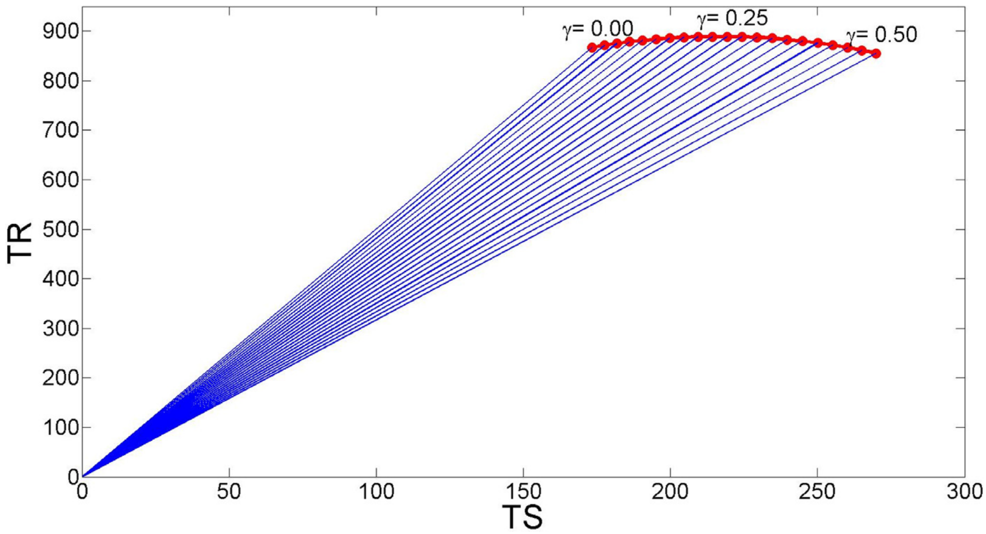

Fig. 5. Change in total revenue and total sales, for a sample scenario (case I, $\alpha = 2$, $\beta = 1$), as γ increases. Slope of segment represents resulting average price charged.

Fig. 4 also allows us to comment that an obvious way to reduce spoilage and, at the same time, increase revenue is by increasing the demand rate (e.g. through promotion). Doing so, however, has costs and also its effectiveness is marginally decreasing. Thus, it can be seen in Fig. 4 that the effects of D_0 increases are marginally decreasing.

Also, before we show the results obtained for the different scenarios, it is interesting to take a look at the type of information that can be derived from the proposed approach. Thus, for example, Fig. 5 shows, for $\alpha = 2$, $\beta = 1$ and case I of the initial inventory age profile, the total sales and total revenue obtained with the different price discount policies from $\gamma = 0$ (i.e. no discount) to $\gamma = 1/\alpha$ (which is the maximum discount rate considered). For each value of γ, a different point is obtained. In this case, small values of γ slightly increase TR but those disappear as γ approaches $1/\alpha$. The effect on TW of varying γ is monotonic, i.e. TW always decreases as γ increases. This confirms the theoretical result presented in Section 4; that is because the price discounts offered to customers stimulate demand and thus reduce spoilage. But what we would like to focus on is that the slope of the segment joining each of these points with the origin represents the average price charged. It can be seen that the higher the discount the lower the average price and, what is more interesting, higher revenue, lower spoilage and lower average prices can be obtained using the appropriate dynamic pricing policy.

This gives the best of both worlds: profitability and corporate social responsibility. Unfortunately, as we will see, this situation, which benefits the company, consumers, the environment and society in general, does not always occur. For this to happen, certain factors must concur, among them that the price elasticity of demand is sufficiently large. It is clear that if demand is not sufficiently price elastic, then price discounts would not produce a demand increase large enough to compensate for the loss of revenue due to the price reduction. In other words, a dynamic price strategy increases its effectiveness and attractiveness as the price elasticity of demand increases. The other two factors, i.e. the age profile of the

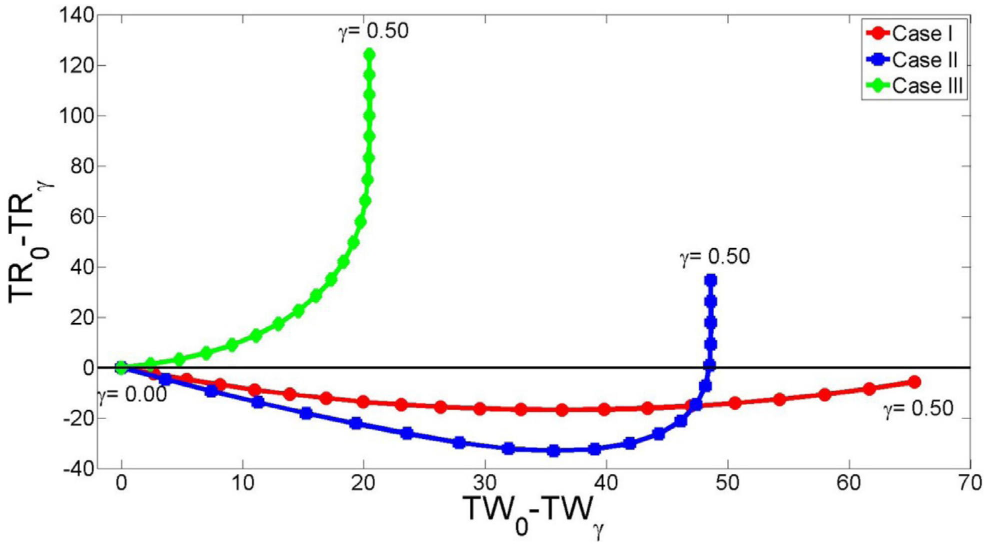

Fig. 6. Revenue loss (w.r.t. no-discount benchmark) versus total waste reduction ($\alpha = 2$, $\beta = 2$).

initial inventory and the sensitivity of demand to age, also have an influence, but not as significant as that of the demand elasticity.

5.1. *Revenue loss vs. spoilage reduction*

From the above discussion it follows that, although spoilage reductions are warranted with a dynamic price strategy, the total revenue may fall. In that case, the proposed approach allows us to see the trade-offs between both magnitudes. Thus, for example, Fig. 6 shows, for $\alpha = \beta = 2$, the reduction in total revenue versus the reduction in total waste that occurs as the discount speed parameter γ increases. The slope of the curve represents the marginal loss of revenue for a unit waste reduction. Note that the curves are not generally monotonic. Parts of the curves have a positive slope, meaning that the reduction in waste brings about revenue losses but, also, in some parts, the slope is negative indicating increases in total revenue compatible with waste reduction. Thus, in the case of initial inventory age profile I, total revenue first slightly increases (w.r.t. the $\gamma = 0$ no-discount benchmark) but, after reaching a maximum, decreases if higher price discounts are made. This type of trade-off analysis is different from the one carried out in the simulation study of Chung and Li [14], which reaches the conclusion that an additional 2% augmentation in sales is required to compensate for every 5% increase in markdown.

Figs. 7 and 8 show the effects on TR and TW of changing the discount speed factor γ for varying values of parameters α and β, and for the three initial inventory age profile cases. Note that the scale of the TW axis indicates that, as mentioned above, case I is the one that generates the largest spoilage while case III generates the least. The decrease in spoilage as γ increases is significant, reaching zero total waste in the cases of initial inventory age profiles II and III. Since in age profile I there exists initially an inventory with a close to zero remaining shelf life, it is not possible to reduce TW to zero. As regards the total revenue, it can be seen that because of the high price elasticity of this scenario $\alpha = 3$, it increases (or at least does not decrease) for small γ, although when one TW reaches zero further γ increases are unnecessary and only lead to a reduction in TR. TR increases are more significant in cases I and II because they involve more spoilage than in case III.

Almost the same effects can be observed in Fig. 8. Thus, again, cases I and II lead to larger spoilage in the no-discount $\gamma = 0$ scenario. However, independently of the scenario, TW is always reduced when γ increases. As regards TR, although, as we mentioned above, for high price elasticities TR can be increased, for lower price elasticities TR decreases as γ increases, because the increases in demand induced by the price discounts are not large enough to compensate for the lower unit price. It is also evident that faster price discounts (i.e. larger γ values) than the one required to reduce TW to a small value (close to zero) are not recommended since they only contribute to further reduce TR.

Note that the proposed approach can be related to a single-variable bi-objective optimization problem since we consider two objective functions, namely total revenue and total sales volume (or equivalently, total waste) as well as a single decision variable, namely the discount intensity γ. Thus, when plotting the value of the two objective functions for different values of γ (as in Figs. 5, 7 and 8) we can visualize the corresponding Pareto Front, i.e. the non-dominated section of the plot. We have labeled the above proposed approach a "parametric, bi-objective approach" rather than a bi-objective optimization approach because we are not trying to optimize the objective function in the sense of computing the best value of parameter γ. What the proposed approach does is to assess, by evaluating the two objective functions for different values of γ, what the effects on the two objective functions are. These are related to the shape of the corresponding Pareto Front and, as the results show, generally depend on the scenario considered, i.e. on the price elasticity, the age sensitivity of demand and the profile of the initial inventory.

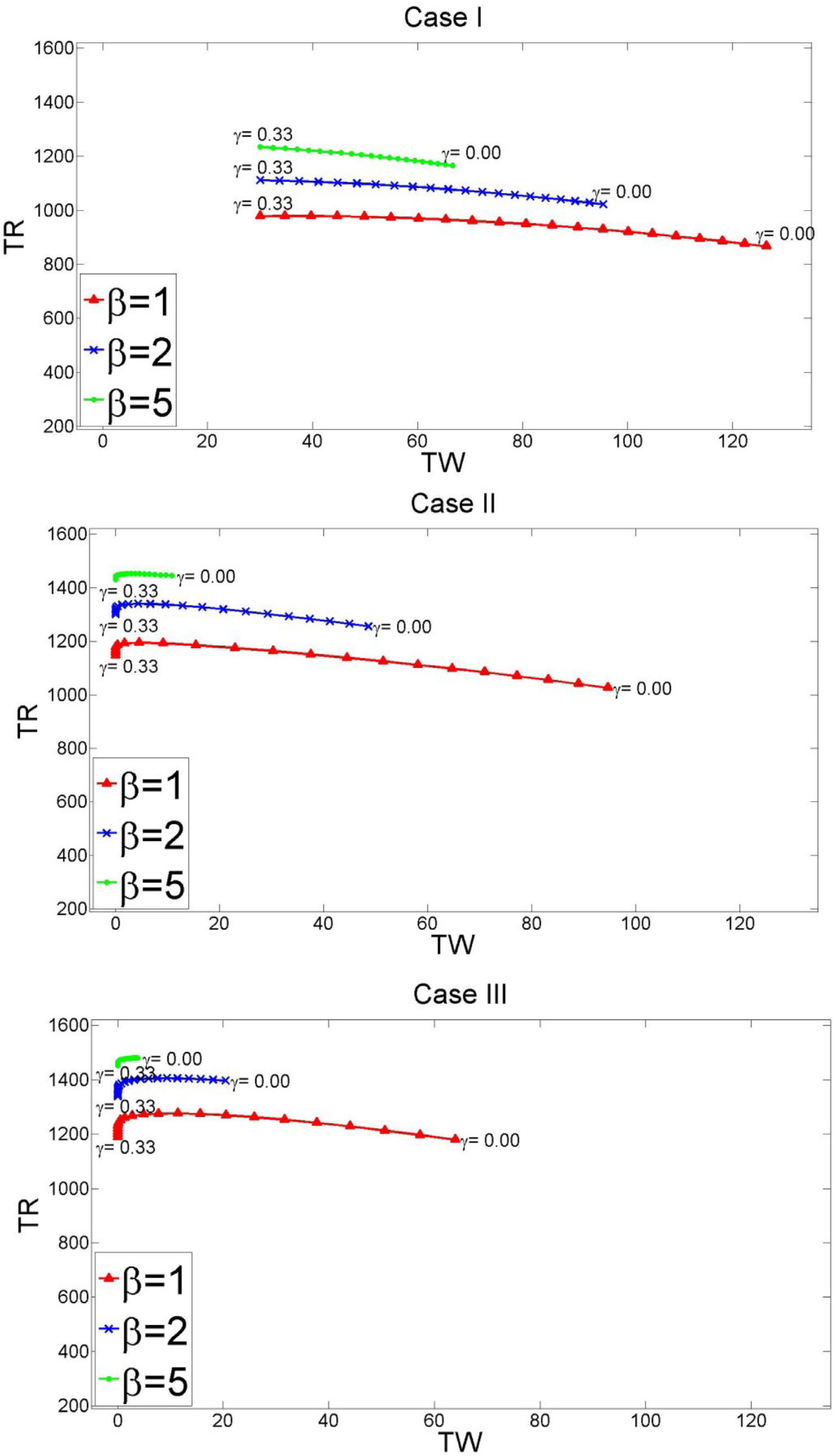

Fig. 7. Change in total revenue and total waste, for $\alpha = 3$ and different β values, as γ increases.

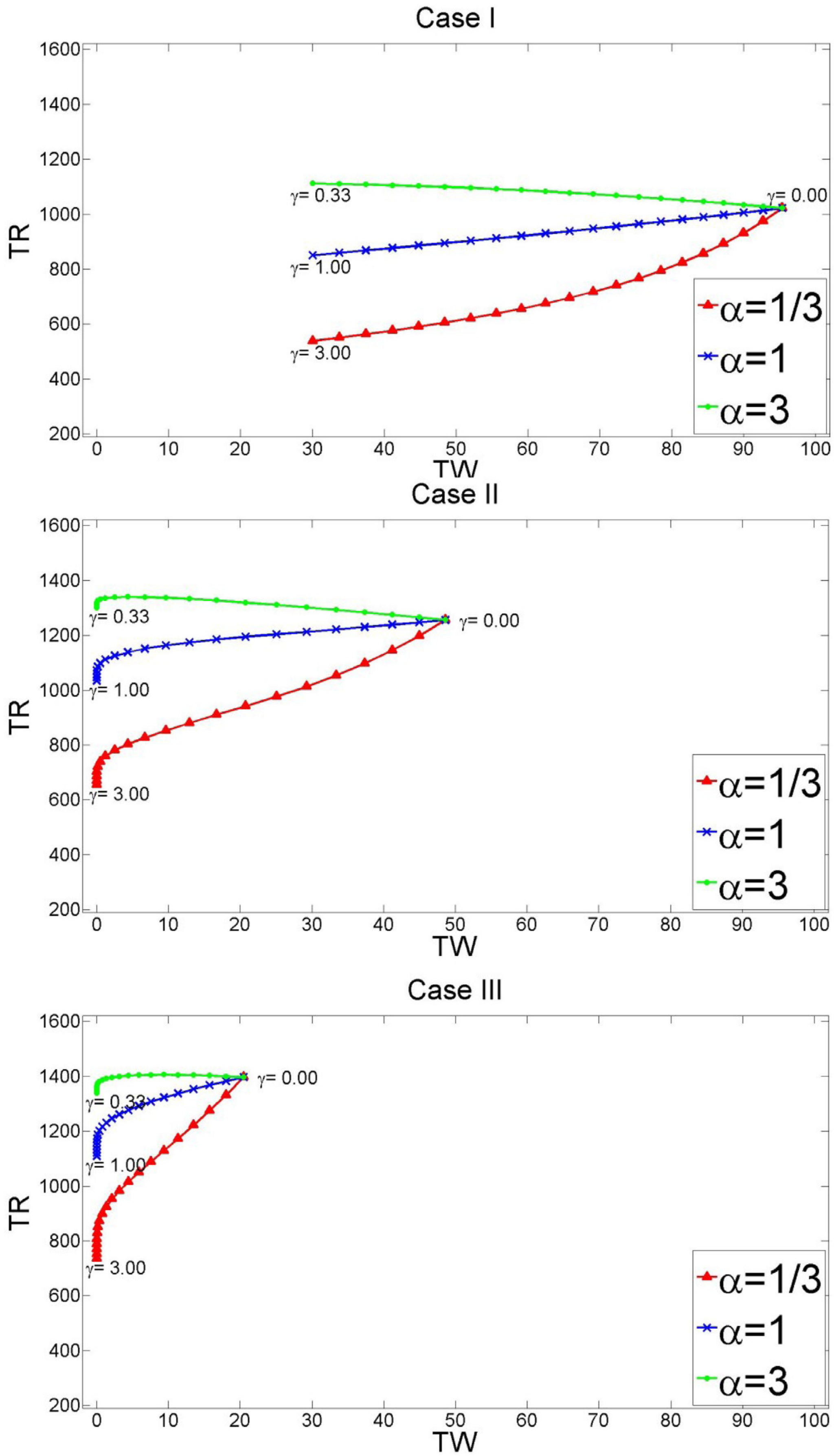

Fig. 8. Change in total revenue and total waste, for $\beta = 2$ and different α values, as γ increases.

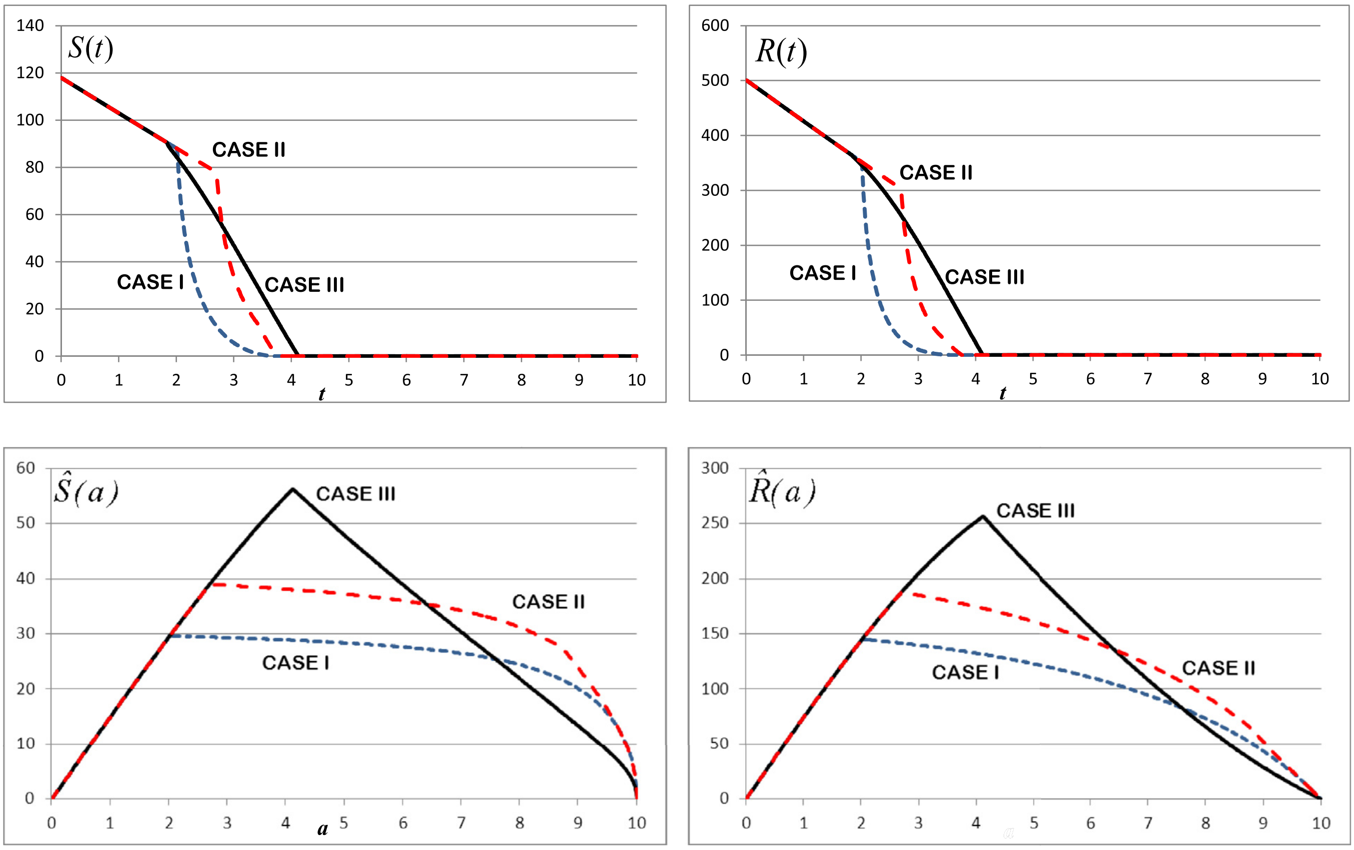

Fig. 9. Age and time distribution of number of sold units and corresponding revenue for a sample scenario ($\alpha = 1$, $\beta = 2$ and $\gamma = 0.5$).

5.2. Sales and revenue as a function of age and time

Fig. 9 shows the detailed results on the time and age distribution of the number of sold units (respectively, $S(t)$ and $\hat{S}(a)$) and their corresponding revenue $R(t)$ and $\hat{R}(a)$ Although only the results of a sample scenario are shown, the proposed approach allows us to study the distribution patterns for any dynamic pricing scenario. For the scenario shown in Fig. 9, corresponding to $\alpha = 1$, $\beta = 2$ and $\gamma = 0.5$, although there is little difference in the average age of units sold between the three cases (5.09, 5.16 and 4.79 for cases I, II and III, respectively), it can be seen that there are differences in their respective shapes, with cases I and II involving a larger share of aged units and a smaller share of fresher units than case III. The area below each of these curves represents the TS of these scenarios, which are, respectively, 234.6 p.u., 290.2 p.u. and 297.7 p.u. As regards the revenue contribution of units of different ages, the distribution has a similar shape to that for the units sold, except that the curves reflect that, slightly at the beginning but more pronounced with age, the more aged units are sold at a lower price and therefore their relative revenue contribution is decreasing with age. Similarly, the area below each of these curves represents the TR of these scenarios, which are, respectively, 940.7 u.m., 1136.2 u.m. and 1246.4 u.m.

As regards the evolution of sales and revenue with time, it can be noted that the sales and revenue at time zero, i.e. $S(0)$ and $R(0)$, are the same for the three initial inventory profiles. This is due to the fact that those two values do not depend on the initial inventory profile. Thus, according to (9), (10) and (13),

$$S(0) = \int_0^L S(a, 0)da = \int_0^L D(a)da = \int_0^L D_0\left(1 - (a/_L)^{\beta}\right)^{1-\alpha\gamma} da. \tag{26}$$

For the $\alpha = 1$, $\beta = 2$ and $\gamma = 0.5$ scenario considered in Fig. 9, this leads to

$$S(0) = \int_0^L D_0\left(1 - (a/_L)^2\right)^{1/2} da = \frac{D_0}{L}\int_0^L \sqrt{L^2 - a^2} da = \frac{D_0 L\pi}{4}. \tag{27}$$

For the parameter values assumed to be $D_0 = 15$ and $L = 10$, a value of $S(0) = 117.81$ units sold results, which is the same for all three initial inventory cases considered.

Analogously, according to (12), (13), (2) and (3),

$$R(0) = \int_0^L R(a, 0)da = \int_0^L p(a)D(a)da = \int_0^L p_0 D_0\left(1 - (a/_L)^{\beta}\right)^{1-\alpha\gamma+\gamma} da. \tag{28}$$

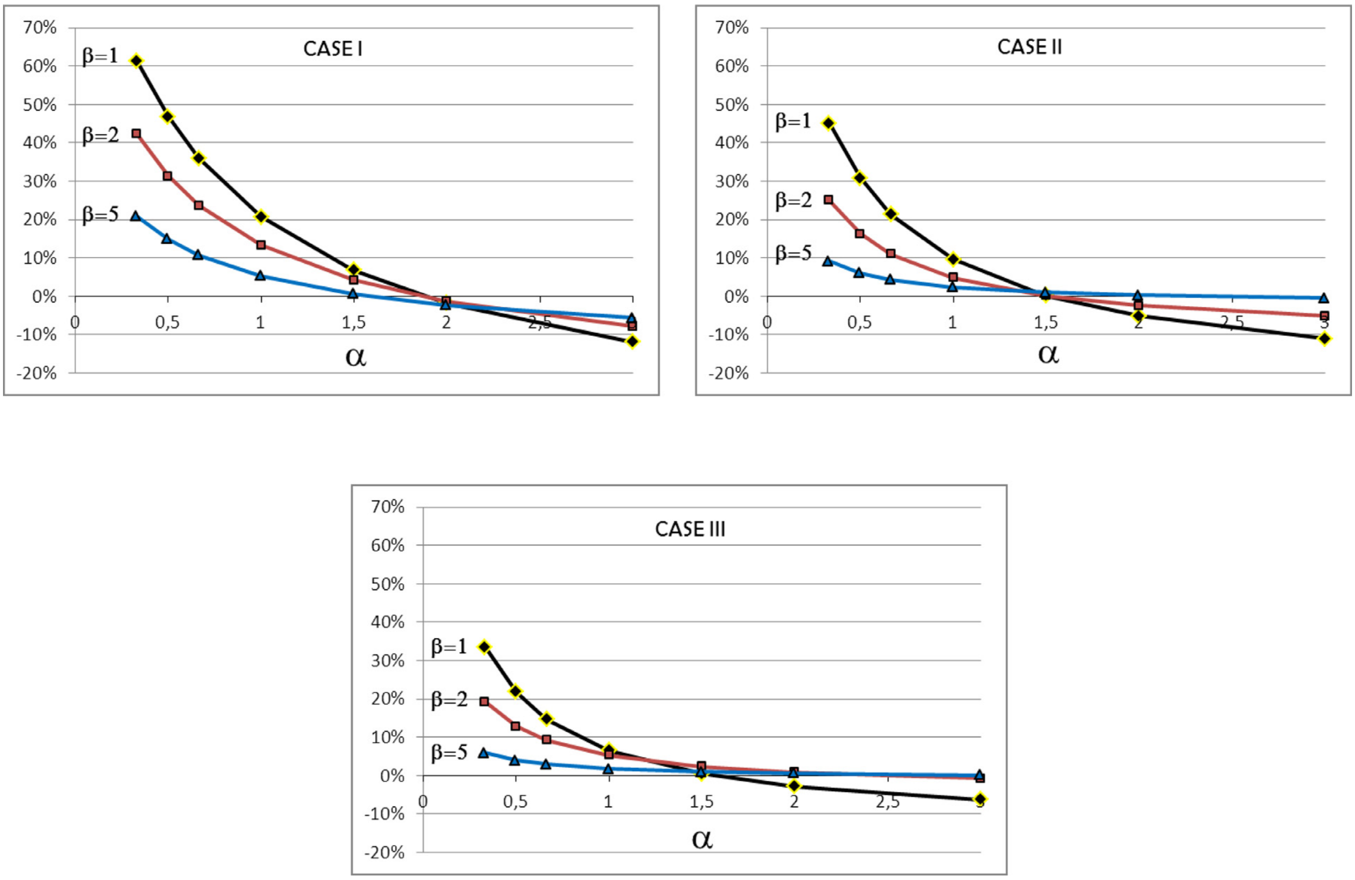

Fig. 10. Loss in total revenue corresponding to a discount speed factor $\gamma_{50\%}$.

For the $\alpha = 1$, $\beta = 2$ and $\gamma = 0.5$ scenario considered in Fig. 9, this leads to

$$R(0) = \int_0^L p_0 D_0 \left(1 - (a/_L)^2\right) da = \frac{p_0 D_0}{L^2} \int_0^L \left(L^2 - a^2\right) da = \frac{2 p_0 D_0 L}{3}. \tag{29}$$

For the parameter values $p_0 = 5$, $D_0 = 15$ and $L = 10$, this results in a value of $R(0) = 500$ m.u., independent of the initial inventory case considered.

Finally, note that if there is no price reduction, i.e. if $\gamma = 0$, the shape of both functions $S(t)$ and $R(t)$ is the same since they are proportional, i.e. $R(t) = p_o\, S(t)$. The difference in shape that can be observed in Fig. 9, however small, reflects the existence of price reductions in the $\gamma = 0.5$ scenario considered.

5.3. Effects of demand elasticity on total revenue

In order to measure the effect of demand elasticity, the reduction in total revenue corresponding to a reduction of 50% in spoilage will be considered. Let $\gamma_{50\%}$ be the smallest value of the discount speed factor γ that leads to a reduction larger than 50%. Such a value is variable and depends on the scenario considered. Fig. 10 shows the loss in total revenue (w.r.t. the $\gamma = 0$ no-discount scenario) that corresponds to the $\gamma_{50\%}$ policy.

It can be seen that the loss of total revenue clearly depends on the demand elasticity α, although that dependence is smaller as β increases. Note also that, actually, total revenue losses generally exist for demand elasticities below 1.5. Above that threshold, total revenue is practically maintained or even slightly increased. Interestingly, for high α values, the improvements in total revenue are higher as β decreases.

The scenarios in which the (negative) economic impact of spoilage reduction is higher, correspond to an inelastic demand (i.e. $\alpha < 1$). This is not surprising since, when demand is price inelastic, the effectiveness of price discounts, as a means to achieve demand increases, is rather limited. Actually, as α decreases below the unity threshold, the loss in total revenue increases at an exponential rate. This behavior occurs for the three initial inventory age profiles, although it is somewhat less acute for case III. As a rule of thumb, using the middle scenario (i.e. case II and $\beta = 2$) as the reference, it can be estimated that the total revenue loss for a 50% reduction in spoilage can be around 20% for the worst case of a rather low demand elasticity ($\alpha < 0.5$).

6. Conclusions

In recent times the interest in reducing spoilage, especially of food products, has increased not only because of its economic significance but also because of its social and environmental impact. Dynamic price strategies, i.e. offering aged units at a lower price than fresh units, are an effective way of reducing spoilage since customers are thus encouraged to demand less fresh but cheaper units. There is the risk, however, that if the price reduction is too steep or the price elasticity of demand too low, the price dynamic strategy may lead to a lower total revenue.

In order to measure and quantify the effects of these and other factors (such as the initial inventory age profile or the sensitivity of demand to the product age) on sales, revenue and spoilage, this paper proposes a continuous-time mathematical model that allows studying the depletion of a given initial inventory. The aim of this model is to gain insight and learn about the interactions between the dynamic price strategy and different factors considered.

In addition to the total sales and revenue, the corresponding age distribution can also be computed and analyzed. And not only can the total sales and revenue for the whole horizon be computed but also the value of those magnitudes in each time period. It has also been proven that an age-dependent price discount policy, such as the one considered, always reduces the number of units spoiled/wasted so that the higher the discount rate, the fewer the number of units reaching their end of life. Moreover, this effect is more evident as the price elasticity of demand increases.

A number of experiments have been carried out considering many different scenarios and the first remark to make here is that the behavior is different, depending on the scenario considered. In all of them, however, it is confirmed that the dynamic price strategy can significantly reduce total waste, often theoretically to a value close to zero. However, the effect on total revenue is not always positive. In some scenarios with high price elasticity of demand and large potential spoilage, total revenue can be slightly increased if the price is discounted. In some other cases, total revenue may be kept more or less constant, provided the price-discount speed is not too high. And in some other cases, generally involving low price elasticity, an age-insensitive demand or a not too aged initial inventory, there can be a substantial revenue loss that increases as the price-discount is performed faster.

The numerical results depend on the initial inventory profile and indicate, in some specific cases (e.g. those in which the price elasticity and/or the age sensitivity of the demand is small), that reducing the price reduces revenues without hardly increasing sales or reducing waste. In such cases the proposed approach would warn against (and discourage) the use of dynamic pricing. Thus, the advantage of the proposed approach is its ability to assess and compute the effects of a given price reduction policy in any specific situation.

Regarding the managerial consequences of the study carried out, we observed that the effects on revenue of marking down the products as they are approaching their expiry date, are very dependent on the demand elasticity, but, even when the product is very price inelastic, we have estimated that, in general, reducing the spoilage by 50% would have an impact on total revenue loss not exceeding 20%. In a more desirable scenario, if the demand elasticity is between 1 and 2, the loss in total revenue compatible with spoilage reduction is, in general, very small or non-existent. And, if the demand elasticity is above or equal to 2, it is possible to combine a significant reduction in spoilage with a small increase in revenue. As a conclusion, we can expect the dynamic price policy to be very effective in reducing spoilage without large reductions in total revenue (or even with small increases) for a large fraction of possible demand and consumer behavior scenarios, excluding those cases of low to very low values of price elasticity, especially when combined with insensitivity of demand to product age. In those unfavorable cases, some other alternative, different from price discounts, should be sought.

As regards limitations, there are some on which we would like to comment. Thus, for example, we have not considered the feasibility or the cost of implementing a continuous-time dynamic price strategy. Moreover, some researchers [35] argue that, in practice, prices are not generally changed smoothly, since only significant discounts will increase demand significantly. In addition, other issues that also affect demand and that can interact with the dynamic price strategy, such as displayed quantity effects, i.e. how the display of larger quantities of products can attract customers and increase demand, have not been considered. Also, although we have considered a deterministic scenario in our analysis, in principle, that price reduction can eliminate or reduce waste without hurting sales also applies to the case of stochastic demand. The experiments would have to be replicated a number of times to carry out a Monte Carlo simulation of the effects on total revenue and on total waste of each discount intensity value γ. The fact that we would have confidence intervals would complicate the analysis but similar conclusions might be expected, i.e. that, depending on the scenario, it is feasible to achieve waste reduction and revenue increase/preservation.

In any case, the present research can be considered as a first step, a proof of concept that the best of both worlds (more revenue and less spoilage) can be achieved through this type of dynamic pricing. The theoretical and empirical results obtained in this simplified approach are encouraging to further study more realistic and complex approaches. Thus, for example, it is possible to extend the analysis to an infinite horizon approach with successive cycles of a given length T (not necessarily equal to L) so that the initial inventory of each cycle is endogenously determined by the replenishment decisions and pricing policy used. Thus, for a given order size, at the beginning of each cycle (e.g. the first day of the week), the existing stock is replenished with fresh product, which ages along the week so that the inventory profile at the start of the following cycle depends on the order size and the dynamic pricing policy used (which determines the sales level). The decision problem is to determine the optimal values (in a Pareto sense) of the order size and the price reduction rate. Revenue and waste would be the two objective functions considered.

The proposed approach can also be extended so as to consider a discrete-time finite horizon with replenishment in every period and with fixed initial and final inventory profiles. The idea is to compute the amount to order each period and the price reduction rate (which can be the same or different in each period) that are optimal, in the bi-objective sense of maximizing revenue and minimizing waste. Studying those more realistic scenarios is, however, left for further research, provided that the advantages of the dynamic pricing policies studied in this paper have been well established.

Finally, although the proposed approach adopts a simplified, aggregate perspective in which differences in customers' behavior are not distinguished, from a micro perspective these differences between customers can be essential and should be modeled. Other factors, such as operating costs (including ordering and holding costs), lead times and reliability of suppliers, etc., would also increase the realism and practicality of the approach, which in turn would contribute to its implementability.

Acknowledgments

This research was carried out with the financial support of the Spanish Ministry of Science grant DPI2013-41469-P and the European Regional Development Fund (ERDF).

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Apéndice B

Informe con el Factor de Impacto de las publicaciones

El siguiente informe se ha realizado con los datos publicados en la Web of Knowledge.

Network and Spatial Economics

Publisher: Kluwer Academic Publishers.

ISSN: 1566-113X.

Subject area: Operations Research & Management Science.

Año	Factor de Impacto	Factor Impacto 5 años	Cuartil	Ranking
2015	3,25	2,438	Q_1	5/82
2014	2,085	2,081	Q_1	15/81
2013	1,803	1,64	Q_1	16/79

Tabla B.1: Índice de impacto anual revista Network and Spatial Economics

Transport

Publisher: Vilnius Gediminas Technical University.

ISSN: 1648-4142 E-ISSN:1648-3480.

Subject area: Transportation Science & Technology.

Año	Factor de Impacto	Factor Impacto 5 años	Cuartil	Ranking
2015	0,594	0,625	Q_4	27/33
2014	0,553	0,618	Q_4	25/33
2013	0,529	0,642	Q_3	23/32

Tabla B.2: Índice de impacto anual revista Transport

Applied Mathematical Modelling

Publisher: Elsevier Inc.

ISSN: 0307-904X

Subject area: Engineering, Multidisciplinary.

Año	Factor de Impacto	Factor Impacto 5 años	Cuartil	Ranking
2015	2,291	2,4	Q_1	12/85
2014	2,251	2,326	Q_1	11/85
2013	2,158	2,195	Q_1	12/87

Tabla B.3: Índice de impacto anual revista Applied Mathematical Modelling

Apéndice C

Artículo en revisión

Analysing the factors that influence the Pareto frontier of a bi-objective supply chain design problem

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Abstract — In this paper a bi-objective multi-product model for the design of a production/distribution supply chain logistic network with four echelons is considered. The proposed optimization model minimizes the total cost of the network (including the fixed cost to open facilities and the transportation costs between them) and the total CO_2 emissions. Five factors (network size, product complexity, cost variability, CO_2 emissions generation and over-capacity) are considered for the experimental framework. The problem is solved using the ε-constraint method and the resulting Pareto frontiers are characterized using five new metrics specifically developed for analysing how those factors affect the resulting optimal configurations. The results show that over-capacity and product complexity are the two most influential factors regarding the characteristics of the Pareto frontier, and that their effects are in the same direction: more complexity and capacity mean a wider set of optima alternatives, some close to the ideal point, and in general with a smaller number of links used.

Keywords: logistics network design; bicriteria optimization; Pareto frontier; cost minimization; emissions minimization; product complexity

1. Introduction

A supply chain logistic network can be described as a graph where the nodes represent suppliers, producers/manufacturers, distribution centres, warehouses, and customers; and the set of arcs represent the transportation links between these facilities. Although there are other nodes that can be considered when designing a supply chain logistic network (e.g. recycling centres, assemblers, recovery plants) those four echelons are those traditionally taken into account when analysing supply networks (Sabri and Beamon, 2000).

During the last decades the study of logistic networks has grown notably with many works studying different kinds of problems related to supply chains. Note that most of these studies only consider a single objective function, usually cost (Mangiaracina et al., 2015). However, this may be insufficient today due to the increase in the complexity of the management of supply chains in recent decades, with an increase in competition, lead times reduction, operational risk, environmental constraints, etc. Hence, considering multiple objectives simultaneously when designing logistics structures is a field that represents a more realistic view of the current situation.

This research effort in designing better multiobjective logistics networks is expanding this field and involves different approaches. They can be divided into different groups according to their research objectives, the corresponding decisions in the design process, and the corresponding solution methodologies.

Regarding the first dimension, there are many different objectives that have been studied simultaneously in multiobjective optimization problems; revenue, sustainability, lead times, service level, financial criteria, and production-related objectives are the most popular. Profit-related objectives are included in almost every piece of research because minimization of costs (or maximization of profit) is generally considered as the first key objective. The rest of the objectives can be found in combination with the cost minimization objective, depending on the particular interest of the company or researcher, with sustainability, lead time and service level (i.e. percentage demand fulfilled) as the most popular. Figure 1 gives a summary of the number of references dealing with multiobjective approaches to logistic network design.

--FIGURE 1----------------------------------

The second dimension, namely the decisions to be made in a logistic network design process, is another important aspect when dealing with a multiobjective problem. The most common decisions in a logistic network are the facilities' locations and the transportation flows. There are some cases where this problem is extended to include capacity decisions both for the facilities and the transportation links, or routing (Lopes et al., 2013). Other decisions in multiobjective logistic networks that are frequently studied are the number of products manufactured, the inventory levels of the facilities and the uncertainty level (Mangiaracina et al., 2015).

Finally, regarding the solution methodologies for multiobjective logistic network design problems, many different alternatives exist, including exact and metaheuristic methods, depending on the type of mathematical model and its complexity. A well known taxonomy for multiobjective optimization techniques can be found in Marler and Arora (2004), which presented a review, dividing them into methods with *a priori* articulation of preferences, methods for *a posteriori* articulation of preferences, methods with no articulation of preferences, and multiobjective evolutionary algorithms.

Regardless of whether a single objective or a multiobjective approach is used to design a supply chain network, it is clear that there are many factors, some of them uncontrollable (e.g. infrastructure, Customs clearance, etc., see Önsel Ekici et al., 2016) that affect the optimal design. In their review of the topic, Mangiaracina et al. (2015)

identified 42 factors affecting the performance of supply chain networks, which they grouped into five clusters; the most recurrent were related to demand as well as to service requirement. They note that issues, such as number of plants and specialisation level of factories, have been considered in many researches (e.g. Ambrosino and Scutella, 2005). Also, supplier related variables, such as number of suppliers and items, are relevant from the point of view of the modeller (Creazza et al., 2010). Many researchers have studied how some relevant factors, such as network size (e.g. Özceylan, 2016), or collection complexity in the case of reverse supply chains (e.g. Zikopoulos and Tagaras, 2015), affect the design of the supply chain, but these studies generally consider a single criterion, namely cost minimization. To the best of our knowledge there has not been any previous attempt to study how different factors affect the performance of a supply network gauged using multiple objective functions.

In this paper, we consider a bi-objective multi-product model for a production/distribution supply chain logistic network with four echelons (suppliers, plants, warehouses and customers). The aim of the model is to minimize the total cost of the network (including the fixed cost of suppliers, plants and warehouses, the cost of the components' flows between suppliers and plants, the cost of the products' flows between plants and warehouses, and the cost of the products' flows from warehouses to customers) as well as to minimize the total CO_2 emissions (including the total CO_2 emissions of the facilities and of transport). Regarding the solution methodology, the ε-constraint method (Ehrgott and Ruzika, 2008) is used to find the set of Pareto-optimal solutions for the problem. The research objective is to use this model to better understand how the quality of the potential solutions (in terms of cost and CO_2 emissions targets) change, depending on certain characteristics of the network (size, complexity, capacity, cost variability, etc.). Note that this means analysing the characteristics of different Pareto-optimal solutions sets, each one corresponding to a different instance, trying to come to some conclusions about the nature of the solutions, depending on some factors characterizing the instances. As far as we are aware, nothing similar has been done before. There are many papers (see for example Berezkin and Lotov, 2014) that compare different approximations of the Pareto frontier (PF) (obtained using different methods) but for a specific instance. However, in this paper we compute, using the ε-constraint method, the PF corresponding to different instances, proposing different metrics to analyse and compare the characteristics of these solutions sets.

The structure of the paper is as follows. In section 2 a brief literature review of multiobjective production/distribution networks is presented. In section 3 the bi-objective model and the proposed solution methodology are presented. Section 4 reports the results of the experimental design carried out. Finally, in section 5, the summary and conclusions of this study are presented.

2. Literature review

Although supply production/distribution networks have been studied for years it has not been until recently that researchers began to consider multiobjective supply chains' designs. The different objectives considered in the literature can be classified into four main groups: economic, sustainability, service level and time-related. Since historically supply chain network design has been strongly linked to the profit/cost criterion, most of the multiobjective papers have at least one of their objectives related to economic aspects such as cost minimization, profit maximization or network present value (NPV) maximization.

Several authors have considered, along with the economic objective, the minimization of the environmental impact or sustainability-related objectives. Thus, Luo et al. (2001) considered the maximization of productivity and the minimization of cycle time in addition to costs and environmental impact. Meanwhile, Dotoli et al.

(2006) considered, as additional objectives, the minimization of both energy consumption and total lead time. For measuring the environmental impact Life Cycle Assessment (LCA) is the most common methodology. Thus, for example, Amin and Zhang (2013) modified their three-echelon closed-loop supply chain network cost minimization model, introducing environmental issues and defining new parameters for the use of environmentally friendly materials and clean technology. You et al. (2012) also used LCA in the design of sustainable cellulosic biofuel supply chains. Other researchers have used well-known Life Cycle Impact Assessment (LCIA) methodologies, such as Eco-Indicator 99 (e.g. Hugo and Pistikopoulos, 2005; Pishvaee and Razmi, 2012) or Ecoinvent (e.g. Ruiz-Femenia et al., 2013). But perhaps the most common multiobjective approach is to minimize cost and CO_2 emissions (e.g. Puji Nurjanni et al., 2016), sometimes also minimizing other pollutants (e.g. Kadziński et al., 2016).

Another type of objective that is often studied, combined with cost minimization, is related to the time dimension, such as minimizing tardiness, lead time or transport time. Thus, for example, Farahani and Elahipanah (2008) designed a three-echelon supply chain to determine the transportation flows between facilities by considering two objective functions: the minimization of transportation, holding and purchasing costs, and minimization of the earliness and tardiness of deliveries. Similarly, cost and tardiness minimization can be found in Du and Evans (2008) and Pishvaee and Torabi (2010). These two objectives plus a third one (maximization of the coverage of customer zones) can be found in Li et al. (2012); they study the location of the collection points and repairing centres as well the transportation flows among facilities in a reverse logistics network. Minimizing costs and delays are also considered in Javanshir et al. (2012); these determine the production plan, flows and number of distribution centres that must be opened to satisfy customers' demand. Other researchers (e.g. Cardona-Valdés et al., 2011; Olivares-Benitez et al., 2012) have studied the Capacitated Fixed Cost Facility Location Problem with Transportation Choices determining the location of distribution centres and the flows between the facilities, in order to minimize the costs and transportation time of the product from the plant to the customer.

Another objective, usually related to time, is maximization of the customer service level (a.k.a. fill or service rate). That is because improvements in transportation times, tardiness or delivery times, lead to improvements in customer service levels. Pishvaee et al. (2010) studied an integrated forward/reverse network determining the location, number and capacity of facilities and the transportation flows between them. They considered as objectives the minimization of the total cost of the system and the maximization of the responsiveness as the ratio of the quantity of products shipped from distribution centres to customers and the total amount of products demanded by customers. Latha Shankar et al. (2013) measured the customer service level by the product fill rate and the cycle service level (i.e. fraction of replenishment cycles that result in all the customer demands being met). Razmi et al. (2013) also considered the service level by maximizing the coverage percentage of customer demand delivered within the preferred delivery lead time, by considering multiple scenarios with a given probability of occurrence.

Other criteria that can be found in combination with cost minimization are total cost variance and financial risk (Azaron et al., 2008), delivery reliability (Pokharel, 2008), etc. It is also common, in the case of closed-loop supply chains, to minimize costs and risk due to uncertainty in demand, recovery and disposal rates (e.g. Dai and Dai, 2016).

Other papers maximize profit instead of minimizing cost. Thus, for example, Chen et al. (2003) consider as objectives the maximization of profit and the maximization of the average inventory level. Chen and Lee (2004) added to those objectives the maximization of the average customer service level and the maximization of the network robustness. Franca et al. (2010) considered as objectives the maximization of profit and the minimization of the suppliers' defects. Pinto-Varela et al. (2011) combined the maximization of profit with minimization of the environmental impact. Amin and Zhang (2012) maximize profit, minimize defect rates and maximize the importance of external suppliers. Ramezani et al. (2013) maximize total profit and customer service level and minimize total defective raw material.

3. Methodology

Let us consider a standard supply chain logistic network (e.g. Sabri and Beamon, 2000; Pokharel, 2008) with four echelons (suppliers, plants, warehouses and customers; see Figure 2) in a multiproduct environment where the customer demand for each product is known. The aim of the problem is to satisfy the demand of each customer from the different plants using the appropriate warehouses and suppliers' configuration.

--FIGURE 2----------------------------------

We will consider a bi-objective optimization approach, taking into account on the one hand the minimization of the total cost, and on the other hand the minimization of the total CO_2 emissions. Two different costs are considered: fixed cost (i.e., the operating cost of the facilities) associated with each node of the graph (excluding customers), and the costs of the transportation links between nodes (i.e. the transportation costs between facilities, and between facilities and customers). Regarding the emissions, each node (again excluding customers) and transportation link has an associated index, which represents the amount of emissions generated expressed as a percentage of the flow in that node or link.

The operation of the supply chain represented in our model is as follows: suppliers provide components and raw materials to plants for manufacturing the products. The number of components and the composition of products (i.e. the quantity of each component needed to be manufactured) are known as well as the types of components that can be provided by each supplier. With the components/raw materials received from suppliers, plants manufacture the products and send them to warehouses. Finally, products are distributed from warehouses to each customer satisfying their demand. We consider a capacitated model, i.e. every facility and transportation link has an associated limit on the amount of each product or component processed or transported.

The notation used in our model is as follows (see Figure 2):

B(k): Set of components/raw materials needed to manufacture product k.

S(b): Set of suppliers that provide component/raw material b.

P(k): Set of plants that manufacture product k.

D_c^k: Demand of customer c for product k.

g_b^k: Quantity of component/raw material b needed to manufacture a unit of product k.

U_s^b: Capacity of suppliers as regards component/raw material b.

U_p^k, U_w^k: Capacity of plant p and warehouse w, respectively, as regards product k.

$U_{sp}^b, U_{pw}^k, U_{wc}^k$: Transport capacities between two consecutive echelons.

$c_{sp}^b, c_{pw}^k, c_{wc}^k$: Transport unit cost between two consecutive echelons.

F_s, F_p, F_w: Fixed operating cost for suppliers, plants and warehouses.

$r_{sp}^{b}, r_{pw}^{k}, r_{wc}^{k}$: Emission rate between two consecutive echelons.

$r_{s}^{b}, r_{p}^{k}, r_{w}^{k}$: Emission rate of suppliers, plants and warehouses.

z_{s}, z_{p}, z_{w}: Binary variables for the opening of suppliers, plants and warehouses.

$x_{sp}^{b}, x_{pw}^{k}, x_{wc}^{k}$: Quantity of material sent between two consecutive echelons.

With all this information, the proposed model used for deciding the optimal configuration is [1]-[12]:

$$Min \sum_{k}\sum_{w}\sum_{c} c_{wc}^{k} \cdot x_{wc}^{k} + \sum_{k}\sum_{p\in P(k)}\sum_{w} c_{pw}^{k} \cdot x_{pw}^{k} + \\ + \sum_{k}\sum_{p\in P(k)}\sum_{b\in B(k)}\sum_{s\in S(b)} c_{sp}^{b} \cdot x_{sp}^{b} + \sum_{w} F_{w} \cdot z_{w} + \sum_{p} F_{p} \cdot z_{p} + \sum_{s} F_{s} \cdot z_{s} \quad [1]$$

$$Min \sum_{k}\sum_{w}\sum_{c} (r_{wc}^{k} + r_{w}^{k}) x_{wc}^{k} + \sum_{k}\sum_{p\in P(k)}\sum_{w} (r_{pw}^{k} + r_{p}^{w}) x_{pw}^{k} + \\ + \sum_{k}\sum_{p\in P(k)}\sum_{b\in B(k)}\sum_{s\in S(b)} (r_{sp}^{b} + r_{s}^{b}) x_{sp}^{b} \quad [2]$$

s.t.

$$\sum_{w} x_{wc}^{k} = D_{c}^{k} \quad \forall c\ \forall k \quad [3]$$

$$\sum_{p\in P(k)} x_{pw}^{k} = \sum_{c} x_{wc}^{k} \quad \forall w\ \forall k \quad [4]$$

$$\sum_{s\in S(b)} x_{sp}^{b} = \sum_{k} g_{b}^{k} \sum_{w} x_{pw}^{k} \quad \forall p\ \forall b \quad [5]$$

$$x_{wc}^{k} \le U_{wc}^{k} \quad \forall w\ \forall c\ \forall k \quad [6]$$

$$x_{pw}^{k} \le U_{pw}^{k} \quad \forall w\ \forall k\ \forall p \in P(k) \quad [7]$$

$$x_{sp}^{b} \leq U_{sp}^{b} \quad \forall p \in P(k) \forall b \in B(k)\ \forall s \in S(b) \tag{8}$$

$$\sum_{c} x_{wc}^{k} \leq U_{w}^{k} \cdot z_{w} \quad \forall w\ \forall k \tag{9}$$

$$\sum_{w} x_{pw}^{k} \leq U_{p}^{k} \cdot z_{p} \quad \forall k\ \forall p \in P(k) \tag{10}$$

$$\sum_{p} v_{sp}^{b} \leq U_{s}^{b} \cdot z_{s} \quad \forall k\ \forall b \in B(k)\ \forall s \in S(b) \tag{11}$$

[11]

$$x_{wc}^{k}, x_{pw}^{k}, v_{sp}^{b} \geq 0 \quad \forall c\ \forall w\ \forall k\ \forall p \in P(k)\ \forall b \in B(k)\ \forall s \in S(b)$$

[12]

$$z_{w}, z_{p}, z_{s} \in \{0,1\} \quad \forall w\ \forall p\ \forall s$$

The first objective function represents the total cost, including the fixed cost of open suppliers, plants and warehouses, the cost of component/raw material flows between suppliers and plants, the cost of product flows between plants and warehouses, and the cost of product flows from warehouses to customers. The second objective function minimizes the total CO_2 emissions, including the total CO_2 emissions at the facilities and the total CO_2 emissions due to transport.

Regarding the constraints, [3] ensures that the demand of all customers must be satisfied; [4] ensures that the quantity of product *k* transported from the different plants to warehouse *w* is exactly the same as the total amount of product *k* transported from warehouse *w* to customers; [5] ensures that the quantity of component/raw material *b* transported from suppliers to plant *p* is equal (using the corresponding gozinto factors) to the quantity of products generated in plant *p* and hence transported from plant *p* to warehouses; [6]-[7] ensure that the transportation flows of product *k* from plants to warehouses and from warehouses to customers do not exceed the corresponding capacities on those links; [8] ensures that the transportation flows of component/raw material *b* from suppliers to plants do not exceed the corresponding capacities on those links. Analogously, [9]-[11] ensure that the capacities of facilities are not exceeded. Finally, constraint [12] ensures that all flows are non-negative and that the facilities opening decision variables are binary.

4. Experimental results

In order to solve the above model, the ε-constraint method is used. This methodology, introduced by Haimes et al. (1971), consists of the minimization of the main objective function considering all the other objectives as additional constraints on the model, using appropriate bound parameters ε_i (for the emissions in our case). By a systematic variation of the value of the bounds ε_i, a set of Pareto solutions is found (Figure 3). However, an incorrect selection of ε_i can lead to a formulation without a feasible solution. However, there are multiple studies on the methods for the selection of the values ε_i reflecting preferences (e.g. Goicoechea et al., 1976; Cohon, 1978; Carmichael 1980). Thus, if they exist, the solutions obtained using the ε-constraint method are weak, Pareto-optimal and every weak Pareto-optimal point can be obtained if the feasible region is convex and all the objective functions are explicitly quasi-convex (Ruíz-Canales and Rufian-Lizana, 1995). If the solution is unique, then it is Pareto-optimal. Obviously, verifying uniqueness is difficult, so it is generally accepted to obtain solutions belonging to the weak Pareto-optimal frontier.

---FIGURE 3----------------------------------

4.1. Comparing Pareto frontiers

For the analysis of the solutions of the proposed approach, we will generate 22 points in each of the PFs for each instance solved. However, having obtained the frontiers, for analysing the results how to compare these sets of solutions is not straightforward. For this purpose, we have developed five different measures for the evaluation of the PF that can be used to identify the main characteristics of each PF. These measures are:

1. **Average difference in open facilities (ADOF).** We note that each point of the PF is a specific design of the logistic network (i.e. a configuration), including open facilities and flow (Figure 3). Ignoring the network flows $\{x^*_{**}\}$, that point can be assigned a vector $Z=\{0,1\}^n$ defining just which facilities (i.e. nodes) are open. Looking at that information, we can compare two solutions A and B of the PF by using the Hamming distance $d(A, B) = \sum |Z_i^A - Z_i^B|$. The ADOF is defined for each instance by calculating the distance between each pair of points (i.e. 22x21/2=231 distances) and taking the average of all of them. Small values of ADOF mean that most points in the PF open the same facilities (independently of the product flows among them).
2. **Number of different "open facilities" solutions (NDOFS) in the PF.** A variant of the previous idea is to count the times that the exact same facilities are open in the solutions of the PF. A small value means that there are only a few optimal alternatives regarding the facilities opened (although the flows among them could imply different costs and emissions).
3. **Percentage of links used (PLU) in the solutions.** Considering now the flows in the solutions, an interesting characteristic of a specific solution is the total number of links used (number of links with non-zero flows x_{sp}^b, x_{pw}^k, x_{wc}^k), as a percentage of the total number of potential links of the network, and calculate the average for the different points of the PF. High values of PLU mean that the

network density and complexity increases as more connections (i.e. transportation links) are used.

4. **Percentage of area of the triangle covered (PATC).** Another characteristic of interest is how far the PF is from the segment CD (see Figure 3). To measure PATC, the ratio between the area of the curved region CDI (delimited below by the PF), and the area of the triangle C-D-I are calculated. Therefore, a value close to 1 means that there are solutions in the PF close to the Ideal Point I, so that solutions with a good compromise between both objective functions can be found.
5. **Distance between extreme solutions (DES) C-D.** The last measure we consider is the Euclidean distance of the segment CD, i.e. the Euclidean distance between the best cost solution and the best emissions solution. High values of DES mean that Pareto-optimal solutions are very different in quality (some with low cost and high emissions, and others with low emissions and high cost).

4.2. Experimental framework

The above five measures are used to analyse the shape of the PFs obtained in an experimental framework involving five different factors (each with two levels) that were considered relevant for this problem:

F1. Network size. This factor considers the number of nodes on each echelon of the network. At the low level we consider N=5 nodes for suppliers, plants and warehouses and M=250 nodes for customers; the high level considers N=10 nodes for suppliers, plants and warehouses and M=500 nodes for customers.

F2. Product Complexity. This factor takes into account the complexity in the manufacturing of the products (the number of products manufactured and the number of facilities that can supply each component or manufacture each product). We consider two complexity levels with instances randomly generated using the values shown in Table 1.

--------------------------------------- TABLE 1 --

F3. Cost Variability. The influence of the difference of the cost coefficients inside the echelons is considered here. For each echelon, the fixed costs of the facilities and unit transportation costs of the links are randomly generated from uniform distributions according to the two levels considered (see Table 2).

--- TABLE 2--------------------------------------

F4. Emissions generation. This factor determines the intensity of the emissions generation in the facilities and links. The values are randomly generated from uniform distributions according to the two levels considered (U(0.008,0.12) for the low level; U(0.05,0.15) for the high level, in all the cases).

F5. Over-capacity. The last factor considered is the over-capacity of the facilities and links with respect to the demand to be satisfied. In this case, the two levels are low and high over-capacity. For the low over-capacity level we consider that the ratio between the demand and the overall sum of capacities is around 0.5, while for the case of high over-capacity we consider that the ratio between the demand and the overall sum of capacities is around 0.25 (i.e. the demand is not so critical, when considering the available capacity).

Therefore, the experimental framework has a total of 2^5=32 factor level combinations. Five instances for each factor level have been generated and each one has been solved using the ε-constraint method. Thus, in total we have 160 instances and a 22-point PF for each instance. R statistical software (https://www.r-project.org/) was used for all the statistical analysis.

4.3. Results

Starting with the ADOF metric, the boxplot charts (Figure 4) suggest that factors F2 (product complexity) and F5 (over-capacity) results are especially significant regarding the ADOF values of the resulting PFs. The corresponding ANOVA (Table 3) confirms that both factors are the most significant affecting this metric. Therefore, a smaller number of similar configurations regarding the opening of facilities are obtained when the product complexity is low or when the capacity is becoming a problem. Also, ANOVA shows that factor F1 has a somewhat significant influence as well.

--------------------------------------- FIGURE 4 ---

--------------------------------------- TABLE 3 ---

For the second metric (NDOFS) the boxplot chart (Figure 5) indicates again that factors F1, F2 and F5 seem to significantly affect the number of different optimal solutions that can be found for each instance – something that ANOVA confirms. This means that when the size of the problem is smaller, the product structure is simpler or the over-capacity is low (no over-capacity); in general, there are just a few optimal options as regards the different facilities to open.

--------------------------------------- FIGURE 5 ---

Regarding the PLU, it can be clearly seen in Figure 6 that factor F5 (over-capacity) and also F2 (product complexity) have a big influence in this metric. Since in this case normality is not granted, we used a nonparametric Mann-Whitney U Test to confirm ($p \approx 0.0$) the influence of both factors. Therefore, a smaller number of links are used when the product structure is more complex or when the capacity is enough for the requested demand.

--------------------------------------- FIGURE 6 ---

As regards the PATC metric, according to the boxplots shown in Figure 7, the factors with more influence in this measure seem to be F1, F3 and F5, which is confirmed by the corresponding ANOVA. In general, solutions closer to the ideal point can be found for smaller networks (F1 low level) than for larger ones. When cost variability in each echelon is low, solutions closer to the ideal point can also be computed. Finally, the same result is obtained when there is large over-capacity.

--------------------------------------- FIGURE 7 ---

Finally, as regards the DES, the boxplots in Figure 8 suggest that factors F2 and F5 are those with the largest influence. As this DES response variable does not fulfil the conditions required for an ANOVA study, the nonparametric Mann-Whitney U Test is used again to confirm the assumption that F2 and F5 are significant ($p \approx 0.0$). Therefore, when the product structure is less complex or when the over-capacity is low (tight capacity available), the difference between the minimum cost and the minimum emission solution is smaller.

--------------------------------------- FIGURE 8 ---

The influence of each of the five factors on each metric is summarized in Table 4. The most influential factor is the amount of over-capacity (F5): when the over-capacity is high (i.e., there are enough resources to cover the demand), more optimal solutions with different open facilities appear in the PF, a smaller percentage of links are used, the distance between the minim cost and minimum emissions solutions is larger and the PF in general contains points close to the ideal solution. Similar effects can be observed for the next influential factor, product complexity (F2).

Network size (F1) also has some influence on the number of different open facilities solutions (higher when the network size is large) as well as on the possibility of finding solutions close to the ideal (less likely when the network size is large). Cost variability (F3) also has an influence as regards the possibility of finding solutions close to the ideal (more likely when costs are more similar). Finally, the emissions generation factor (F4) does not seem to have much influence on the type of solutions that form the PF.

--------------------------------------- TABLE 4 --

5. Conclusions

This paper defines a bi-objective multi-product model for a production/distribution logistic network with four echelons considering not only the cost of the operating facilities and the costs of transport between suppliers, warehouses and customers, but also the emissions generation in each facility and in the transport operations. Five factors are considered in order to study different scenarios, our goal being to study the characteristics of the PF solutions obtained, depending on the network type. To do so, five new measures were defined to characterize the different PFs obtained: the average difference in the facilities open, the number of different open facilities solutions, the closeness to the ideal point, the percentage of arcs used in the solutions, and the distance between extreme solutions.

The results obtained were analysed with R software in order to study the influence of the different factors on each measure. It was found that the level of over-capacity and the product complexity have the largest influence in the Pareto-optimal solutions of the supply chain design problem, having a significant impact on all five measures defined. Large over-capacity implies more alternative solutions with different facilities open, more extreme optimal costs/emissions solutions, fewer arcs used and less difficulty to obtain solutions close to the ideal. High product complexity has almost the same effects (except in the difficulty to compute solutions close to the ideal). A smaller influence has the network size, with larger networks leading to more alternative Pareto-optimal solutions and solutions less close to the ideal. Finally, higher cost variance seems to affect the possibility of finding solutions close to the ideal.

We can therefore conclude that the consideration of more than one objective function allows trade-offs between them and that the shape and extension of the corresponding PF depend on a number of factors, especially on the over-capacity level and the product complexity. Thus, the higher both factors are, the smaller is the number of arcs used and the higher the number and diversity of Pareto-optimal solutions that can be computed. With respect to further research, an important issue to consider is to analyse the case when not only emissions are generated but there can also be different levels of spoilage depending on the facilities and the transportation links used.

Acknowledgements. This research was carried out with the financial support of the Spanish Ministry of Science grant DPI2013-41469-P and the European Regional Development Fund (ERDF).

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	FINANCE	PROD	SERV	TIME	SUST
FINANCE	2				
PROD	2	2			
SERV	3	7	7		
TIME	2	4	4	12	
SUST	1	1	1	3	14

Figure 1. Number of references (period 2000-2015) dealing with multiobjective supply chain network design (all of them include in addition cost/profit optimization, i.e., dealing with sustainability, time, and cost/profit, three papers were found)

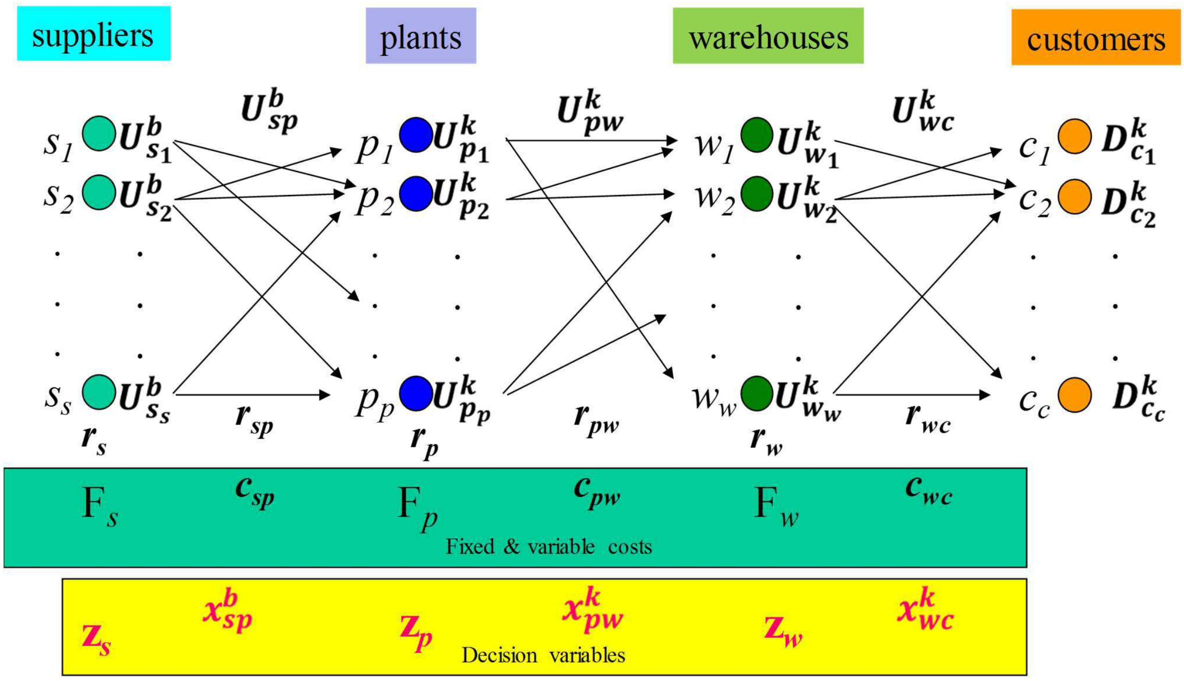

Figure 2. Four-echelon supply chain, and involved parameters and decision variables

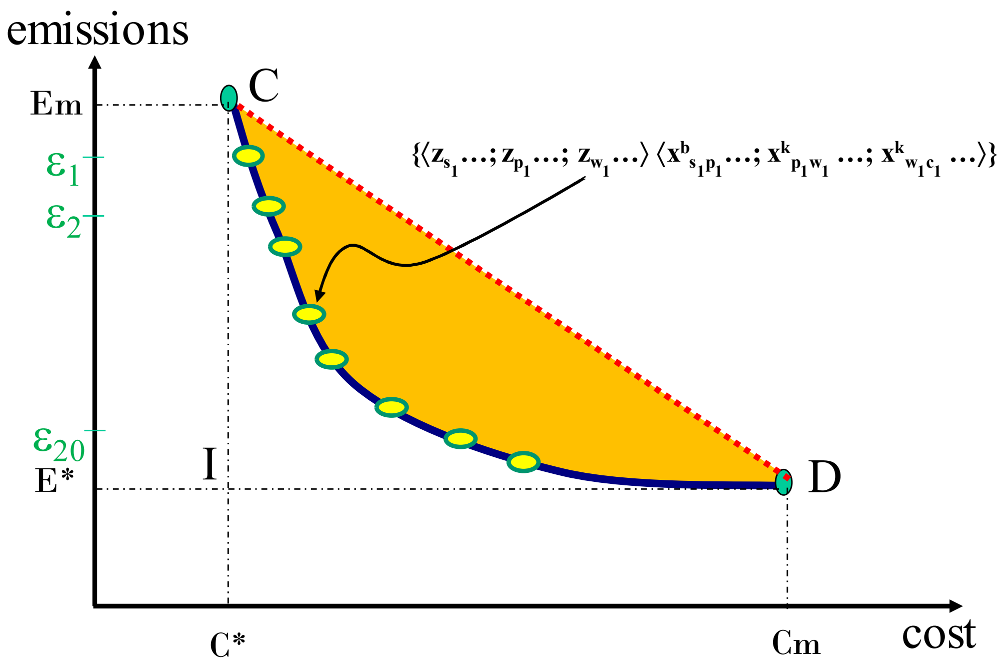

Figure 3. Pareto Frontier for cost and emissions

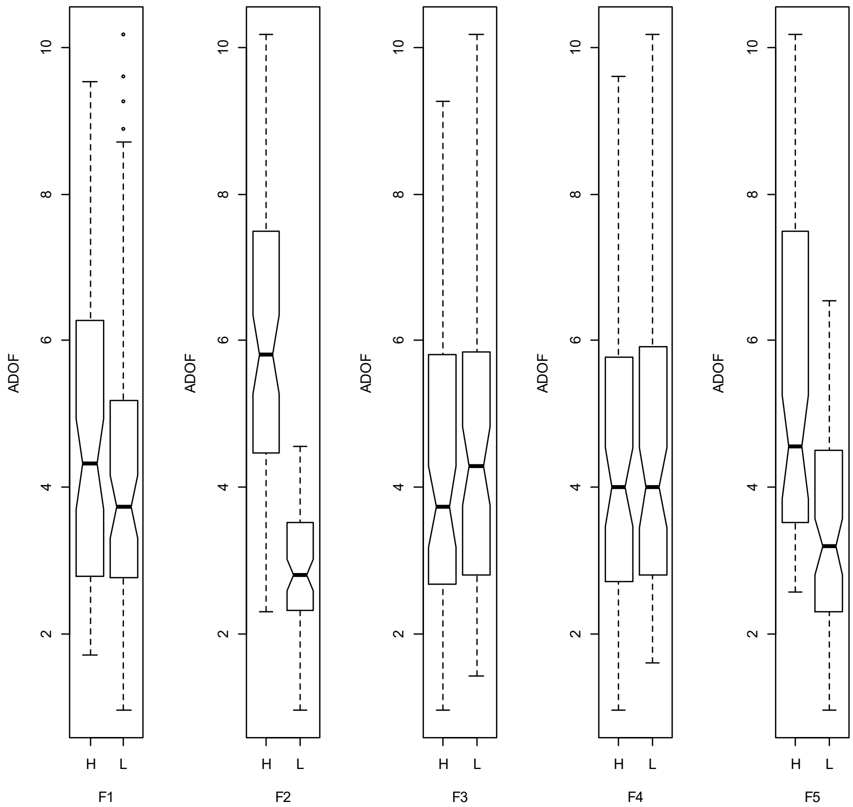

Figure 4. ADOF boxplot for each factor

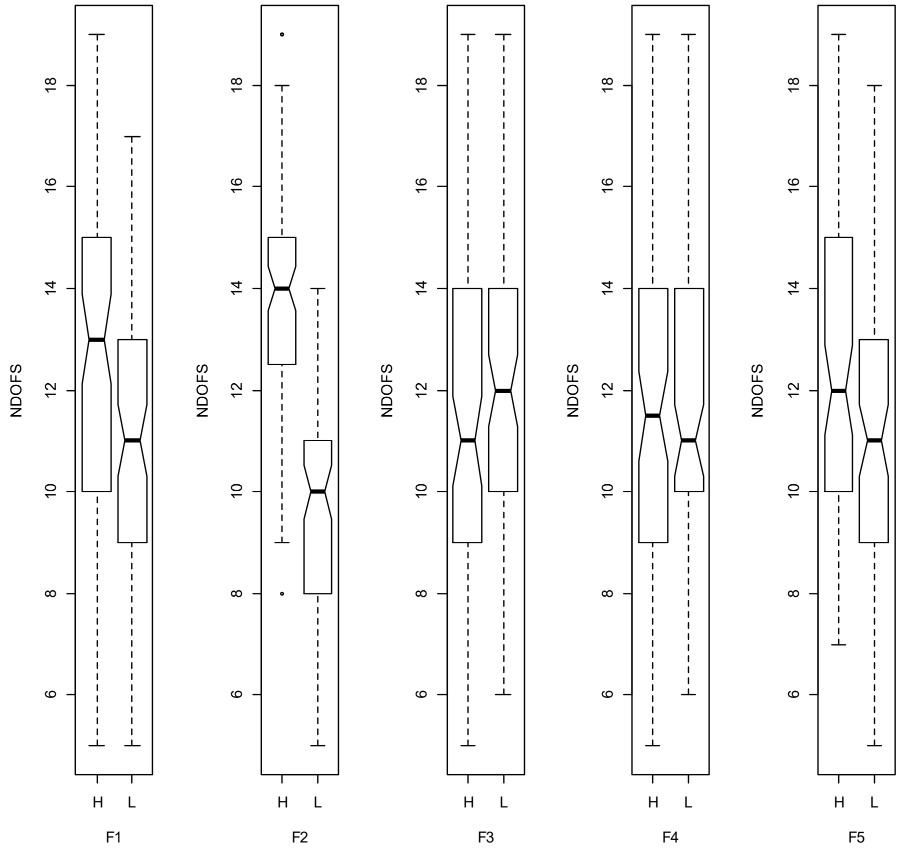

Figure 5. NDOFS boxplot for each factor

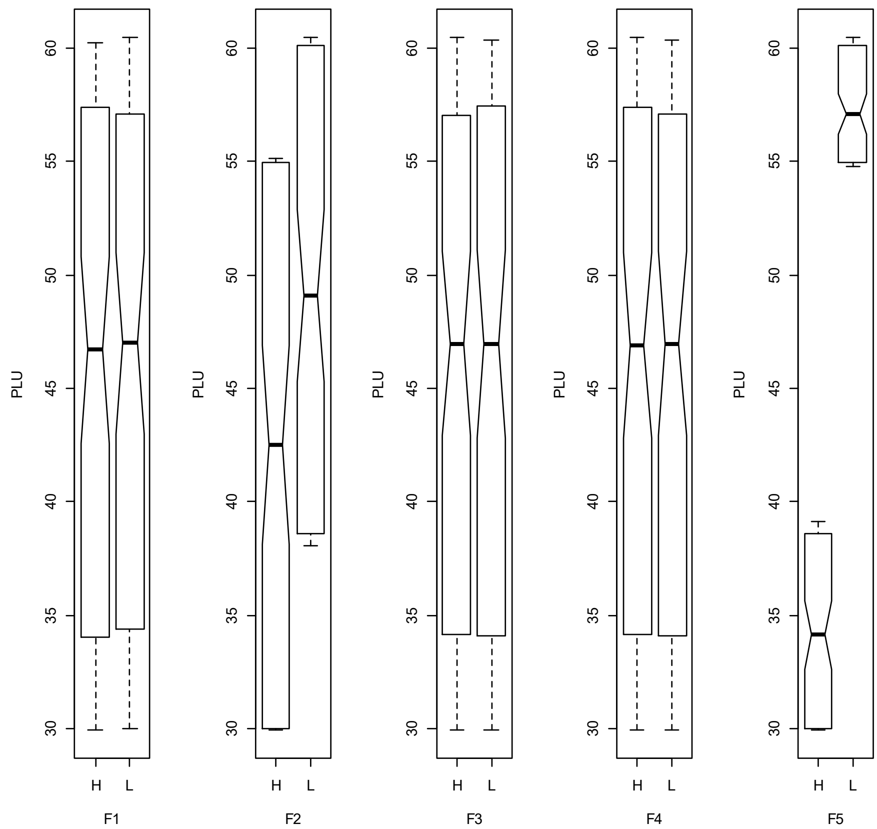

Figure 6. PLU boxplot for each factor

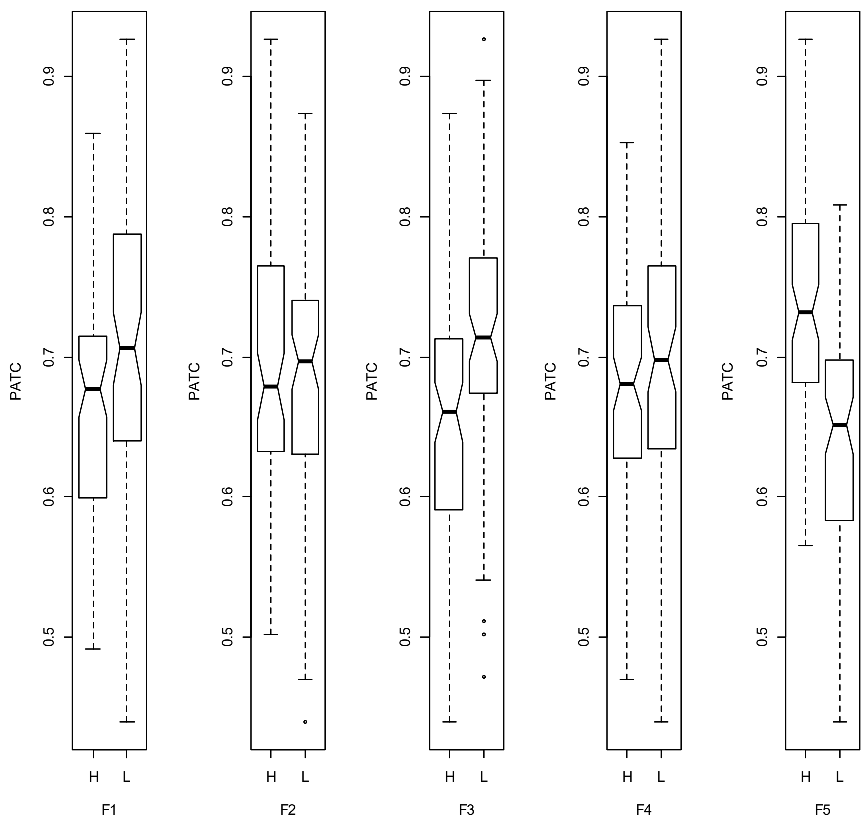

Figure 7. PATC boxplot for each factor

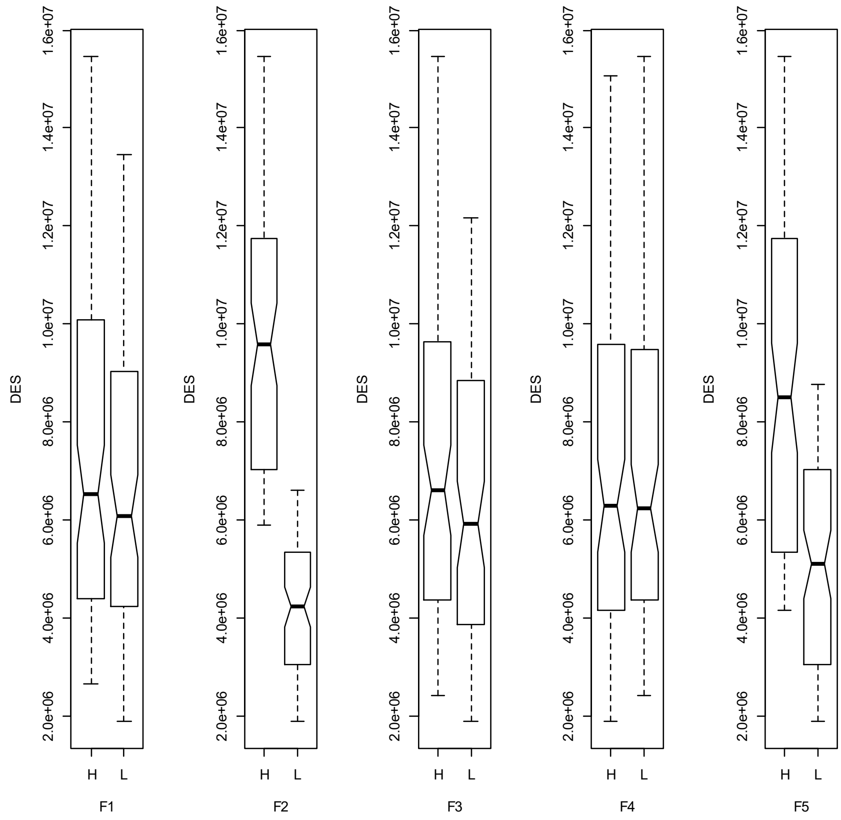

Figure 8. DES boxplot for each factor

Suppliers	Plants	**F2**	Products	Components/Product	Components	Plants/Product	Components/Supplier
5	5	**Low**	4	2	8	3	3
5	5	**High**	7	4	8	5	5
10	10	**Low**	4	2	8	3	3
10	10	**High**	7	4	8	10	5

Table 1. Levels corresponding to F2 (product complexity)

Cost Variability	Fixed costs			Variable costs	
	Suppliers	Plants	Warehouses	Mean	Coef. Variat.
Low	U(580000,820000)	U(1000000,1400000)	U(290000,410000)	[5,15]	0.1
High	U(350000,1050000)	U(600000,1800000)	U(175000,525000)	[5,15]	0.3

Table 2. Levels corresponding to F3 (cost variability)

Analysis of Variance Table Response: ADOF					
	Df	Sum Sq	Mean Sq	F value	Pr(<F)
F1	1	8.76	8.76	10.074	0.001816**
F2	1	397.3	397.3	457.0132	< 2.2e-16***
F3	1	5.66	5.66	6.5135	0.011679*
F4	1	0.14	0.14	0.1651	0.685061
F5	1	182.18	182.18	209.567	< 2.2e-16***
Residuals	154	133.88	0.87		

Significance levels: 0*** 0.001** 0.01* 0.05.'

Table 3. ANOVA for ADOF

	F1 Network size	F2 Product Compl.	F3 Cost variability	F4 Emissions gen.	F5 Over-capacity
ADOF	⇑	⇑			⇑
NDOFS	⇑	⇑			⇑
PLU		⇓			⇓
PATC	⇓		⇓		⇑
DES		⇑			⇑

Table 4. Summary of the factors with clear influence in the different metrics, and their influence (⇓ means that as the factor goes from a low to high level, the corresponding metric decreases, while ⇑ means that the metric increases its value)